Analysis of Women's Rugby 7s Match Demands

Matthew Kan

BAppSc(Ex&SpSc), The University of Sydney, 2014

MHPS, Australian Catholic University, 2017

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Name: Matthew Kan

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Signed:

Name: Professor Rhonda Orr

Date: 27/02/2025

Faculty of Medicine and Health

Author Contribution Statement

Candidate Name: Matthew Kan

Degree Title: Doctor of Philosophy

Thesis Title: Analysis of Women's Rugby 7s Match Demands

As the research supervisor of the above candidate, I confirm that the above candidate has made the following contributions to the above papers presented in this thesis:

- Conception and design of the research
- Analysis and interpretation of findings
- Writing the review and critical appraisal of content
- Creation of figures and tables

Signed:

Name: Professor Rhonda Orr

Date: 27/02/2025

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Abbreviations

ACC	Acceleration Count
ACWR	Acute to chronic workload ratio
ALD	Acceleration Load Density
AU	Arbitrary Units
$AU.min^{-1}$	Arbitrary Units per minute
B	Back
BIP	Ball In Play
BOP	Ball Out of Play
CV	Coefficient of variation
d	Cohen’s effect size
CI	Confidence interval
$count.min^{-1}$	Count per minute
ES	Effect Size
F	Forward
XV	Fifteen’s
GPS	Global Positioning System
G	Gravitational force
Hz	Hertz
HSBC	The Hong Kong and Shanghai Banking Corporation
HSR	High speed sunning
HDOP	Horizontal dilution of precision
IMU	Inertial Measurement Unit
IRB	International Rugby Board
$J.s\text{-}1.kg^{-1}$	Joules per second per kilogram
kHz	Kilohertz
$km \cdot hr^{-1}$	Kilometres per hour

MV	Maximal velocity
m	Metres
$m \cdot min^{-1}$	Metres per minute
$m \cdot s^{-1}$	Metres per second
$m \cdot s^{-2}$	Metres per second per second
N	Number
VO_2	Oxygen Consumption
PLD	Peak locomotor demands
%	Percentage
P90	90th Percentile
p	p-value
RPE	Rating of perceived exertion
RHIE	Repeated high-intensity efforts
ROLL	Rolling method
VT_2 Speed	Second Ventilatory Threshold
s	Seconds
sRPE-ML	Session rating of perceived exertion match load
7s	Sevens
SSG	Small-sided game
SD	Standard Deviation
SEE	Standard error of estimate
SEM	Standard error of the mean
TD	Total Relative Distance
TRIMP	Training impulse
UBP	Utility/Ball Player
VHSR	Very-high speed running
$VHSR.min^{-1}$	Very-high speed running per minute
W.kg-1	Watts per kilogram
WCS	Worst-Case Scenario

ABSTRACT

Rugby 7s has evolved into a dynamic sport that has seen the game progress to new fronts on the world stage to be showcased at major sporting competitions, including the Olympic Games and Commonwealth Games. The women's game, in particular, has expanded rapidly over recent years, underscoring the growth of the game and women's sport in general. The application of microtechnology devices has become prolific tool in sporting settings and with the expansion of the women's game, an accompanied need to capture the demands of a sport and offer practitioners objective insight to adequately prepare athletes for these demands.

The thesis aims to evaluate and expand how match demands are assessed in women's rugby 7s and highlight novel contextual match factors that can affect running demands. A scoping review highlighted the scarcity of empirical evidence to analyse peak match demands, which aim to capture the fluctuations in training intensity, often overlooked when assessing whole-game and match-half averages. Similarly, there was a lack of distinction between positions beyond the traditional forwards and backs categorisation, under-reporting of hybrid roles with unique running and tactical characteristics in women's rugby 7s. The analysis of peak running demands highlighted the variability in reported values when assessing intercepts and slope values as part of power-law models. The variance between and within athletes are further complicated by the choice of the aggregation method (maximum, percentile, mean), as each method captured a unique match component and should be considered when applied in practice.

An analysis of international-level match demands was introduced as an innovative expanded method was developed to allow for future replication and accounts for inter- and intra-athlete variance and positional groups. The study explored the effect of tournaments and opponent rankings on running outputs. Analysis was structured into four categories: absolute time, relative time, absolute distance, and relative distance. Findings demonstrated that utility/ball players consistently cover more distance than backs and forwards. Velocity bin analysis highlighted significant differences with backs covering less distance between 4-6 $m \cdot s^{-1}$ than utility/ball players and forwards. Matches against invitational international teams showed lower distances between 40 to 60% speed bins than the top four teams. In contrast, more distance was covered overall when playing the bottom four teams, especially at lower velocities. The study findings highlighted that positions play a crucial role in understanding running demands, and adding a third role, utility/ball players, demonstrated the unique demands that require more time at higher running speeds compared to other positions. The thesis also provides scope for future studies to replicate the methods detailed within the thesis to analyse findings in diverse contexts, including the sub-elite competition level, as well as advance knowledge on female-appropriate classification of running demands.

CHAPTER ONE:

INTRODUCTION AND THESIS OVERVIEW

Rugby 7s

The sport of rugby 7s has grown prolifically in popularity by offering a dynamic alternative to the traditional 15-a-side game. Originating in Scotland in 1883, rugby 7s is played with seven players on each team on a full-size rugby field. Matches are significantly condensed lasting between 14-20 minutes consisting of two 7-minute halves and a two-minute break in between.[1]

The intensive physical demands of the sport require speed, agility, and endurance to sustain the fast pace, as well as strength, as part of the collision component of the game, which includes tackling and ruck contesting.[2] Rugby 7s entails a high level of tactical insight and technical precision to allow for accurate passing, quick decision-making, and effective execution under fatigue.[3] Furthermore, the fewer players on the field in rugby 7s places a strong emphasis on strategies, to create space through quick ball movement, strategic kicking to open space, and coordinating support lines that are critical for success.[3,4] Rugby 7s is unique to other team invasion sports as a typical tournament may consist of up to three games on a single day, over a two-to-three-day competition.

The sport has since grown into an internationally recognised sport, with the first official Rugby 7s World Cup taking place in 1993, which was a milestone in its global development.[5] Since then, rugby 7s has expanded beyond traditional rugby nations, gaining a foothold in countries such as Fiji, Kenya, and Japan. Today, more than 100 nations field both men's and women's teams.[1] A significant growth in popularity in both the men's and women's rugby 7s game has seen nations excel on the international stage, including teams such as New Zealand, Fiji, Australia, and South Africa[5], while nations such as the USA, Kenya, and France are becoming increasingly competitive, reflecting the sport's global expansion.

During the 20th century, there was a broad growth of women's rugby with informal matches being played as early as the 1980s, which gained more organisation and international recognition in the 1990s.[6] In 2009, the first Women's Rugby 7s World Cup held in Dubai, was conducted in parallel to the men's competition and showcased the skill and athleticism of female athletes.[5] The launch of the Women's HSBC World Rugby 7s Series during the 2012-2013 season marked a big step forward for the sport[7] along with its inclusion in the 2016 Rio de Janeiro Olympic Games[8] and the 2018 Commonwealth Games[9] generating further recognition.[5] These milestones not only boosted the sport's visibility but also encouraged nations to prioritise the growth of the women's game into an essential part of rugby 7s worldwide.

Intensity, Match Characteristics, and the Training Process

The concepts of *intensity* and *match characteristics* are central to understanding athlete performance and are frequently referenced across sports science literature and applied practice. Despite their widespread use, these terms are often poorly defined or used interchangeably, particularly in settings involving performance monitoring or training design. Clarifying these constructs is essential, as they directly shape how training is prescribed, how performance is interpreted, and how measurement tools such as GPS microtechnology are applied in practice.

Match characteristics broadly refer to the physical, technical, and tactical demands experienced during competition.[10] From a physical standpoint, this includes the total work performed (e.g., total distance, number of sprints), the distribution of effort across movement intensities,[11] and the frequency of sport-specific actions such as collisions or set-pieces.[12] The demands experienced during a match are shaped by contextual factors such as competition level, tactical approaches, and positional roles, and are inherently sport specific.

Intensity, by contrast, refers to the rate at which work is performed. While in general terms it may reflect how hard a task feels, scientifically, intensity can be interpreted through various lenses. Physiologically, it may be represented by metrics such as heart rate, oxygen consumption (VO_2), or energy expenditure.[13] Mechanically, intensity may relate to speed, acceleration, or ground reaction forces.[14] In practice, GPS-derived metrics, such as metres per minute are commonly used, yet they conflate spatial and temporal dimensions and may not truly reflect the effort involved, especially during low-movement but high-effort situations, like a ruck. As Whitehead et al. (2018) noted, misinterpreting such values can lead to misleading conclusions about workload or fatigue.[15]

In the training context, intensity is a primary driver of adaptation.[16] However, its definition and application are influenced by multiple interacting factors, including the internal response (heart rate, rating of perceived exertion) and the external work performed (distance, sprints). As such, intensity should not be viewed in isolation but rather within the broader training load framework, which includes volume, frequency, and specificity.[17,18] A useful distinction is made between *internal* and *external* load,[19] where internal load reflects the athlete's biological response, and external load represents measurable physical output. Although both are important, external measures are more frequently used in team sport contexts due to the logistical challenges of real-time physiological monitoring.[20]

The ecological dynamics framework offers an alternative approach to understanding training intensity, suggesting that athlete behaviour emerges from interactions between task, environment, and individual constraints.[21,22] Within this framework, intensity is not only about load; it is shaped by task complexity and contextual demands. For instance, manipulating field size or player numbers can elevate both physical and cognitive intensity,[23] encouraging behaviours more representative of competition. This approach contrasts with traditional periodisation models, which define intensity primarily in terms of mechanical output.[16]

Recent work suggests integrating physiological thresholds with ecological principles to improve the realism and effectiveness of training.[24,25] Training that simulates the complex, dynamic nature of competition is more likely to transfer to performance than training based solely on volume or speed metrics.

Empirical evidence supports the need for training programs grounded in match demands.[26] Peak match intensities, such as those captured through rolling average analyses, represent the upper bounds of physical stress encountered in competition and are useful benchmarks for conditioning targets.[27]

Training sessions designed around these benchmarks improves specificity and ensures that athletes are prepared for the most demanding periods of play.

Nonetheless, applying match-derived data to training requires caution. Reproducing peak intensities too frequently may increase injury risk or result in overtraining, particularly if not aligned with athlete readiness or recovery.[28,29] Intensity must therefore be integrated with technical, tactical, and psychological considerations, not used as an isolated variable.[30]

Traditional periodisation models, including linear and undulating schemes, quantify intensity using external metrics such as a percentage of one repetition maximum or percentage of maximal velocity (%Vmax).[31] While evidence-based, these models may lack ecological validity in sports like rugby 7s, where match demands are unpredictable and multifaceted.[32] By contrast, constraint-led training allows coaches to shape intensity through contextual task demands. Empirical data show this method can match or exceed the intensity of isolated drills while also developing decision-making and technical skill.[22]

In applied rugby 7s contexts, where athletes are subject to high-frequency, high-intensity demands, combining GPS microtechnology data with ecological task design offers a practical and effective method for replicating match intensity. Coaches can use positional data and rolling average outputs to design task-specific drills that mirror game constraints, ensuring both physical overload and contextual relevance.[33]

Ultimately, intensity should be viewed as one element in a multifactorial training process. While metrics provide valuable insight, they must be interpreted within the broader context of the athlete's readiness, match role, and developmental objectives. To optimise training, practitioners must understand the physiological, mechanical, and behavioural dimensions of intensity and match characteristics—and how these interact in shaping performance outcomes.

The alignment of training with the demands of competition are particularly critical in light of the principle of specificity, which requires that training replicate the intensity, structure, and variability of actual competition.[26] To do so, practitioners must first identify what the sport demands of the athlete, including peak periods, position-specific movement patterns, and how these vary by context. Without clear definitions of intensity and match characteristics, training risks becoming misaligned with competition goals.

Further, the growing emphasis on individualised training has elevated the need to capture within-athlete variability. To better explain the individual athlete, research have examined the adoption of relative thresholds (e.g., %Vmax) for monitoring and prescribing high-speed exposures.[14,15] Yet this raises a conceptual challenge: are we seeking to match mechanical output, internal stress, or perceived effort? Each conceptual domain represents a distinct component of intensity, and each requires a tailored approach to measurement and application.

Tools such as GPS, accelerometry, and metabolic models help quantify these constructs. However, their value depends on how well they reflect the underlying concepts they're intended to measure. For example, GPS microtechnology-derived distance may underestimate intensity during low-displacement, high-effort activities such as rucks or mauls.[34] Similarly, using acceleration or speed alone may misrepresent load in sports with frequent decelerations, contact events, or positional play.

Given the limitations discussed above, the term "exposure" may better reflect the multifactorial nature of training load. Unlike "workload," which often implies a purely mechanical accumulation, exposure incorporates both the quantity and *type* of demands imposed on an athlete over time.[35] This broader framing is more compatible with complex team sport demands and emerging models of athlete monitoring, which seek to integrate load, context, recovery, and readiness.

To draw meaningful insights from microtechnology and tracking data, practitioners must first achieve clarity around what they are measuring. Without clear conceptual boundaries, metrics lose their practical utility, and decisions around training design, athlete management, or performance evaluation become compromised.

Global Positioning Systems

Global positioning system (GPS) technology initially emerged in the 1980s for military navigation and was later adapted for civilian and sports use in the early 1990s.[36] Presently, GPS devices are used routinely across a variety of sports, from team games such as football, rugby, and basketball to individual sports such as athletics and cycling, as a method to track the position and movement of athletes during training, competitions, and matches. Real-time measurements of distance, velocity, acceleration, and deceleration are common measures that provide instantaneous feedback on player outputs, ultimately providing practitioners with continuous streams of data that can used in assessments of training and match prescription. GPS devices more commonly grouped as 'wearable microtechnology' have evolved to integrate with other technologies such as accelerometers, which are integral components of many GPS devices used in sports performance monitoring.

Accelerometers are capable of measuring acceleration along three orthogonal axes (x, y, z) and often operate at higher sampling rates, commonly around 100 Hertz (Hz), allowing for precise detection of changes in movement and acceleration forces. The data collected from these axes can be used to calculate composite vector magnitudes, often referred to as the G-force (g), which represents the overall acceleration experienced by the athlete. When combined with other microtechnology sensors, such as gyroscopes and magnetometers, they form a more advanced system in the form of inertial measurement units (IMU).[37] This integration allows for the implementation of algorithms that are utilised to detect actions such as tackles and collisions in rugby league,[38] scrums and lineouts in rugby union[39,40] and kicking movements in soccer.[41]

The validity and reliability of GPS technology are essential considerations in its application for monitoring performance. Validity refers to the accuracy of the device in measuring intended parameters, while reliability refers to the consistency of measurements across repeated assessments.[37] GPS devices generally demonstrate strong validity and reliability for metrics such as total distance and average speed during continuous, steady-state activities.[42,43] However, precision diminishes when assessing rapid high-intensity movements such as accelerations, decelerations, and directional changes, particularly in devices with lower sampling frequencies.[11] Devices drawing on higher sampling frequencies have been shown to provide greater reliability when assessing these high-intensity movements with the main differences observed between various GPS manufacturers predominantly governed by filtering methods and data-processing algorithms.[44] The differences observed between manufacturers create challenges when examining the literature, as comparisons between providers identified trivial to small effect sizes (ES) between providers when assessing total distance (ES ± 95% CI: -0.3 ± 0.4) and low-speed running (ES ± 95% CI: 0.5 ± 0.5), with large to very large magnitude of effect for moderate-speed (ES ± 95% CI: -3.1 ± 0.7) and high-speed running (ES ± 95% CI: -1.3 ± 0.5) measures.[45] Despite this limitation, GPS devices are critical tools for monitoring and informing training interventions in sports.[46,47]

Application of GPS Microtechnology in Sport

The integration of GPS microtechnology into sports analysis has evolved from its early adoption for tracking basic movement metrics to more complex metrics such as impacts, accelerations, decelerations, and metabolic power.[38,39,48] These advancements are, not only beneficial for assessing individual performance but also play a crucial role in understanding the broader tactical and team dynamics.[36] As research into the application of GPS in sports progresses, the scope of its utility has expanded, especially in areas such as match profiling, load monitoring, injury prevention, and the development of sports-specific algorithms.[38]

Identification of Match Demands

Analysis of performance demands forms a key pillar in profiling any sport, with GPS microtechnology having become prolific as a tool to assess these demands in both a match and training context.[39,49] In team sports such as rugby 7s, demands can often be categorised into locomotive metrics (e.g., total distance, high-speed running, accelerations, and decelerations) and sport-specific actions that involve the use of detection-based algorithms to classify specific movements such as collisions, scrums, and lineouts.[50,51]

Research has predominantly examined match demands in the context of whole-game totals where rugby 7s players can typically cover total distances between 916 to 1,660 m per game at the team level. However, these demands vary by playing position depending on the metric selected, reflecting the unique requirements of each role.

More nuanced approaches have been examined to reflect the intermittent nature of sports such as rugby 7s, where players experience fluctuating intensities in a match. The highly intensified periods are termed 'worst-case scenarios' (WCS).[52] Comparisons between WCS and whole-game averages of relative total distance ($m \cdot min^{-1}$) can differ between approximately 25-30%, whereas measures of relative sprint distance ($m \cdot min^{-1}$) span a larger variance in outputs between 60 to 265%.

Analysing the WCS requires processing sample-by-sample positional data derived from GPS microtechnology, where a rolling average duration is applied over pre-defined number of rows (i.e. 1 minute is equal to 600 rows of data) to determine an average value that is specific to the duration and metric being examined.[53] The rolling average process is repeated across other durations to establish duration-specific running demands before being modelled against power-law relationships. The power-law model demonstrates the inverse relationship that as duration increases, running intensity decreases non-linearly.[53] Practitioners can use the power-law model to extrapolate a straight line with associated slope and intercepts to compute running intensities based on a chosen duration.

The computation of running intensities from power-law models has been used as a tool to compare rugby 7s positional groups where it was demonstrated in a match that peak backs experienced higher high-speed running demands compared to forwards when analysed over 1-minute intervals.[52] Additionally, the distinctions in peak acceleration activities in rugby 7s were evident when compared to rugby union, where small differences in intercepts (ES ± 90% CI: 0.31 ± 0.20) were observed (26. Interestingly, trivial differences (ES ± 90% CI: -0.12 ± 0.17) in intercepts were observed when comparing rugby union vs rugby 7s in relation to 1-minute peak total distance activities (161 vs 155 $m \cdot min^{-1}$, respectively).[52] While peak values provide valuable insights into positional and sport-specific demands, they may not always clearly differentiate between positions or seamlessly translate into training implications. This underscores the need to understand the composition of match demands as measures that can be expressed in absolute (m and m·s^{-1}) and relative terms (e.g. percentage of an individual's maximal velocity).

Relative thresholds, such as those based on individual maximal velocity, offer a more athlete-specific approach by contextualising running outputs to an individual's physical capabilities.[54,55] However, the lack of standardised speed thresholds across studies is an evident critical issue when employing this method.[56-60] Metrics of high-speed running (HSR) and sprinting can differ between studies, leading to inconsistencies in reported data. For example, HSR has been established at 5 m·s^{-1} [61] but has also been reported at speeds greater than 5.5 m·s^{-1} [62,63] while sprinting can typically have a bandwidth between 6 to 7.5 m·s^{-1}.[66] The lack of uniformity in sprint metrics has the potential to misrepresent running outputs which complicates direct comparisons between studies, may obscure meaningful insights, and lead to increasing injury risk due to inappropriate prescription of training.[65]

While the lack of standardisation complicates comparisons between studies, contextual factors have also been examined to identify the effect on match demands. Match outcomes such as winning, losing, and score differentials[66] had a significant effect on match outputs, for instance, greater score differentials were associated with higher total distances and high-speed running outputs, whereas closer matches led to increases in defensive exposures that involve locomotive demands that are typically lower in speed. These findings, together, highlight the intricate interplay of physiological, tactical, and contextual factors that influence performance, which must be understood at both the team and individual levels.

Performance Monitoring

Early concepts of monitoring are evident through Bannister's Fitness-Fatigue model which aimed to describe the impact of training on athletic performance.[67] Bannister's model is based on the concept that a physical stimulus (i.e., training) leads to two opposing physiological responses: fitness and fatigue. This paradigm has led to models such as the acute-to-chronic workload ratio (ACWR) being developed, where the acute workload is representative of an athlete's fatigue response and chronic workload representing long term benefits from training that improve performance (fitness).[68]

Measures such as total distance can be used to quantify the ACWR, where the ratio of acute (measured in the past week) divided by chronic workload (average weekly workload over the previous four weeks), reflects an athlete's balance of short- and long-term training loads.[69] Studies have demonstrated the link between ACWR and outcome measures such as injuries and monitoring return-to-play progressions.[70] Similar to debates on the classification of speed thresholds, categorising ACWR ranges as descriptors (i.e. low, moderate, high, very high) has lacked consistency.[71-73] For example, assessments of very-high ACWR reported a wide array of cut-offs ranging from 1.4[74] to 2.32,[75] which is further complicated by the sport being examined as very-high ratios up to 3.0 have been reported in Australian Football.[74] Furthermore, some researchers have proposed methodological flaws in the calculation of ACWR, raising concerns regarding the extent to which this method is used interchangeably with the original model.[68] It has been advocated that the normalisation process associated with the calculation of ACWR may introduce noise when examining exposure-injury models[49] through statistical artefacts.[76]

Despite its potential limitations, ACWR remains a viable assessment tool to monitor athlete readiness and inform decision-making processes to identify players that are at risk of overtraining or undertraining.[28] ACWR should, however, be contextualised as part of multiple factors that contribute to performance, injury risk, and ensuring physical preparedness. When used alongside GPS microtechnology, which has transformed the understanding of the performance demands of sports, ACWR serves as a simplified monitoring tool employed in a practical setting.[77]

GPS devices track the movements of athletes which are used by performance coaches and sports scientists to provide instantaneous feedback on volumes of load and intensity. Thus, data-driven decisions can be made regarding adjustments to match-play and training loads and strategies that aim to promote optimal physiological adaptations and improve training load capacity.[78]

Longitudinal monitoring of a season leading into an Olympic men's rugby 7s campaign identified lower volumes of high-speed distance (-11.0 ± 7.8%, ES ± 90% CI: -0.26 ± 0.18; small) when comparing in-season to pre-season periods.[79] A similar reduction was observed for total distance over the third mesocycle (5 weeks) compared to the first in-season mesocycle (-32 ± 4%, ES ± 90% CI: -

1.1 ± 0.14; moderate). When combined with other wearable devices such as heart rate monitors, a gauge of internal load can be used to measure the physiological response to training load[80] and in turn, promote the management of loads to improve regeneration, player availability, and athletic performance.[49,81]

Sport-Specific Movement Detection

The combination of wearable technology (GPS, magnetometer, accelerometer, gyroscope) has led to the development of innovative solutions to capture sport-specific movements through the use of microtechnology and algorithms developed to detect unique movements, such as collisions.

In rugby, accurately detecting and quantifying collisions is crucial for assessing a key demand of the sport apart from the locomotive measures that are well established.[82] Traditional analysis through video footage offers detailed insights into specific events and player techniques but can often be time-consuming and prone to error.[83] Microtechnology provides an automated and potentially more objective assessment of collision events, quantifying metrics of intensity, frequency, and duration.[83] Although the validity and reliability of some GPS metrics have not been established, microtechnology has a high sensitivity (97.6 ± 1.5%) and specificity (87.6 ± 2.9%) in the identification of collision events.[38]

The use of collision data provides several practical applications including the monitoring and manipulation of contact loads in training, potentially reducing the risk of injury through contact-related mechanisms and ensuring physical preparedness.[38] This facilitates comparisons of collision characteristics across different playing positions, enabling greater specificity in developing conditioning programs.[84] While no longitudinal studies have examined its efficacy as part of traditional load monitoring measures, microtechnology can be employed as a tool to evaluate training drills and their similarities in replicating match demands.[27]

Performance Characteristics in Women's Rugby 7s

The study of performance characteristics in women's rugby 7s has historically been overshadowed by research conducted in the men's game, with findings in men often generalised to female athletes without sufficient consideration of the unique physiological, physical, and metabolic differences between the sexes.[85-87] The unique distinction of the female athlete raises critical questions on the appropriateness of applying male-derived speed thresholds and performance metrics to the female cohort, and the validity of reported match demands in women's rugby 7s. Furthermore, the literature's sparse representation of female athletes, particularly at the sub-elite level, highlights a significant gap in understanding the demands of the sport for this population.

The Male and Female Athlete

Research indicates that women's rugby 7s players exhibit lower absolute high-speed running[88] and sprinting distances than their male counterparts which can largely be attributed to inherent physical and physiological differences.[88,89] The female athlete typically has lower muscle mass, high body fat percentages, and distinct hormonal profiles, influencing energy metabolism, recovery, and performance outputs.[90,91] Physiologically derived assessments of running capacity have since been considered as a method to understand the physiological difference between males and females.

The accurate classification of locomotor and metabolic intensities in team sports is contingent upon the thresholding methods used to define effort zones. Multiple approaches exist, each with distinct theoretical foundations, strengths, and limitations. Traditionally, absolute thresholds, such as high-speed running defined as movement exceeding 5.5 $m \cdot s^{-1}$ have been commonly applied for their simplicity and ease of comparison across players and teams.[59] However, such fixed thresholds are insensitive to individual variation in physical capacity, which can lead to potential underestimation or overestimation of load for players with relatively lower or higher maximal running speeds.

Alternative thresholding methods, grounded in physiological profiling, attempt to overcome these limitations by anchoring intensity to internal markers of exertion. These include thresholds based on maximal aerobic speed (MAS), lactate thresholds (LT), or ventilatory thresholds (VT), typically derived from structured field or laboratory assessments such as the 30–15 Intermittent Fitness Test or graded treadmill protocols. These thresholds delineate specific physiological zones, including the transition from steady-state to supra-threshold effort, and are generally considered to reflect individual internal capacity more accurately than arbitrary cut-offs.[92,93] Despite their physiological precision, these methods require periodic testing, precise equipment (such as lactate analysers or respiratory gas analysis), and controlled environments. The specialised requirements may be impractical in elite, high-performance settings with large squads and limited testing windows.

The second ventilatory threshold (VT_2 speed) corresponds to the point where there is greater production of carbon dioxide compared to oxygen consumption[61] and has been proposed as a method to determine appropriate HSR thresholds for female athletes.[94] Compared to HSR thresholds that are more commonly reported in absolute terms, with emphasis on speeds at 5 $m \cdot s^{-1}$ and greater,[95] Clarke and colleagues (2015)[94] deemed speeds greater than 3.5 $m \cdot s^{-1}$ to be female-appropriate thresholds for international players. Utilising male derived speed zones of 5 $m \cdot s^{-1}$ have led to underestimations of running performance by 30% when compared to the 3.5 $m \cdot s^{-1}$ proposed.

Assessments of maximal velocity to determine appropriate speed zones have also been predominantly based on data from male athletes. Female athletes generally exhibit lower maximal velocity capacities closely linked to the reduced force and power capabilities.[66,94,97] Male rugby 7s players' maximum speeds range from 7.25 to 8.7 $m \cdot s^{-1}$ [4,88,96] while female values range from 6.36 to 8.05 $m \cdot s^{-1}$ [66,88,97] thereby making general comparisons flawed when utilising absolute measures ($m \cdot s^{-1}$) as determinants of speed thresholds.

Expressing maximal velocity outputs relative to an individual's maximum may diminish the discrepancies seen when comparing absolute maximal velocities between genders. However, direct comparisons between cohorts have not been examined in the literature to definitively determine the similarity in percentage of maximal velocity in a match context. Reported percentage of maximal velocity (%) in elite women's rugby union athletes are 85.7 ± 8.95 $m \cdot s^{-1}$ with positional groups accounting for the variance in percentages achieved.[99] From a research perspective, this method enhances the sensitivity and specificity of locomotor profiling. It reduces misclassification of effort intensity and improves internal validity when comparing across individuals or positions. This is particularly relevant in rugby 7s, where significant variability exists in sprint capacity based on positional roles and tactical demands. From a practical standpoint, V_{max} values are readily available from GPS microtechnology systems, allowing for ongoing monitoring without the need for additional testing. Moreover, using match-derived V_{max} ensures thresholds reflect performance achieved in the competitive environment, which may exceed velocities observed during controlled sprint testing.[28]

Discrepancies have also been reported for measures of acceleration and deceleration profiles between genders, where males typically have longer acceleration phases and shorter deceleration phases compared to women further emphasising the importance of context-specific interpretation when comparing the differences between sexes.[100]

The lack of distinction between male and female speed zones raises concerns for the generalisability of GPS thresholds and the potential to obscure meaningful insights into the true demands of the female game. The risk of underestimating locomotive and metabolic demands is heightened, resulting in sub-optimal training prescriptions to potentially hinder performance and increase injury risk.

Beyond Traditional Measures

While traditional analyses of metrics such as total distance, HSR, and sprinting have been reported, albeit difficult at times, to provide comparisons between studies, there is a growing need to explore additional performance indicators that may better capture the unique demands of women's rugby 7s. There is a distinct underutilisation of metrics such as repeated high-intensity efforts (RHIE)[101] and metabolic power[58] in the female cohort, despite their potential to provide deeper insights into the intermittent and high-intensity nature of the sport. RHIE refers to actions performed by an athlete repeatedly in bouts of maximal or near-maximal interspersed with short recovery periods.[102] These involve actions such as sprinting, collisions, and accelerations, which are critical in sports like rugby 7s where players must sustain high-intensity outputs and actions.[52] Male rugby 7s players can experience 26.7 ± 7.2 high-intensity efforts with 3.7 ± 1.7 repeated efforts, which is defined as three or more high-intensity actions with less than 21 seconds recovery between efforts.[52] To the author's knowledge, there are no studies that have been conducted in women's rugby 7s to allow for comparative assessments between sexes.

Similarly, metabolic power also aims to quantify high-intensity actions through derivatives of instantaneous energy expenditure calculations based on GPS-derived speed and acceleration data. Estimates of energy cost are based on biomechanical equivalence to flat terrain running and uphill or downhill running at constant speeds.[103] Metabolic power has been predominantly examined in Australian Football and rugby league in which it was demonstrated that women's rugby 7s had comparable mean metabolic power outputs to men's rugby league matches (8.2 – 9.0 $W.kg^{-1}$)[104] but substantially lower than Australian Rules Football (9.2 – 10.9 $W.kg^{-1}$).[105] Similar to RHIE, the literature is scarce when comparing men's and women's rugby 7s. However, existing data highlight a pronounced gap between developmental and international level players for elevated (35-55 $W.kg^{-1}$) and maximal effort (> 55 $W.kg^{-1}$) metabolic power.[58] These findings underscore the need for sport- and sex-specific benchmarks to better interpret performance demands.

Positions and Competition Level

There is a distinction between positional groups in women's rugby 7s as research has traditionally categorised players into two broad groups (forwards and backs). The binary classification of positions may not adequately capture the diversity of roles and physical demands within the sport. A distinct difference was observed in elite male rugby 7s forwards that engage in 25% more collisions and accelerations in a match compared to backs, whereas backs would typically cover 20% more HSR.[106] Comparatively, elite women's rugby 7s players have comparable sprint distances between forwards and backs, while preliminary data suggests smaller positional differences when examining collision frequencies greater than 10 g (ES ± 90% CI: 0.55 ± 0.66).[94]

There is also a paucity of research on sub-elite female athletes, creating challenges when comparing research findings across multiple playing levels. While elite-level international competitions have been the primary focus of existing studies, the majority of female rugby 7s players compete at sub-elite levels, where access to advanced performance technology, such as wearable microtechnology, is at times, limited. This creates a significant gap in understanding the performance characteristics of the female cohort, particularly when compared to men's rugby 7s. Sub-elite male players exhibit ~15% less HSR and ~26% fewer sprint distances than elite players.[88] Similar trends likely exist in women's rugby 7s, but the limited data on this population obscures clear distinctions and potentially leads to the misapplication of training models that were modelled from elite rugby 7s players with heightened physiological, technical, and tactical capacities.

Presently, the analysis of match demands has traditionally focused on whole-match averages, often neglecting the significance of peak values and peak passages of play in a match. This limitation is particularly important, as identifying peak demands provides an understanding of physically demanding periods of play and how peak running demands can be quantified using GPS microtechnology. While these intensified periods are essential to match analysis, their application in women's rugby 7s is scarce and largely remains unexplored compared to other sports. Furthermore, existing research in rugby 7s has primarily focussed on broad position categories (forwards and backs) potentially overlooking the growing prevalence of hybrid roles, which require more distinctive analysis and therefore expand the profiling of diverse physical demands across all player roles.

Another notable gap lies in the aggregation of speed zones that rely on fixed bands to quantify running demands, which can mask variability and unique requirements across different positions. Comprehensive analysis involving the examination of an entire spectrum of velocities is an area that requires more granular exploration to underscore the key element of speed in rugby 7s. Furthermore, there is little to no evidence examining the variance in tournaments and opponent rankings within a rugby 7s season, with a primary focus on a key component of rugby 7s, speed. Considering that tournaments are typically structured around consecutive games played over short timeframes, providing a holistic understanding of the sport's demands will aid in informing evidence-based practical strategies that are tailored to the unique characteristics of the sport.

THESIS AIMS

This research addresses critical gaps in the existing literature by evaluating and redefining how match demands are currently analysed in women's rugby 7s. This research aims to enhance match demand assessments to accurately quantify the unique demands of elite women's rugby 7s competition and highlight novel contextual match factors that can affect locomotive demands. Furthermore, the research adds to existing literature or at times the limited empirical evidence that adequately examines methods of match analysis and the implications the findings can have in practice. By providing a transparent methodology for analysing match demands, the research facilitates the replication of studies across different teams and, most importantly, can be analysed for sub-elite competition levels.

The specific objectives and hypotheses are to:

1. Conduct a scoping review to evaluate the current literature to identify peak and match demands in women's rugby 7s;
2. Investigate aggregation methods when analysing peak match demands in current international women's rugby 7s players and identify the variability in reported values;

   It is hypothesised that:

   - Peak values will differ across GPS metrics examined allowing for differentiation of positional groups; and
   - There is a large variance of reported values across individuals and matches.
3. Propose an expanded methodology to quantify match demands that incorporates individual player variability, positional distinctions, and tournament-specific contexts
4. Conduct a retrospective cohort study to identify player, position, and tournament associations to match demands in women's rugby 7s.
   - It is hypothesised that distance and time accumulated across absolute ($m \cdot s^{-1}$) and relative (%) measures will differ between position groups

THESIS OVERVIEW

This thesis investigates the whole match and peak demands of women's rugby 7s through a scoping review and empirical analysis using GPS microtechnology. The thesis is presented across six chapters:

Chapter One: Overview and Thesis Aims

Chapter One provides a brief overview of the sport of rugby 7s, use of GPS microtechnology, the application of GPS microtechnology in sport as well as women's rugby 7s. This chapter will also frame the aims of the dissertation and outline the direction of the thesis based on its structure and chapters.

Chapter Two: Match Demands of Women's Rugby 7s: A Scoping Review

Chapter Two presents a scoping review of current literature to examine the peak and overall match demands of women's rugby 7s through GPS microtechnology. Eighteen studies were examined as part of this review, highlighting the current match demands and lack of understanding regarding peak demands in this cohort. The chapter also discusses the limitations with the current approach of analysing match demands.

Chapter Three: Analysis of Peak Running Demands

Chapter Three addresses the scarcity of data and analysis of peak match demands, both as an investigation into its current methods which includes the aggregation of peak values and examination of the variability in reported values when utilising peak running demands in practice. This chapter underscores the key considerations when reporting peak values across a team, positional group, and between individuals.

Chapter Four: Methodology Chapter – An Expanded Approach to Match Demands

As Chapter Three identifies multiple methodological considerations when implementing peak locomotive demands analyses, chapter four addresses some of these limitations recognised. This chapter provides a detailed methodology for applying a granular approach in understanding match demands in elite women's rugby 7s players. The transparency of this chapter ensures future studies can replicate the methods, as presented in chapter five, contributing to a deeper understanding of the complexities involved in analysing match demands.

Chapter Five: Match Demands of Women's Rugby 7s

The detailed methodology developed in chapter four is applied in this chapter, using a longitudinal retrospective cohort design. The analysis draws from a robust dataset from elite competitions, including the HSBC World Sevens series and Olympic Games, providing detailed insights into the dynamic nature of match speeds and performance demands.

Chapter Six: Discussion

Chapter six synthesises findings from chapters two to six, highlighting the relevance of findings to practitioners while also addressing study limitations and suggesting future research directions. Conclusions regarding the use of GPS-derived measures to assess match demands, alongside practical applications of the findings, are presented in this chapter.

SIGNIFICANCE OF THIS RESEARCH

This research provides critical insights into the match demands of women's rugby 7s, addressing a vital gap in the existing literature. Current methods for assessing match demands using GPS are explored, questioned, refined, and applied, ensuring the findings contribute to a more accurate and nuanced understanding of match dynamics.

Significantly, the thesis advances the growing body of evidence related to match demands in rugby 7s and makes a substantial contribution to the underrepresented area of women's rugby 7s. These insights have implications for improving training practices, optimising performance, and guiding future research to replicate methodologies employed in this thesis while offering direction within the area of match demands.

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CHAPTER TWO:

MATCH AND PEAK DEMANDS OF WOMEN’S RUGBY 7S

A SCOPING REVIEW

ABSTRACT

Objective: This scoping review aims to explore the use of GPS and microtechnology devices to quantify typical match and peak demands in women's rugby 7s.

Data Sources: Electronic databases including Medline, SPORTDiscus, Web of Science, SCOPUS, and Embase were searched from earliest publication to August 2024. Reference lists of retrieved papers were also reviewed for potential studies.

Study Selection: Studies were included if they reported GPS and/or microtechnology-derived examination of rugby 7s match-play and were examining a female population. Review papers and original investigations not written in English or those that could not be translated were excluded.

Results: The search returned 164 studies, with 18 studies being eligible for inclusion in this review. Methodological quality scores for the studies included were high, ranging from 8 to 10 out of 11 criteria. Across the range of device metrics, distance was most used, while acceleration, deceleration, and metabolic power were limited in the literature. Elite women's rugby 7s players covered a mean match distance 1,408 ± 350 m and running speed of 7.33 ± 0.8 $m \cdot s^{-1}$, based on aggregated descriptive statistics from individual studies. Elite players endorsed greater maximal sprint speeds and higher running and physiological demands than lower-level players. When pooling both forwards and backs, players demonstrated a small reduction in peak locomotor output from the first half (mean = 106 $m \cdot min^{-1}$) to the second half (mean = 93 $m \cdot min^{-1}$), with an estimated effect size of $d = 0.31 \pm 0.39$, indicating a small but meaningful decline in running intensity across halves. A lack of uniformity and suitability of speed thresholds for women's rugby 7s was identified. Inconsistencies were observed in positional play in running, acceleration and deceleration demands. The emerging use of ball in play analysis and power law modelling may enhance our understanding of peak demands, periods of highest intensity and positional play differences.

Conclusion: The scoping review provides a detailed analysis of the use of GPS microtechnology devices to quantify match and peak demands in women's rugby 7s. Analysis of peak demands is novel when examined in the context of women’s rugby 7s. It underscores the key performance measures and methodological considerations in this area of research.

Keywords: global positioning system, microtechnology, tournament

1 INTRODUCTION

Wearable global positioning system (GPS) devices equipped with microsensor technology (accelerometer, magnetometer, and gyroscopic sensors)[1] are widely used in team sports to quantify player movements during training and match play.[2,3] The technology allows coaches and scientists to measure a wide range of player kinematic and exposure demands, including speed, acceleration, distance covered, work rates, intensity, and collisions. Recent research has focused on identifying maximal periods of match play to inform training program design based on match-play demands to optimise performance and minimise injury.[4]

In recent years, the significant progression of women's rugby 7s to being an Olympic event has been accompanied by growing scientific research in the sport.[12,14,17,19,22] The game is played on a full-sized pitch with only seven players on each time rather than the 15 players typically found in rugby union with 2 x 7-minute halves. This results in a faster, more open game with a higher number of tries and greater emphasis on skill and speed.[6] Rugby 7s has utilised GPS microtechnology to aid in understanding its fast-paced nature and the identification of key physical demands of the sport, such as high-intensity running and repeated sprint efforts.[5] Comparisons between both the fifteen-a-side and 7s format of women's rugby identified that rugby 7s exhibited higher running intensities and volumes compared to rugby union when extrapolating for time which is likely due to fewer players on a same sized pitch, thereby leading to more space and opportunities for high intensity running and accelerations.[18] Women's 7s athletes can expect to cover 133 metres at high speeds (> 5.5 m·s^{-1})[21] compared to 106 metres in international women's rugby matches.[7]

Global positioning system devices typically have an array of sampling rates, micro-processing chip set and data-processing capabilities which can introduce errors as part of the data collection process and is highly advised to determine reliability and validity of measurements.[58] Microtechnology now allows for the auto-detection of collisions and contacts, presenting new opportunities for analysis. Clarke et al. (2017b)[31] were the first to include impacts greater than 10g, derived from GPS devices in their study basing the unvalidated metric on manufacturer recommendations and an earlier study.[31]

Subsequent studies have since been reported that the microtechnology devices have a sensitivity of 97.6 ± 1.5%, and a high specificity (87.6 ± 2.9%) for impacts >10g[38] and were strongly correlated with video coded collision events, thereby displaying its viable use as a tool for training load management and quantification of matches that improves processes that were predominantly manual notational analysis.[19,62]

Collision loads experienced during match play have since been compared between the two formats of the game. Compared to rugby 7s, rugby union matches experience a higher absolute number of collisions but lower relative frequencies, which refers to the number of events occurring per unit of time (e.g., collisions per minute). The higher relative count can be attributed to the shorter duration of a match and the need for all players to be involved due to the lessened numbers playing on the field.[40,41]

Research has also contributed to knowledge of the differences between men and women within rugby 7s. Male rugby players typically cover greater relative distance, distance at high intensity, and have a higher maximal velocity than female rugby 7s players.[16] This finding is consistent with research in rugby union.[41] The proposed mechanisms that may result in differences include lower physical capacities of female athletes and differences in muscle architecture that aid in force production, high-intensity running, and impacts.[16] Based on these findings, establishing speed zones modelled on male athletes (>5.5 $m \cdot s^{-1}$) has led to underestimating the amount of high intensity running performed by women, which can be as high as 20%.[14] Adjusted thresholds for female players, set at 4.7 $m \cdot s^{-1}$ (equivalent to 61% of a player's maximal velocity), provide a comparable basis for analysing running outputs between male and female rugby 7s matches.[22] When speeds are expressed relative to an individual's maximal velocity, similar high-intensity running outputs have been observed between males and females during match-play.[22]

Understanding the overall match demands of rugby 7s can inform the development of training programs that target specific physical and technical requirements of typical matches but may not reflect the varying and unpredictable nature of the game, which involves periods of intensified demands and decrements in match outputs.[8] Studies conducted in other sports have gathered worst-case scenario (WCS) thresholds that can be applied to training modalities to assess relative intensities to a match and replicate these moments in training.[9] Examination of the WCS found that international male rugby 7s players can experience periods that were 16% higher than the average demands while also demonstrating a subsequent reduction in relative distance and metabolic power proceeding a 2-minute intensified period of running demands.[9] This analysis method, however, is sparse when applied within the women's space. As such, this scoping review will explore the use of GPS microtechnology in women's rugby 7s to quantify typical and peak match demands to enhance the understanding of the specific nature of the sport.

2 METHODS

2.1 Design and Search Strategy

A scoping search was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) checklist.[33] using five electronic databases (Medline, SPORTDiscus, Web of Science, SCOPUS, and Embase) from the earliest publication to August 2024. The following terms were devised based on the PICO framework, which utilises a specific population, intervention, comparator, and its outcomes in order to devise the given search strategy; ("rugby 7*" OR "rugby seven*" OR "rugby-7") AND ("female*" OR "women*" OR "woman") AND ("GPS" OR "global positioning system" OR "microtechnology" OR "accelerometer" OR "accelerometry" OR "PlayerLoad" OR "triaxial" OR "inertial measurement unit" OR "IMU"). Reference lists of the retrieved papers were also reviewed manually for other potentially relevant studies. No additional journal articles were found.

2.2 Study Eligibility and Selection

During the screening process, duplicates were removed along with title and abstract level screening, which were assessed by two researchers independently against the eligibility criteria. A third reviewer resolved any disagreements. Studies were included if they (1) reported GPS microtechnology-derived data related to rugby 7s match-play, (2) examined a female population, and (3) included players from any competitive level (e.g., amateur, semi-professional, and professional). Eligible study designs included prospective, retrospective, and cohort studies. Studies were excluded if they were review articles, did not report GPS-derived data specific to match-play, or were published not in English and could not be translated.

2.3 Data Extraction

Data were extracted into structured, pre-designed tables. Data pertaining to the study design, participant characteristics (age, country of origin, level of competition), number of matches analysed, type of analysis, GPS device (brand & model), and GPS microtechnology-derived outcome measures (total distance (m) and % of total distance), high-speed running (total distance (m) and % of total distance covered greater than thresholds ranging between 3.8 to 5.0 $m \cdot s^{-1}$), very high-speed running (at speeds greater than 7.5 $m \cdot s^{-1}$) distance (m), sprinting (s, m and count covered greater than thresholds ranging between 5.5 to 6.5 $m \cdot s^{-1}$), accelerations ($m \cdot s^{-2}$ and count), acceleration load (arbitrary units (AU)), decelerations ($m \cdot s^{-2}$ and count), maximum velocity (% of and individual's maximal velocity obtained, $m \cdot s^{-1}$ and $km \cdot hr^{-1}$), speed exertion (arbitrary units (AU)), maximum deceleration ($m \cdot s^{-2}$ and count), PlayerLoad (arbitrary units (AU)), an accelerometer-derived measure that examines changes in acceleration across three planes (anteroposterior, mediolateral, and vertical)), metabolic power ($J.s^{-1} \cdot kg^{-1}$, $W.kg^{-1}$), an estimate of the energetic cost of locomotion that utilises speed and acceleration to derive physiological demand, contacts (total count, total count > eight gravitational force (g)) were extracted by two researchers and included in the review. GPS microtechnology-derived measures were also differentiated based on the method to quantify the metric, whereby absolute measures typically include counts or totals, and metrics expressed in relative terms are given as a rate per minute or a percentage.

2.4 Methodological Quality Assessment

Studies were independently assessed by two researchers for methodological quality using a modified assessment of the Downs and Black.[10] Any differences between researchers were resolved by discussion until a consensus occurred, and any disagreements should no consensus be reached were reviewed by a third researcher. Eleven of the 27 of the criteria displayed in the Downs and Black assessment were utilised due to their logical applicability in the studies analysed.[10] Elements that were included examined the quality of the reporting (criteria 1-3, 6, 7, and 10), external validity (criteria 11, 12), and internal validity bias (criteria 16, 18, and 20).

3 RESULTS

3.1 Selection of studies and methodological quality

The initial searched returned 164 studies, of which 35 studies were duplicates and were excluded, leaving 129 studies to be screened for eligibility with 18 studies being assessed as eligible for inclusion in this review.[11-28] A manual reference search was conducted to identify any additional papers relevant to the review, of which no other papers were included that satisfied the inclusion criteria. Figure 1 depicts the process of screening for eligible papers.

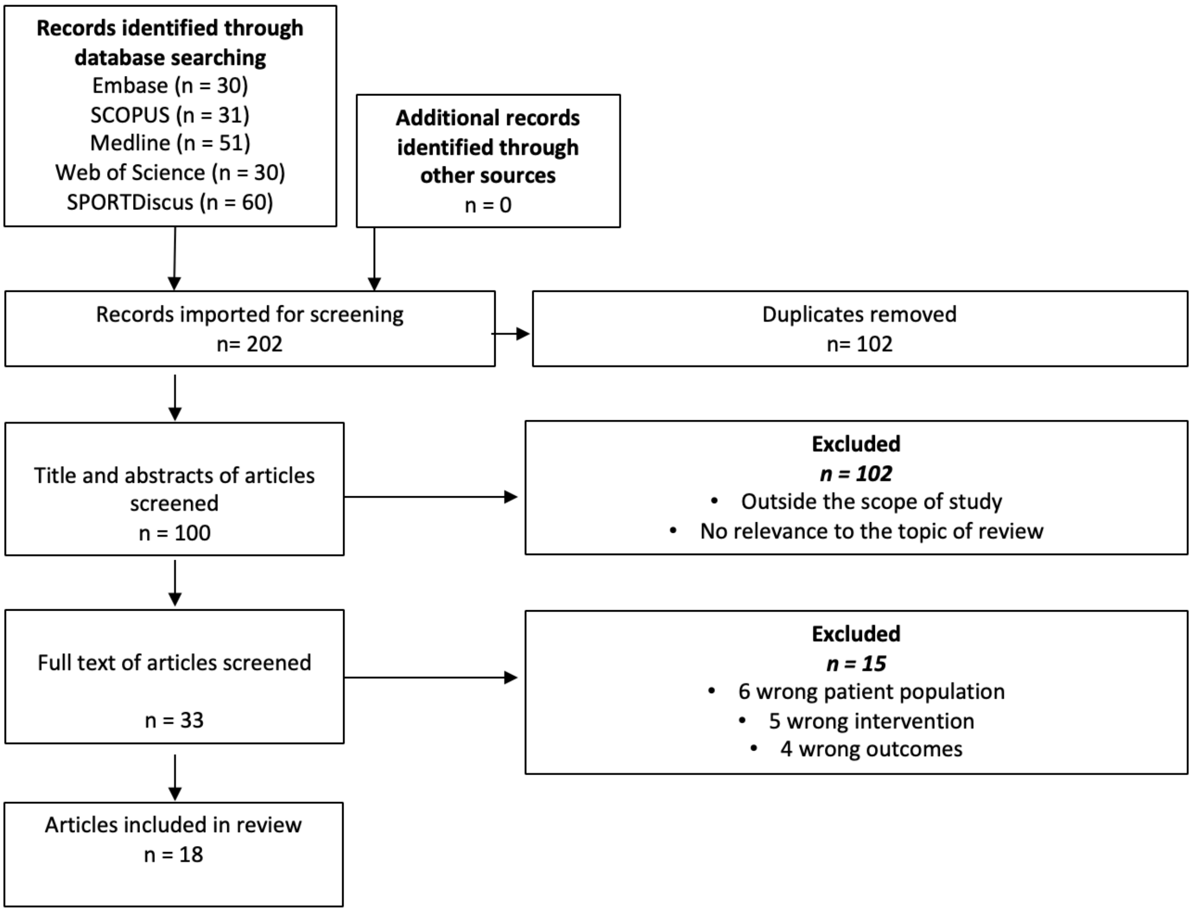

Figure 1 Flow of eligible articles included in the scoping review

Methodological quality scores for the studies included were high, ranging from 8 to 10 out of the applicable 11 criteria (Table 1). All but one study[16] addressed the criteria of external validity.

Table 1 Downs and Black – Methodological quality and bias assessment of included studies

	Modified Downs & Black Criteria											
	Reporting						**External Validity**		**Internal Validity - Bias**			
	1	**2**	**3**	**6**	**7**	**10**	**11**	**12**	**16**	**18**	**20**	
Author (year)	**Hypothesis/Aim clearly Stated**	**Main outcomes described in Intro**	**Subject Characteristics clearly**	**Main findings described**	**Estimate of random variability**	**Actual probability value reported**	**Potential recruits'**	**Participants representative of entire population from which**	**Data dredging**	**Statistical tests appropriate**	**Outcome measures valid and**	**Score (Maximum 11)**
Bicudo et al. (2024)[11]	1	1	1	1	1	1	0	0	1	1	1	9
Brosnan et al. (2024)[12]	1	1	1	1	1	1	0	0	1	1	1	9
Couderc et al. (2023)[18]	1	1	1	1	1	1	0	0	1	1	1	9
Conte et al. (2021)[17]	1	1	1	1	1	1	0	0	1	1	1	9
Misseldine et al. (2021)[22]	1	1	1	1	1	0	0	0	1	1	1	8
Rodŕiguez-Baena et al. (2021)[25]	1	1	1	1	1	0	0	0	1	1	1	8
Malone et al. (2020)[21]	1	1	1	1	1	1	0	0	1	1	1	9
Doeven et al. (2019)[19]	1	1	1	1	1	1	0	0	1	1	1	9
Reyneke et al. (2018)[24]	1	1	1	1	1	0	0	0	1	1	1	8
Goodale et al. (2017)[20]	1	1	1	1	1	0	0	0	1	1	1	8
Clarke et al. (2017)[16]	1	1	1	1	1	NA	1	1	1	1	1	10
Vescovi & Goodale (2015)[28]	1	1	1	1	1	1	0	0	1	1	1	9
Clarke et al. (2015a)[13]	1	1	1	1	1	NA	0	0	1	1	1	8
Clarke et al. (2015b)[14]	1	1	1	1	1	NA	0	0	1	1	1	8
Clarke et al. (2015c)[15]	1	1	1	1	1	NA	0	0	1	1	1	8
Portillo et al. (2014)[23]	1	1	1	1	1	0	0	0	1	1	1	8
Suarez-Arrones et al. (2012)[27]	1	1	1	1	1	0	0	0	1	1	1	8
Suarez-Arrones et al. (2011)[26]	1	1	1	1	1	0	0	0	1	1	1	8

0 = No, 1 = Yes, NA = Not Applicable, except for question 16 where 0 = Yes, 1 = No

3.2 Study Characteristics

A total of 385 participants (mean age 17.0 - 30.4 years) were included in the 18 eligible studies, with 13 studies reporting players predominantly competing at an international level (72%)[12,14,16-24,26,27], four studies at national level (22%)[15,23,25,28] and four studies at a domestic level (22%)[11,12,13,16]. Four studies provided comparative analyses at different tournament levels (22%),[12,13,15,22] while two studies examined playing positions (11%).[16,21]

Most studies analysed overall match demands (n = 17, 94%) [11-17,19-28] while two studies (11%)[11,18] examined peak demands in women's 7s match play (Table 2). Of these 17 studies, six studies (33%) analysed an entire season [12,16,17,19,20,24], the classification being based on more than three tournaments, eight studies examined 1-3 tournaments (44%)[13,14,15,16,19,22,24,27,28], two studies included 1-2 matches (11%)[11,25], while one study did not specify the duration of the study.[22]

The studies predominantly examined senior and elite athletes aged 18 years and above (89%)[12-27] with two studies including participants that were classified as junior athletes < 18 years (11%).[11,16] One study examined participants at junior, senior and elite playing levels[15] while one did not specify the age demographic of their participants but it is likely that they were aged 18 years and above as they were participating at university level.[28]

Table 2 Participant and study characteristics

Author, (Year)	Study Design	Population		Country of Origin	Competition Level	Study Duration	Individual Match Samples (n)	GPS Microtechnology Model
		Sample size (n)	Age (mean ± SD) (y)					
Bicudo et al. (2024)[11]	Cross-sectional study	14	17.3 ± 1.02	Brazil	Domestic	1 Training match	14	Playertek, Catapult
Brosnan et al. (2024)[12]	Cross-sectional observation study	54 (Domestic: 33, International: 21)	Domestic: 24.8 ± 4.0 International: 23.4 ± 3.5	Australia	Domestic & International	2 Seasons / 9 Tournaments	Unspecified	GPSports EVO & GPSports HPU, GPSports
Couderc et al. (2023)[18]	Retrospective cohort study	19	24.2 ± 2.4	France	International	1 Season	210	Sensor Everywhere, Digital Simulation
Conte et al. (2021)[17]	Observational study	16	Backs: 24.2 ± 3.2 Forwards: 22.4 ± 2.7	Brazil	International	1 Season / 3 Tournaments	110	OptimEye X4, Catapult
Misseldine et al. (2021)[22]	Cross-sectional observational study	12	Backs: 24.6 ± 4.7 Forwards: 27.0 ± 2.5	United Kingdom	International	1 Tournament / 6 Matches	Unspecified	JOHAN Trackers, JOHAN Sports
Rodfiguez-Baena et al. (2021)[25]	Quasi-experimental study	21	21.2 ± 2.4	Spain	National	3 Seasons / 21 Tournaments	82	SPI HPU, GPSports
Malone et al. (2020)[21]	Observational study	27	24.4 ± 2.1	Ireland	International	2 Seasons	250	Viper Pod, STATSports
Doeven et al. (2019)[19]	Cross-sectional study	12	25.3 ± 4.1	Netherlands	International	1 Tournament	Unspecified	JOHAN Trackers, JOHAN Sports
Reyneke et al. (2018)[24]	Prospective longitudinal study	15	24.3 ± 3.9	New Zealand	International	3 Tournaments / 15 matches	Unspecified	VX Sport 220, Visuallex Sport International
Goodale et al. (2017)[20]	Observational study	21	24.0 ± 3.6	Canada	International	5 Tournaments	191	S4 Minimax, Catapult
Clarke et al. (2017)[16]	Cross-sectional study	57 (Junior: 24, Senior: 22, Elite: 11)	Unspecified Junior < 18.0 Senior & Elite > 18.0	Australia	Domestic & International	2-days 2 Tournaments	Junior: 83 Senior: 90 Elite: 89	SPI HPU, GPSports

Author, (Year)	Study Design	Population		Country of Origin	Competition Level	Study Duration	Individual Match Samples (n)	GPS Microtechnology Model
		Number (n)	Age (mean ± SD) (y)					
Vescovi & Goodale (2015)[28]	Cross-sectional study	47	Unspecified	Canada	International University	1 Tournament	5 Matches	SPI Pro, GPSports
Clarke et al. (2015a)[13]	Cross-sectional observational study	22 (National: 12, State: 10)	National: 22.3 ± 2.5 State: 24.4 ± 4.3	Australia	Domestic	1 Tournament	National: 64 State: 51	SPI HPU, GPSports
Clarke et al. (2015b)[14]	Cross-sectional observational study	12	23.5 ± 4.9	Australia	International	1 Tournament	68	SPI HPU, GPSports
Clarke et al. (2015c)[15]	Cross-sectional observational study	22 (National: 12, State: 10)	National: 22.3 ± 2.5 State: 24.4 ± 4.3	Australia	National	1 Tournament	National: 64 State: 51	SPI HPU, GPSports
Portillo et al. (2014)[23]	Cross-sectional observational study	20 (International: 10, National: 10)	International: 26.27 ± 4.05 National: 31.12 ± 6.40	Spain	International & National	Unspecified	Unspecified	SPI Pro X, GPSports
Suarez-Arrones et al. (2012)[27]	Cross-sectional observational study	12	27.8 ± 4.0	Spain	International	1 Tournament / 5 Matches	Unspecified	SPI Elite, GPSports
Suarez-Arrones et al. (2011)[26]	Observational study	4	25.3 ± 0.4	Spain	International	2 Matches	8	SPI Elite, GPSports

3.3 Physical performance measures

A summary of performance measures assessed by GPS microtechnology is presented in Figure 2. Distance travelled was the most reported metric with 16 (89%) studies reporting total distance (m). The remaining metrics ranged between one to six in terms of number of studies that reported its use.

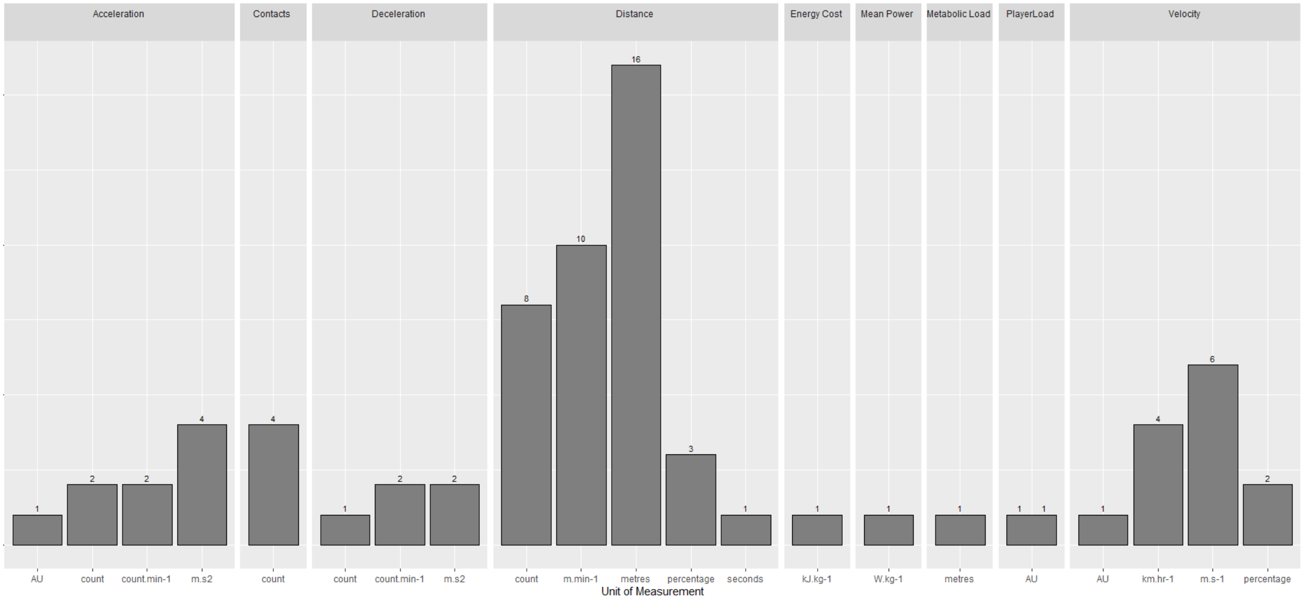

Figure 2 Summary of GPS microtechnology metrics examined based on category and unit of measurement.

AU = Arbitrary units, kJ.kg^{-1} = kilojoules per kilogram, W.kg^{-1} = watts per kilogram, km·hr^{-1} = kilometres per hour, m·s^{-1} = metres per second, m·s^{-2} = metres per second per second

3.3.1 Distance

Reported distance from a single match were typically higher for backs compared to forwards; ranging from 1154 to 1728 m and 1084 to 1601 m, respectively.[16,20,21,22] However, Brosnan et al. (2023) provided detailed data across a tournament and observed little difference in distances for backs (1475 ± 164 m) and forwards (1490 ± 163 m).[12] Total distance (m) outputs between first and second halves reported a decrease of 10 – 18%,[11,20,23] ranging from 776 to 793 m in the first half and 640 to 659 m in the second half.

When categorised in playing level, junior athletes typically covered less distance (1060 ± 318 m) when compared to national (1363 ± 222 m) and international-level players (1642 ± 171 m).[15,22] A meaningful mean difference of 6.1% was observed in backs across a tournament when comparing international to domestic level playing groups (1544 m v 1452 m; ES = 0.55, p = 0.01).[12] Moderately higher outputs were observed during a loss across total distances when reporting on the effect of match outcomes (1455 m v 1312 m; ES = 0.6 ± 0.2).[20]

3.3.2 Relative Distance

Eleven (61%) studies reported measures of relative distance which aids in interpreting match demands by normalising locomotor outputs based on match time played.[11-16,18,20,22,24,28] Compared to absolute reporting measures of distance (metres), relative distance allows comparison between players that have varying participation within the context of a match. Moderate effect sizes for relative distance were reported when examining state compared to national players over a two-day tournament.[13] During day one state players had a higher relative distance (105 ± 7 m·min^{-1} v 100 ± 7 m·min^{-1}; ES = - 0.69 ± 0.68) whereas national players had higher relative distances across the second day (83 ± 14 m·min^{-1} v 93 ± 4 m·min^{-1}; ES = 0.61 ± 0.54).[13] Domestic level backs typically covered more relative distance than international players across a tournament (91.4 ± 8.8 m·min^{-1} v 95.6 ± 8.1 m·min^{-1}; ES = 0.50, p = 0.01). [12] Match outcome had a significant effect on relative distance ($p < 0.05$) with losses displaying slightly higher outputs (89.0 m·min^{-1} vs 86.0 m·min^{-1}).[20] The authors also reported significant differences when comparing opponent rankings on relative distance outputs.[20] Comparisons between first half and second half performance had a large effect (ES = 1.98 when utilising the rolling method;[11] mean (90% CI), 88.82 (83.46 – 94.18) m·min^{-1} v 77.65 (72.43 – 82.88) m·min^{-1}, respectively.[11]

3.3.3 Distance by Velocity Zones

Fourteen (82%) studies reported total distance across velocities classified into six zones: low, moderate, moderate-high, high, very high, sprint.[11-13,16,17,19-28] Low speed running was typically categorised as speeds less than 2 $m\cdot s^{-1}$, varied greatly among studies, whereby distances ranged from 32 – 1188 m.[13,19,22,24] Moderate speed running had an array of thresholds to classify zones which included: 1.67 – 3.33 $m\cdot s^{-1}$,[23, 27, 28] 1.9 – 3.9 $m\cdot s^{-1}$, [21] 2 – 3.5 $m\cdot s^{-1}$,[13,19,24] 2.25 – 4.44 $m\cdot s^{-1}$,[28] 3.3 - 6 $m\cdot s^{-1}$,[12] > 3.5 $m\cdot s^{-1}$,[14, 16] and speeds greater than an individual's ventilatory threshold (VT_2 Speed).[14] Based on the array of thresholds reported, moderate distances were as low as 29 m and up to 932 m.[13,24]

Moderate to high-speed running thresholds were more closely reported as speeds between 3.5 – 5.0 $m\cdot s^{-1}$ ranging from distances of 18 – 629 m as well as speeds between 3.33 – 3.89 $m\cdot s^{-1}$ with outputs between 90 – 305 m in a match.[13,19,20,23,24,26,28] High-speed running (HSR) zones were more commonly reported as metres > 5.0 $m\cdot s^{-1}$ with backs typically reporting higher distance values compared to forwards in a match, 223 m vs 174 m, respectively.[13,14,16,20,24] There were differences in HSR distances (> 5.0 $m\cdot s^{-1}$) across playing levels when examining the following: elite (120 ± 41 m), senior (102 ± 41 m), and junior athletes (89 ± 89m).[16] A moderate effect size (ES = 0.87) was reported when comparing state and national players during the second day of competition; 513 ± 330 m v 774 ± 160 m, respectively).[13]

The more commonly reported threshold for very high-speed running (VHSR) was between 5 – 5.55 $m\cdot s^{-1}$,[23,26,27] while others reported VHSR as distance run at speeds greater than 7.5 $m\cdot s^{-1}$.[12,16] There was a significant difference when comparing international to domestic outputs (ES = 0.25, $p = 0.03$) across VHSR distances, which was also evident when examining the forwards group in both playing levels (15.6 ± 24.7 m v 2.8 ± 6.8 m; ES = 0.81, $p<0.001$).[12]

Aggregated measures of maximal sprint (m) were reported in one study (6%)[21] with a significant difference between backs (mean (90%CI): 29 (21- 44) m)) and forwards (mean (90% CI): 15 (11 – 28) m)) ($p \leq 0.05$). No significant difference was reported for average minimal sprint. The use of relative velocity zones to derive running thresholds were reported for single zones and not used as a method to derive multiple threshold classifications.[22,25]

3.3.4 Relative Distance by Velocity Zones

Relative distance thresholds established for low, and moderate did not show statistically significant differences when examining full games, playing level and score differentials.[20,24,28] Large differences (ES = 1.47, p = 0.001) were observed between international and development players across relative HSR bands between 4.44 – 5.55 $m \cdot s^{-1}$ (14 ± 3 $m \cdot mins^{-1}$ v 10 ± 4 $m \cdot min^{-1}$, respectively).[28] Differences between relative sprint distances between 5.58 to 8.89 $m \cdot s^{-1}$ were also observed as development players covered less than international players (4.0 ± 3.0 $m \cdot min^{-1}$ vs. 8.0 ± 4.0 $m \cdot min^{-1}$; ES = 1.09, p = 0.007).[28]

3.3.5 Relative Distance by Contextual Factors and Analysis Methods

Contextual factors during international women's rugby 7s had moderate differences for relative distances (3.5 – 5.0 $m \cdot s^{-1}$) for: match half (first half v second half), match outcome (win v loss), opponent ranking (top four v bottom four), points differential (margin of victory v margin of defeat).[20]

Comparisons of the rolling method (ROLL) and ball in play (BIP) method for relative sprint distance were significantly different when examining the second half (9.38 ± 6.34 $m \cdot min^{-1}$ v 24.92 ± 2.21 $m \cdot min^{-1}$; ES = 0.89, p= 0.008).[11] ROLL method relative sprint distance between match halves were also meaningful (ES = 1.11, p = 0.001). No statistically different values observed between first and second half using the BIP method (p = 0.953).

3.3.6 Efforts and Duration by Velocity Zones

Measures of time (s) and efforts (n) completed above a particular threshold were also reported.[16, 25] Average time spent sprinting after accelerating greater than 2.0 $m \cdot s^{-1}$ and for longer than one second was 3.93 seconds, while the count of repeat sprints which is defined as two consecutive sprints above 61% of an individual's maximal speed within 30 seconds were 1.11 ± 0.31 for forwards and 1.82 ± 0.76 for backs.[25]

3.3.7 Maximal Velocity

Measures of maximal velocity were examined by ten studies (56%).[12,16,20-23,25-28] Five studies (28%) reported maximal velocity values across match halves[20,21,23,25,27] while one was based on match outcome.[20] Maximal velocity values across playing levels were: international-level players: 6.28 - 8.05 $m \cdot s^{-1}$;[12,16,23,26,28] national/domestic-level players: 5.78 - 7.40 $m \cdot s^{-1}$;[12,16,23] and junior-level players: 7.08 ± 0.83 $m \cdot s^{-1}$.[16] Maximal velocity values for positional groups were reported as follows: backs ranging between 7.10 - 7.71 $m \cdot s^{-1}$,[12,20-22] forwards: 6.70 – 7.60 $m \cdot s^{-1}$,[12,20-22] and speed-edge players reaching 7.90 ± 0.60 $m \cdot s^{-1}$.[12] Only one study reported on speed exertion (AU) values for positional groups at domestic and international level, which examines the accumulation of maximal speed and acceleration-based indices.[12] International players had higher speed exertion values compared to domestic players (11.7 vs 9.8 AU).

3.3.8 Accelerations, Decelerations and Player Load

Accelerations were reported by six (33%) studies.[11,12,16,17,21,23] Acceleration counts at varying zones were consistent in studies that reported the metric. Thresholds established for low (> 1.5 $m \cdot s^{-2}$) and high (> 2.5 $m \cdot s^{-2}$) were uniform for two studies;[21,23] moderate zones varied and were set at > 1.8 $m \cdot s^{-2}$ [17] and > 2.0 $m \cdot s^{-2}$.[21,23] and very high (> 2.75 $m \cdot s^{-2}$) was reported in one study.[23] These measures were based on halves of a match, playing level and positions. Portillo et al.(2014) reported low acceleration counts of 6.0 and 4.9 when examining first and second half outputs, respectively for international-level players and 6.0 and 4.5 counts, respectively for national players.[23] Average high accelerations ranged from 0.30 – 2.50 counts across halves[21] but also displayed a difference when comparing international and national level players (1.2 – 1.3 and 0.4 – 0.5, respectively).[23] Maximal acceleration values were reported between 2.80 – 3.49 $m\cdot s^{-2}$ [12,16] with acceleration load values being accounted for in one study with values ranging from 442.30 to 471.70 AU.[12]

Three (17%) studies reported deceleration metrics.[11,12,17] No significant difference was reported when comparing maximal deceleration values across aggregated domestic and international levels as well as positional groups (backs, forwards, speed-edge). Total decelerations across the first half of a match showed minimal difference between methods of examining half or whole-game averages (ROLL) and BIP values. In contrast, BIP values for decelerations per minute (1.50 ± 0.52 decelerations per minute) were greater in the second half compared to the ROLL method (0.70 ± 0.29 decelerations per minute). WCS values for relative decelerations (1.78 ± 1.17 decelerations per minute) were higher in the first half when matched against BIP values (1.62 ± 0.82 decelerations per minute).

Player Load for match play was reported in one (6%) eligible study.[20] Differences were moderate when comparing first half and second half outputs (84 ± 18 AU and 69 ± 20 AU, ES = 1.0 ± 0.4, respectively) and trivial effect size (ES = 0.1 ± 0.4) when comparing match outcomes (win or loss).

3.3.9 Contacts

Four (22%) studies reported contact-natured metrics.[13,16,19] There was a moderate effect size when comparing the number of impacts above 10g between junior and senior athletes and a small (0.55 ± 0.60)[15] effect size between state to national players, and senior to elite athletes.[16] Total impacts count between days and playing level were reported as 3855 (day one) to 4126 (day two) in national-level players and 2519 (day one) to 2642 (day two) for state-level players (day one: ES = 0.87 ± 0.58, moderate; day two: 1.00 ± 0.57, moderate).[13]

3.3.10 Energy Cost, Metabolic Power, Metabolic Load

One (6%) study reported on the energetic cost, mean power and metabolic load distance.[28] Comparative analysis between development-level and international-level athletes had no observable difference between groups for mean power or energy cost. However, distance across high (20-35 $W.kg^{-1}$), elevated (35-55 $W.kg^{-1}$) and maximal (>55 $W.kg^{-1}$) metabolic power categories were heightened during international matches.

3.4 Peak Match Demands

A single study (6%)[18] utilised power law modelling to report match exercise intensity across playing positions (forwards and backs) for total accelerations > 2.5 $m{\cdot}s^{-2}$ per minute ($n{\cdot}min^{-1}$), relative total distance ($m{\cdot}min^{-1}$) and relative HSR distance ($m{\cdot}min^{-1}$). The mean (± SD) of the intercept, slope and 90th percentile (P90) for all players were: accelerations (5 ± 2 per min^{-1}, -0.47 ± 0.22, 4 ± 1 per min^{-2}); relative distance (161 ± 19 $m{\cdot}min^{-1}$, -0.25 ± 0.07, 134 ± 15 $m{\cdot}min^{-1}$); and relative HSR (66 ± 25 $m{\cdot}min^{-1}$, -0.6 ± 0.16, 47 ± 19 $m{\cdot}min^{-1}$). Reporting of positional data is presented in Table 3.

Table 3 Power Law Modelling of Exercise Intensity in Rugby 7s

Measure		Forwards	Backs
Accelerations per minute (per min^{-1})			
	Intercept	5 ± 2	5 ± 2
	Slope	-0.51 ± 0.16	-0.45 ± 0.24
	P90	4 ± 2	4 ± 1
Relative Total Distance ($\text{m}\cdot\text{min}^{-1}$)			
	Intercept	156 ± 16	163 ± 20
	Slope	-0.25 ± 0.07	-0.26 ± 0.07
	P90	129 ± 13	137 ± 15
Relative HSR per minute ($\text{m}\cdot\text{min}^{-1}$)			
	Intercept	38 ± 18	70 ± 26
	Slope	-0.59 ± 0.18	-0.60 ± 0.16
	P90	38 ± 18	51 ± 19

Extracted from Couderc et al. (2023)[18] Data presented as mean ± SD, m = metres, min = minute, P90 = 90th percentile.

4 DISCUSSION

The scoping review aimed to explore the use of GPS microtechnology in rugby 7s to characterise match and peak demands in female players. The reviewed studies are of sound methodological quality and present a pronounced diversity in the reporting of metrics in studies of women's rugby 7s' performance. Elite players endorsed greater distance ran, relative distance, maximal sprint speed, accelerations, and overall higher running and physiological demands than lower-level players. Total distance and high-speed running distance declined from the first half to the second half in matches. The studies displayed a lack of uniformity in speed thresholds as well as speed thresholds that may not be suited for the female athlete. Peak demands analysis has emerged to highlight fluctuations in running intensities using concepts such as ball in play[11] and power law modelling[18] to quantify physically demanding periods within a match. Peak demands analysis currently lacks empirical evidence in women's rugby 7s.

Positional analysis has demonstrated varied results when identifying differences between positions typically classified as forwards and backs. Velocity-based measures such as high-speed running (HSR) have typically identified differences between positions, while measures of acceleration and deceleration have been homogenous between positions. The use of classification of speeds zones derived from an individual's maximal velocity were examined using a single descriptor (i.e. > 61% maximal velocity and > 75% maximal velocity) compared to the vast number of descriptors when utilising absolute zones ($m \cdot s^{-1}$). Similarly, there is a distinct gap in the literature examining sub-elite athletes and competitions makes generalisations difficult when translating insights from international participants and competitions. Similarly, contextual factors, including match outcomes and tournament stages, have been identified to affect match demand reporting.

4.1 Overall Match Demands

Total distance was the most prominently reported metric to describe match load. Elite female players cover greater total distances during matches than players in lower tiered competitions, highlighting the increased demands at higher levels of play.[28] Presenting averages provides a useful summary of typical match demands, allowing for general comparisons between populations or competition levels. During a match, elite women's rugby 7s players can be expected to cover on average 1,408 ± 350 m, with an average running speed of 7.33 ± 0.8 $m \cdot s^{-1}$ compared to elite development players covering 1387 ± 182 m. These findings also suggest that women's rugby 7s involves substantial running demands, exceeding those reported in the fifteen-a-side women's game when extrapolating for match duration. A 2019 systematic review by Sella and colleagues[43] reported values of 1,623 ± 17 m during international competition reflecting slightly higher values than those aggregated in this review (1,536 ± 143 m), while the national competition shows similar outputs (1,363 ± 222 m). The inclusion of seven publications[11,12,17,18,21,22,25] since that review [43] may have contributed to the reduced total distance match outputs.

Noticeable differences were identified when comparing second half performances to the first half, with a reduction of approximately 16% in total distance covered.[11,20] The decline is likely multifactorial but may be largely attributable to the accumulation of fatigue as the match progresses. In rugby 7s, where the high-intensity nature of the game demands frequent sprinting, tackling, and rapid changes of direction, players are subject to significant physiological stress within a short timeframe. The limited halftime interval, typically just two minutes, offers minimal opportunities for recovery, potentially exacerbating the effects of fatigue in the latter stages of a match.[20] This reduction in physical output during the second half has important implications for tactical planning, substitution strategies, and conditioning programs. Preparing athletes to maintain performance under fatigue and exploring recovery strategies that can be implemented during halftime, may mitigate these declines and enhance second-half effectiveness.

High intensity running is a crucial component of rugby 7s, with elite players covering considerably more ground at high speeds averaging 199 m per match.[21] The review highlights a lack of uniformity in assigning speed thresholds as well as the establishment of speed thresholds inappropriate for women's rugby 7s, which may also lead to underreporting of the true intensity of efforts.[14,22] Comparisons of HSR in junior, senior and elite rugby 7s players found a small effect size between junior and senior players, and between senior and elite players speeds greater than 5 $m \cdot s^{-1}$. This finding is consistent with HSR zones of 6 $m \cdot s^{-1}$ to 7.5 $m \cdot s^{-1}$ for international and domestic players ($d = 0.29$, $p = 0.01$)[12] which may suggest that HSR outputs between competition levels are somewhat similar when aggregating to the level of a match, thereby making the transition to higher levels of competition more progressive. Examination of match halves may offer additional insight into the differences between competition levels. As identified in total distance, there was also a small reduction in high-speed running distance from the first half to the second half when pooling both forwards and backs, first half (mean = 106 $m \cdot min^{-1}$) to the second half (mean = 93 $m \cdot min^{-1}$), with an estimated effect size of $d = 0.31$ (variance = 0.15), indicating a small but meaningful decline in running demands across halves.[21] Furthermore, sprinting measures demonstrated that elite players possess greater maximal sprint speeds compared to their lower standard counterparts.[22,23,28] Interestingly, both elite and sub-elite players achieve peak sprint speeds during matches that are only slightly below their maximal tested values.[28]

Measures of acceleration and deceleration provided greater consistency enabling direct comparison between studies.[21,23] Across measures of low (1.5 – 2.0 $m \cdot s^{-2}$), moderate (2.0 – 2.5 $m \cdot s^{-2}$), and high (> 2.5 $m \cdot s^{-2}$) acceleration, there was a significant difference between national and international level athletes across a match half, with international players completing significantly more accelerations in their respective bands (first half: low and moderate accelerations, $p \leq 0.05$; high, $p < 0.01$; second half: low, moderate, and high ($p<0.01$)).[23] Other studies have only reported significant findings for low accelerations ($p \leq 0.05$).[21] Conte and colleagues examined the relationship between acceleration and match load finding that accelerations per minute were the only external load metric significantly influencing session rating of perceived exertion match load (sRPE-ML).[17] It was suggested that this relationship may stem from the diverse rugby-specific activities that accelerations represent, which contribute to overall player perception of exertion. Additionally, this highlights the importance of considering individual maximal running velocity on physiological responses which may provide a more accurate depiction of the external load imposed by accelerations.

By contrast, decelerations were a heavily underreported metric in the studies examined. Two studies included counts (n)[11,16] of decelerations while one study reported maximal deceleration.[12] Despite collisions being inherent in the game as the main opposing force during locomotive behaviour, future studies should look to include deceleration metrics due to their intense mechanical load, highly fatigue-inducing nature, and resulting tissue microtrauma[44] all of which are important in load management and understanding match loads.

Metabolic power encompasses aspects of accelerations, decelerations and high intensity running, thereby providing a valuable measure of the physical intensity of rugby 7s.[39] During international-level matches, players exhibit greater distances covered in high, elevated, and maximal metabolic power categories compared to lower-level matches.[28] This difference suggests that elite players perform more frequent and intense movements due to the faster pace and heightened competition level. Despite no explicit comparison of metabolic power demands between match halves, the observed decline in accelerations, decelerations and high intensity running in the second half implies a likely decrease in metabolic power output as well.[20, 21]

4.2 Peak Demands

While understanding average match demands is essential , it is crucial to acknowledge the intermittent nature of rugby 7s, characterised by short bursts of high-intensity effort interspersed with periods of lower intensity.[11,20] This pattern underscores the importance of investigating peak demands, representative of the most physically demanding periods within a match, to ensure players are adequately prepared.[11]

Recent research has focused on using ball-in-play time as a more sensitive measure to capture peak demands.[11] The BIP approach considers the dynamic nature of the game and recognises that averaging data across the entire match duration, including periods of inactivity, might not accurately reflect the intensity experienced during active play. The insights gained from BIP analysis can inform training program design, helping coaches to better replicate the intensity and work-to-rest ratios experienced during demanding match periods. Bicudo and colleagues (2024) were the first in women’s rugby 7s to compare BIP analysis to whole-game averages, demonstrating that match demands based on average values underestimates exposure measures by ~25-30%. This is particularly evident when examining first and second half outputs for relative total distance ($m \cdot min^{-1}$) alongside measures of relative sprint distance having a wider variance in outputs, 60-265%.[11]

Furthermore, analysing the longest bouts of BIP revealed even higher physical demands on players.[11] In this study, the worst-case scenario can show variance in match outputs as high as 165% more than the average game demand for relative distance, and a 216-257% differential when analysing relative sprint distances covered in a match. Interestingly, when comparing relative sprint distances, accelerations per minute, total decelerations, and decelerations per minute between BIP and WCS outputs, the WCS values were slightly lower than BIP values. This observation may promote the notion that the longest passages in play (WCS) may not always produce the highest locomotive outputs and that the addition of situational context from a game such as tackling or defending may need to be considered as part of match analyses along with physical capabilities and fatigue.[35,36]

The use of WCS is not novel in studies that examine match demands. Duthie and co.[30] utilise duration specific periods between one and ten minutes to determine peak running intensities across metrics such as relative distance, acceleration, deceleration and metabolic power. Compared to Bicudo et al[11] the WCS was based on a moving average window across sample-by-sample GPS data points and considered periods irrespective of when the ball was in play or out of play. Duthie and colleagues[30] also reported significant differences when comparing outputs across positional groups. Although this study was conducted with Rugby Union athletes, a similar methodology was implemented to examine peak outputs across one-minute segments between rugby union and rugby 7s athletes.[18] There is little difference in peak values when comparing the two rugby formats (XVs and 7s) [18], but considerable differences in the running outputs of players at the 90th percentile (P90) across total distance, high-speed running and accelerations.[18] This observation suggests that use of P90 can provide greater precision when understanding overall match intensities rather than utilising a single one-minute period as a reference.

Furthermore, using the power-law modelling, examined in a single study,[18] highlighted that differences between backs and forwards, may appear similar when examining accelerations per minute and relative total distance during peak periods. However, the slope of the curve reveals a potential distinction: backs tend to experience a smaller decrement in performance compared to forwards. In contrast, for HSR per minute, backs achieve a higher intercept, indicating a greater initial performance level, while the slope remains comparable to that of forwards.[18]

4.3 Positional Demands

Understanding positional differences in match demands is crucial for tailoring programs and recovery strategies to the specific needs of different playing positions as a typical tournament may involve playing two to three matches in each day and repeated over the course of three consecutive days.

There are inconsistencies in running demands between forwards and backs in women's rugby 7s. While some studies have found no significant differences, other studies suggest that backs cover greater distances, particularly at higher speeds.[12,20,21] Malone (2020) observed that elite backs covered significantly greater distances across all speed-dependent variables compared to forwards, while also exhibiting similar declines in HSR outputs between match halves (backs: 16% and forwards: 9%, $p < 0.05$).[21] These conflicting findings highlight the need for further research with larger sample sizes and consistent methodologies to conclusively discern positional differences.

There were no statistically significant findings between backs and forwards for acceleration and deceleration demands ($p=0.344$; ES = 0.11, 90% CI: 0.03-0.21).[21] Drawing on comparisons between rugby union and rugby 7s, rugby union backs often engage in more high-speed runs and evasive manoeuvres, likely resulting in higher frequency and intensity of accelerations and decelerations compared to forwards, who typically are more involved in contact-heavy activities. The lack of distinction observed between positional groups may suggest that in rugby 7s, there is a high homogeneity in acceleration demands between positional groups. However, the reporting of accelerations, decelerations, and other match events, such as collisions and changes of direction is still emerging and warrants further investigation to better understand their contribution to overall match load and player fatigue. The identified similarities between position groups may suggest that practitioners should focus on applying training modalities that target the potential gap between the competition levels.

4.4 Competition Level

Elite players competing at international level, consistently demonstrate greater running and physiological demands compared to lower-level players.[12,28] These differences are particularly apparent in high-intensity metrics, such as total high-intensity running distance, sprint distance, and peak speed.[12, 28] The higher demands placed on elite players reflect a combination of higher fitness levels, technical skills, and tactical understanding.

The current review highlights the prevalence of international-level players, with most studies focusing on elite and sub-elite competition levels and adult participants. There is a notable gap in the literature regarding recreational and adolescent athletes, as only two studies have examined junior players,[11,16] with just one exclusively focusing on this population.[11] Additionally, one study utilised domestic-level athletes, contributing valuable insights to the limited research on this cohort.[11]

Recognising the discrepancies in reported data can help inform training strategies and player advancement as part of development pathways toward higher levels of competition. Identifying the demands of a match as well as the underpinning physical and anthropometric requirement to thrive in international competition may, in turn, provide additional benefits from a technical point of view.[43] Furthermore, establishing training benchmarks based on match demands and the associated preparation leading into tournaments may form the foundation for establishing a high chronic training load that both optimally prepares players for matches and reduces risk of injury.[45,46]

4.5 Methodological Considerations

4.5.1 Inconsistent speed zones

A major challenge in research that utilises GPS microtechnology is the lack of standardized speed zones and thresholds used to categorise running intensities across most sports,[46-52] thereby making direct comparisons challenging.[12] This limitation is also evident in women's rugby 7s research as defining thresholds such as those occurring at high-speed traditional methods have typically been derived from men's rugby, such as 5 $m\cdot s^{-1}$.This tends to underestimate the high-intensity running performed by female athletes due to their different physiological characteristics, such as a lower maximal velocity and ventilatory threshold speed.[14] To date, research has aimed to understand the unique aspects of the female athlete considering anatomical, physiological, physical and contextual factors.[53-55] Physical measures of speed-power and change-of-direction tasks were significantly higher in the men's rugby 7s cohort (ES: 0.61-2.09; $p<0.05$)[56], which are key components in the sport.[4] Other factors such as the menstrual cycle, psycho-social health, external commitments, and potential barriers to access, all contribute to physical performance outcomes related to the prescription and preparation of female athletes.[57] Currently, studies have utilised different bandwidths to define locomotive speed zones, further complicating comparisons. For example, low-speed thresholds have ranged from 0-0.2 $m\cdot s^{-1}$ to 0-3.5 $m\cdot s^{-1}$, across studies.[13,21,27] Similarly, moderate-speed thresholds have varied from > 3.5 $m\cdot s^{-1}$ to 3.9-5.6 $m\cdot s^{-1}$.[13,21,27] High-speed and very-high-speed zones have also varied considerably, with high-speed defined at > 5 $m\cdot s^{-1}$ in some studies and very-high-speed extending to > 7.5 $m\cdot s^{-1}$ in others.[16] In this context, the very high-speed distance used in one study was intended to measure a quality known as 'finishing' speed. The significant differences in these speed thresholds across the literature emphasise the need for greater consistency in defining and measuring speed zones in women's rugby 7s research which can be based on physiologically relevant thresholds and individual physical characteristics, such as a player's maximum speed.

4.5.2 Choice of GPS Device & Metrics

Across most GPS microtechnology devices, good reliability has been reported across measures of distance under various tests including straight line running,[63,64] shuttle endurance testing,[63,65] and team sport based circuits.[69,70] The predominant GPS device reported in the review (GPSports) demonstrated low standard error of the estimate (SEE = 0.5% - 3.7%) for distances covered at speeds less than 4 $m \cdot s^{-1}$.[71] Conversely, SEE increased when examining straight-line sprints across varying distances (20m = 5.5-10.5%; 30m = 4.2-7.6%; 40m = 2.9-7.7%).[71] A 5-Hz sampling rate was utilised to assess reliability, aligning with findings from other devices sampling at higher frequencies (10 Hz and 15 Hz) which show typically small errors (CV = 0.3 – 8.2%; bias = 10.3 – 11.6%) at speeds less than 5.0 $m \cdot s^{-1}$.[66] In contrast, the comparability of 5 Hz and 10 Hz is challenging due to conflicting findings for speeds above 5.0 $m \cdot s^{-1}$ (CV = 0.5 – 112.0%).[66]

While total distance and speed were the more commonly reported in the studies examined, incorporating metrics such as accelerations, decelerations, contacts and metabolic power output can also provide a more comprehensive understanding of the multi-directional and intermittent nature of rugby 7s.[11,13,24] It should be noted that large to very large differences were uncovered when examining inter-manufacturer agreement between two device brands (STATSports and Catapult).[29] Measures that are derived from sample-by-sample acceleration data (counts, average acceleration, and peak velocity) have the potential to underestimate outputs and can have a typical error between 3.8 – 132.7% depending on the metric and threshold utilised.

Metrics such as contacts and metabolic power were underexamined in the review despite current GPS microtechnology devices displaying high specificity (87.6 – 92.7%) and sensitivity (93.7 – 97.6%) in the automatic detection of collision events.[38,62] Similarly, measures of average metabolic power appear suitable for intermittent activities such as shuttle-based running[67] but not during sport specific circuits.[68] Global positioning system devices sampling at 10 Hz were better suited compared to 5 Hz devices when performing analysis on threshold-based assessments of metabolic power (i.e. > 20 $W.kg^{-1}$, > 25 $W.kg^{-1}$).[67]

4.5.3 Contextual Factors

Match demands in women's rugby 7s can be influenced by various contextual factors, such as playing standard (international vs domestic), tournament stage, opponent quality, and match outcomes.[12,20,24] It is essential to consider and, where possible, control for these factors when designing studies and interpreting results to ensure findings are generalisable and applicable to different playing contexts. The score differential in a match can influence physical demands.[24] Research suggests that greater winning margins for the winning team are associated with greater total running distances, high-speed running distances, and fewer missed tackles.[24] Conversely, closer matches might lead to increased match activity demands as teams potentially engage in more defensive efforts and utilise a wider range of skills.[24]

Given the relatively recent establishment of women's rugby 7s, there is the potential for underdeveloped or inconsistent development pathways. As a result, players may join high tiered competitions with wide-ranging levels of prior experience, which can contribute to a wider range of GPS microtechnology metric outputs. This variability emphasises the importance of considering individual playing histories when analysing performance data.

Similarly, differences in training and playing styles across countries may further contribute to variations in GPS microtechnology measurements. Factors such as intensity of domestic leagues, the emphasis placed on certain skills, and the overall playing philosophy of a team/nation can influence player readiness and physical demands during matches.[34]

4.6 Limitations

Despite the significance of this review in determining match and peak demands across GPS microtechnology performance measures, there are limitations inherent in the scoping review. The difference in classification of GPS thresholds (low, moderate, high) made comparisons between all studies challenging which may limit the generalisability of findings across the rugby 7s cohort. In cases where speed threshold descriptors were not explicitly defined, the authors assigned them to the most appropriate category (e.g. low, moderate, high) which may introduce a potential limitation, as the categorisation is based on subjective assessment.

The review focused on external load metrics, such as distance and speed, while neglecting internal load, which reflects the physiological and psychological responses to match demands. Although internal load was not within the original scope of this review, its inclusion could significantly enhance the interpretation of performance data. Metrics such as heart rate, heart rate variability, and perceived exertion could provide a more comprehensive picture of player responses to the stresses of competition. Incorporating these measures would allow for a more holistic understanding of how players cope with match demands, particularly during congested tournament schedules where recovery between games is critical.

A recurring limitation across the rugby 7s literature is the reliance on small sample sizes and homogenous participant groups, which hinders the generalisability of findings. This issue is often a byproduct of limited access to elite players and the logistical convenience of recruiting within a single team or program. While such constraints are common in applied sport science, the field would benefit from efforts to include larger, more diverse samples. Expanding participant pools to include players from multiple teams, competitions, and geographic regions would not only improve the statistical power but also enhance the external validity and applicability of research outcomes. Broader sampling would support more robust conclusions and inform training across different levels of play.

4.7 Future Research Implications

Metabolic power remains an underexplored area within the existing body of rugby 7s research. To date, only one study examined this metric to better understand player energy expenditure during matches. Given its potential to quantify the energetic demands of intermittent high-intensity efforts typical of rugby 7s, metabolic power could serve as a valuable complement to traditional time-motion analyses. Moreover, integrating metabolic power with other underreported variables – such as the frequency of collisions, high-intensity decelerations, and changes in direction - would offer a more nuanced view of the physical demands placed on athletes.[37,59]

Similarly, application of the WCS to better understand the most demanding aspects of play within a given epoch length, has received limited recognition. While this method offers valuable insights into peak physical demands, further research is required to gain a deeper understanding of the factors that influence these values and how coaches and practitioners can apply this information to prepare athletes effectively. Specifically, investigating by what means different playing styles, tactical approaches, opponent strength, and environmental conditions affect WCS demands would be beneficial. Further, understanding the systemised and multivariate nature of the worst-case scenario would inform more robust tactical and physical planning.[60,61]

Examining the long-term application of these findings in an athletic setting is an additional area requiring further investigation. While some studies discuss the implications for training prescription, longitudinal studies are needed to assess how the monitoring and manipulation of training loads informed by match demands, may impact performance, injury rates, and overall physical preparedness over time. For instance, rigorous investigation of the inclusion of training drills that replicate the high intensity running and collision demands to reduce injuries and improve performance outcomes in the long term is warranted.

5 CONCLUSION

Global positioning system devices provides a valuable tool for objectively quantifying movement demands during matches and has evolved the understanding of match demands in women's rugby 7s.[15,20,23,26] This body of work is crucial for optimising training specificity and adequately preparing athletes for matches, tournaments and seasons at an elite level.[13,19] The studies reviewed reported GPS microtechnology-derived performance measures that examine a broad range of match demands, with elite players covering more total distance, engaging in higher intensity running, and achieving greater sprint speeds than lower-tier players. However, methodological inconsistencies, particularly in the categorisation of GPS microtechnology-derived metrics, make comparisons across studies challenging. Examining peak demands, such as BIP and WCS, is crucial for understanding the true intensity of rugby 7s, as averages can underestimate match intensity.

Positional demands, competition level, and contextual factors all influence player performance, and further research is needed to standardise methodologies and address the gaps in understanding, especially concerning lower-tier players, adolescent players and more diverse sample sizes. A more comprehensive approach of integrating collective measures derived from GPS microtechnology could offer a holistic understanding of match demands such as those derived from metabolic load.

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CHAPTER THREE:

ANALYSIS OF PEAK RUNNING DEMANDS

BRIDGING STATEMENT

Chapter Two provides a comprehensive scoping review of the current literature on match demands, emphasising the varying GPS microtechnology metrics used to assess athletic performance in team sports. This chapter highlighted significant gaps in existing research – particularly the lack of literature examining peak running demands (PRD) when applied to women's rugby 7s and the lack of a unified approach for data aggregation across different studies. The review describes how studies have traditionally reported PRD using maximum aggregate techniques without examination into other methods to report on peak demands. Similarly, PRD values often overlooking critical within-subject and positional factors that may result in a wide variance of reported ranges. This critical examination lays a foundation, justifying the need for additional investigation to properly assess peak demands in elite women's rugby 7s.

Chapter Three transitions into an investigation centred on peak running demands. This chapter introduces a novel approach to quantify PRD, utilising GPS data analysis and power-law modelling to examine aggregation methods and reconcile the minimal reporting of variability associated with this match analysis technique. By directly addressing the methodological gaps and lack of empirical evidence in women's rugby 7s, Chapter Three validates the necessity for improved measurement techniques and underscores the need to evaluate peak match demands. The novel insights derived from this chapter offer actionable strategies for coaches and sports scientists, ultimately bridging the gap between research and practice.

ABSTRACT

Objective: This chapter aims to analyse the peak running demands (PRD) of elite women's rugby 7s by examining the different aggregation methods to report PRD and determine if there are any differences. A secondary aim is to examine the variability of reported PRD values to determine differences within-subjects, within-positions, and within-squad averages.

Methods: A total of 52 matches were analysed for a total of 600 match-observations. GPS microtechnology data was analysed using power-law models to illustrate the relationship between exercise duration and running intensity. Three aggregation methods were used: max value, 90th percentile (P90), and mean. A linear mixed models' analysis was used to investigate factors influencing the output value.

Results: Distinct differences were found between aggregation method values (max, P90, and mean) across GPS microtechnology metrics. Max aggregate method values had higher intercepts compared to P90 and mean aggregate vales. Significant within-position differences were observed for intercepts, particularly for comparisons between max vs. P90, max vs. mean, and P90 vs mean ($p<0.01$). A wide variance was observed among reported values when analysed across all groups, with coefficient of variation (CV%) ranging from 14 - 69.5% for intercepts and 22.2 – 346.8% for slope values. Positional variance did not differ significantly for intercept and slope values.

Conclusion: Using max, 90th percentile, and mean values presents unique findings when aggregating values obtained through the rolling average method to calculate and understand fluctuations in running intensities. There were no differences in PRD values across positional groups, suggesting that the use of a squad average may suffice when utilising PRD in practice and improve the scalability of monitoring large groups of players. Recorded values at an individual level varied greatly and should be a key consideration in the adoption of the aggregation method in practice, where the individual response to training stimuli must be accounted for as a part of periodisation approaches.

Keywords: GPS, aggregation methods, power-law modelling, intercepts

INTRODUCTION

In team sports such as rugby, players are exposed to various physical and mental demands during matches that are predominantly unpredictable and rapidly changing, making it challenging for coaches and analysts to prepare players for the wide array of tactical, physical, and situational scenarios encountered during matches. GPS microtechnology is increasingly popular in team sports to monitor elements of a match that are indicative of player performance including demands captured through performance metrics, such as distance covered, speed, and acceleration. To date, studies have provided snapshots of the overall demands of a match but typically do not capture the dynamic nature of team sports, such as rugby 7s. Representations of the speed of a game are predominantly reported in relative terms (i.e. rate per minute) that have been examined based on whole match, match halves, and periods in which the ball is in play (BIP).[1] Examining this data in isolation, without considering contextual factors such as tactical situations or player roles may not provide coaches and analysts with a complete picture of the most physically demanding situations players may encounter during a match. To address this, coaches and analysts have utilised worst-case scenario (WCS) analysis to identify the most physically demanding moments of a game and prepare players for these scenarios.

The WCS has been variably defined in the literature, with a recent study describing it as the "single longest period of continuous play in a game".[1] While definitions can vary, locomotive measures are predominantly reported in isolation (i.e., one metric at a time), raising concerns on whether this approach accurately represents the WCS. The original study that investigated the WCS concept was intended to provide a novel method to examine periods of a match that exceeded the average demands of the game, helping to portray the dynamic demands of team invasion sports and identify periods of a match with heightened locomotor demands.[2] The WCS analyses sample-by-sample positional data derived from GPS microtechnology and applies a rolling average method at pre-defined average window durations. For example, a one-minute duration would consist of 600 data points to determine the average velocity during that period. This process is repeated across varying durations, ranging from one to 10 minutes[3,4] and across metrics including total distance or high-speed running to determine a peak value.

Examining relative values (i.e. metres per minute) using the rolling average method in rugby league identified differences between varying rolling average windows. Apart from 10 second epochs, differences between 30-seconds, 1-minute, 5-minutes, and 10-minutes were trivial when comparing relative distances (e.g., $m \cdot min^{-1}$) between positions.[5] Additionally, in team sports such as rugby union where collisions and impacts form a key physical component of the game, there is the potential to attain peak impacts while demonstrating moderate to high running intensities.[6] This insight contrasts with those presented in rugby league where it was identified that with increasing collision requirements, there is an associated decrease in relative running intensities as a result.[7] Differences in game rules may identify the disparity between the two findings as there are more general play phases in rugby union compared to rugby league that have tackle limits.

When reporting rolling average values in absolute metrics (i.e., metres) there is a high variability in peak reported values that can be seen between individuals when utilising a 5-minute rolling window.[8] Sprint distance above 7 $m \cdot s^{-1}$ demonstrated a high intra-individual coefficient of variation (CV), with a mean of 46.1% (21.1 – 76.4%), while measures of high-speed running (> 5 $m \cdot s^{-1}$) (HSR) and total distance had less variance; 25.2% (15.6 – 37.8%) and 6.2% (4.6 – 8.2%), respectively.[8] Inter-positional differences in soccer varied between metrics: no significant differences were observed for sprinting; a smaller effect was found for high-speed running (HSR); and a strong effect was observed for total distance (with central backs, fullbacks, strikers, and wide midfielders covering more distance than central midfielders; standardized $\beta = -0.910$ to -0.309, $p \leq 0.030$). The amount of variance may be explained by the level of intra-positional variability (i.e., higher intra-positional variance resulted in smaller inter-positional differences). In this context, the WCS can be more accurately described as the most demanding locomotor passages of a game, that is specific to both the metric and duration analysed.[5] Consequently, this chapter will refer to the WCS as 'peak running demands' (PRD) to reflect its relevance in this context.

Power-law models were proposed to illustrate the relationship between exercise duration and running outputs. These models suggest that PRD intensity decreases non-linearly as duration increases, eventually plateauing at longer durations. A power-law curve relationship[9] can be represented in the given formula:

$$Y = cx^{n}$$

Where c and n are constants, Y is the running intensity metric of interest e.g. relative distance and x is the average window duration. With this power relation, when plotted against log (x) results in a straight line with associated intercept (c) and slope (n) for a given metric. Hence, the predictive equation of running intensity as a function of average window duration can be computed as follows:

$$\text{Running Intensity} = \text{Intercept} \cdot \text{Duration}^{\text{Slope}}$$

By utilising power-law modelling, studies have aimed to address previous limitations of assessing match demands through whole-game averages.[2,3,10] Compared to solely utilising pre-determined rolling average windows examined in previous studies,[5,11] establishing power law allows practitioners to predict peak running demands across chosen durations of interest. The associated intercepts and slopes derived from power law modelling serves as an added tool aimed at improving training specificity.[12]

To determine running intensity as measured by average speed, using a 3-minute duration in the power-law formula with an intercept of 165 $m \cdot min^{-1}$ and slope value of -0.32, the expected running intensity will be 116.2 $m \cdot min^{-1}$. Training drills would need to be at or above 116.2 $m \cdot min^{-1}$ for a 3-minute duration to match the running intensities experienced in a match, which can be expressed as a percentage (i.e., 116.2 $m \cdot min^{-1}$ is 100% of match running intensity).

The example scenario is a practical application that utilises the GPS microtechnology-derived peak value as a reference to compare training drill intensities in relation to intensified periods experienced during a match. Practitioners can then prescribe appropriate training intensities to optimise players’ readiness for peak demands experienced in competition.[13] Use of small-sided games (SSG) is a prolific example used to examine the WCS in a training environment. SSG serve as a versatile tool due to their condensed, intensified nature and adaptability for replicating the contextual and physical components of match scenarios.[!4] When compared to game-based training and conditioning training, SSG best replicated the movement intensities within training and expose athletes to running intensities that can exceed those experienced within a rugby union match.[15] However, there have been no longitudinal studies that examine the potential physiological adaptation because PRD is used as a measure of training intensity.

To date, one study has examined use of the PRD in women's rugby 7s and provided comparisons to the fifteen-a-side game (rugby union). While no differences in maximum relative distance were observed for 1-minute peak running activities between rugby 7s and rugby union, a higher 90th percentile intercept was recorded for HSR in rugby 7s and underscores the shift in training content required as players transition between both formats of the game.[16] While the study does not explicitly compare between positions (forwards and backs) within the rugby 7s cohort through hypothesis testing, the use of inferential statistics may inherently allow for an indirect comparison of positional differences. Interestingly, use of percentiles provided a novel approach to identifying peak values as PRD has typically been reported based on the highest value achieved in a match,[12,17] thereby introducing potential variance based on a practitioner's chosen statistical measure (aggregation) used to analyse the running intensity data distribution such as maximums, percentiles, and averages. While there is limited literature on the selection of reported values, use of the 90th percentile appears to be a sound method to report on PRD as it typifies 10% of activity spent by player while also reducing the effect erroneous maximum values can have in skewing reported running intensities.[16]

Despite the novelty of the rolling average method providing additional scope in understanding match demands, there is a paucity of data when analysed in women's rugby 7s. Similarly, challenges emerge when applying PRD analysis into practice as the choice of aggregation can affect the interpretation of peak demands and limit transference into practice. As such, this chapter aims to analyse the PRD of elite women's rugby 7s by examining the differences between aggregation methods to report the PRD and determine if any differences. Secondly, the aim is to examine the variability of reported PRD values to determine differences within-subjects, within-positions, and within-squad average.

METHODS

Participants

Data was collated from elite women's 7s rugby players (n= 26) from one national rugby 7s team (age: 22.6 ± 4.1 years, stature; 169.4 ± 4.1 cm, body mass; 73.3 ± 5.7 kg) participating in international tournaments including the HSBC World Sevens Series and 2021 Olympic Games. Athletes were categorised into groups to allow for inter-positional comparisons; forwards (n = 11), backs (n = 7), and utility/ball player (UBP) (n = 9).

The study was approved by the University of Sydney Human Research Ethics Committee (Protocol 2024/HE001488) in accordance with the Declaration of Helsinki.

Quantifying GPS Physical Performance Measures

Global positioning system (GPS) units were used to quantify running demands during a match. A GPS microtechnology unit (Vector, Catapult Sport, Australia) was placed between the scapulae of the players in bespoke pouches housed on a tightly-fitted playing jersey. Units sampled at 10 Hz with accelerometer data sampling at 100 Hz. At the end of each match, data was downloaded using the company-provided software (OpenField, version 3.4.0) from which game time was included in the analysis. Sample-by-sample positional data was processed through R (RStudio, Version 4.4.1, Boston, USA) for each match for the following metrics: total relative distance ($m \cdot min^{-1}$) (TD), relative high-speed running > 5 $m \cdot s^{-1}$ ($m \cdot min^{-1}$) (HSR), acceleration load density ($AU \cdot min^{-1}$) (ALD), and relative acceleration count > 2.5 $m \cdot s^{-2}$ ($n \cdot min^{-1}$) (ACC).

To ensure the integrity and reliability of the GPS microtechnology data, several quality control procedures were implemented prior to analysis. Sample-by-sample data were visually inspected and processed using manufacturer-recommended software (Catapult OpenField), with specific filtering parameters applied to minimise noise and artefacts commonly associated with satellite-based tracking. A horizontal dilution of precision (HDOP) threshold of ≤1.5 and a minimum satellite count of ≥6 were adopted as acceptable limits for data inclusion, as these are indicative of optimal signal quality and positional accuracy.[35,36]

Acceleration data were smoothed using a low-pass Gaussian filter to reduce signal noise without eliminating genuine movement patterns. Data points exhibiting implausible values, such as instantaneous velocities exceeding 10 $m \cdot s^{-1}$ or accelerations surpassing ±10 $m \cdot s^{-2}$, were flagged for further review and excluded if confirmed to be artefactual. Individual files were removed from the dataset if persistent signal dropout, poor satellite connection, or unrealistic movement traces (e.g., prolonged periods of inactivity during match play) were identified.

These procedures ensured that only high-quality, representative data were retained for subsequent analysis, thereby enhancing the validity of findings related to locomotor demands.

Reporting Peak Running Demand Values

Analysis of the PRD consisted of processing sample-by-sample GPS data sampled at 10 Hz where a rolling average window was overlayed over each data point using pre-defined durations (i.e. 1, 2, 3, 4, 5, 6, and 7 minutes). This was repeated across each GPS microtechnology variable (TD, HSR, ALD, ACC) and for each individual player and match observation and each aggregation method: maximum: the highest recorded value within a given period that represents the absolute peak intensity experienced in a match; 90th percentile (P90): represents the running output value (e.g. relative distance ($m \cdot min^{-1}$)) at which players spent 10% of their activity; and mean: the average output across a match.

Power-Law Modelling

To examine the relationship between peak running intensities and duration, a power-law model was applied to describe the performance decrement over time across multiple locomotor metrics: relative total distance (TD; m·min^{-1}), high-speed running (HSR; m·min^{-1}), acceleration load density (ALD; AU·min^{-1}), and relative acceleration count > 2.5 m·s^{-2} (ACC; count·min^{-1}). For each player-match file, rolling average values were computed for window durations ranging from one to seven minutes. Based on the defined durations, three aggregation methods were applied for each GPS metric: (1) the maximum value representing the single highest intensity value achieved in the match, (2) the 90th percentile value (P90) representing the threshold above which the player spent 10% of time, and (3) the mean, representing the average across the rolling window durations. This process yielded three aggregated values per GPS metric for each player-match instance.

Using these three values (max, P90, mean), linear regression was performed for each player-match file by plotting the GPS metric values (y-axis) against log-transformed rolling window durations (x-axis), producing a straight line from which an intercept (intensity at theoretical zero duration) and a slope (rate of intensity decay over time) were extracted. This modelling approach was applied independently for each aggregation method (max, P90, mean) and each metric (TD, HSR, ALD, ACC), resulting in a set of intercept and slope values per match x player file per metric.

Subsequently, intercept and slope values were averaged at the individual level across all match observations to produce player-level means for each aggregation method and GPS metric. These individual values were then pooled to calculate group-level statistics, mean and standard deviation (SD) — for each positional group (forwards, backs, utility/ball players) as well as for the entire squad. This procedure enabled group-wise comparisons and visualisation of positional trends in both intercept and slope metrics across all four GPS variables.

STATISTICAL ANALYSIS

To determine the difference between intercept and slopes across aggregation methods and GPS microtechnology measures (TD, HSR, ALD, ACC), descriptive statistics were calculated (mean (95% confidence interval)). Comparisons were made by assessing overlap in confidence intervals between different aggregation methods and GPS microtechnology measures to determine potential meaningful differences.

Additionally, descriptive statistics was also computed using R (RStudio, Version 4.4.1, Boston, USA) for factors including GPS microtechnology metrics, aggregation method, positional groups (all players, forwards, backs, utility/ball players (UBP)), across players and matches and for each individual player. Coefficient of variation (CV %) was calculated to assess within-group variability across factors and calculated as:

$$\text{Coefficient of Variation (\%)} = \text{SD}/\text{Mean} \times 100$$

Linear mixed models were used to evaluate differences in each of the slope or intercept with the player included as the subject, aggregation method and position as fixed factors, and the intercept set as random. The model assessed both the main effect of these variables and their interaction effects. Pairwise comparisons were conducted using the Least Significant Difference (LSD) post hoc test to identify statistically significant differences between specific effects. The estimated marginal means were calculated to provide adjusted averages for each factor level after accounting for other variables in the mode. Interaction effects, where applicable, were further examined to identify meaningful differences in subgroup performance. Significance set at $p < 0.05$. Analysis was performed using SPSS V29.0 (Armonk, New York, United States).

RESULTS

A total of 52 matches were analysed for a total of 600 match-observations (players x matches). Data were drawn from 9 international tournaments for a total of 600 match files being included with 27 unique players comprising the match files. When stratified by playing position, the sample comprised 7 backs and 11 forwards, and 8 utility/ball players with 163, 260, and 177 match observations per positional group, respectively. Figure 1 summarises the GPS microtechnology values obtained from all matches based on aggregation, with outputs decreasing as a function of the different rolling average windows. All values were displayed as the mean (standard deviation (SD)) and expressed in relative terms based on the metrics defined in the methods.

Intercept and Slope Values

Intercept and slope values for the comparisons between aggregation methods, GPS microtechnology metrics, and positional groups are presented in Table 1.

Across all analyses, aggregation methods emerged consistently as a main effect across both intercepts (ACC: $F(2, 1663) = 1602.17$, $p < .001$; ALD: $F(2, 1749) = 879.77$, $p < .001$; HSR: $F(2, 1729) = 187.21$, $p < .001$; TD: $F(2, 1764) = 720.78$, $p < .001$) and slopes (ACC: $F(2, 1663) = 569.04$, $p < .001$; ALD: $F(2, 1749) = 422.18$, $p < .001$; HSR: $F(2, 1729) = 54.02$, $p < .001$; TD: $F(2, 1764) = 444.74$, $p < .001$) for all derived metrics. This demonstrates that values in each aggregation method (Max, P90, and Mean) were different and will not be commented on further.

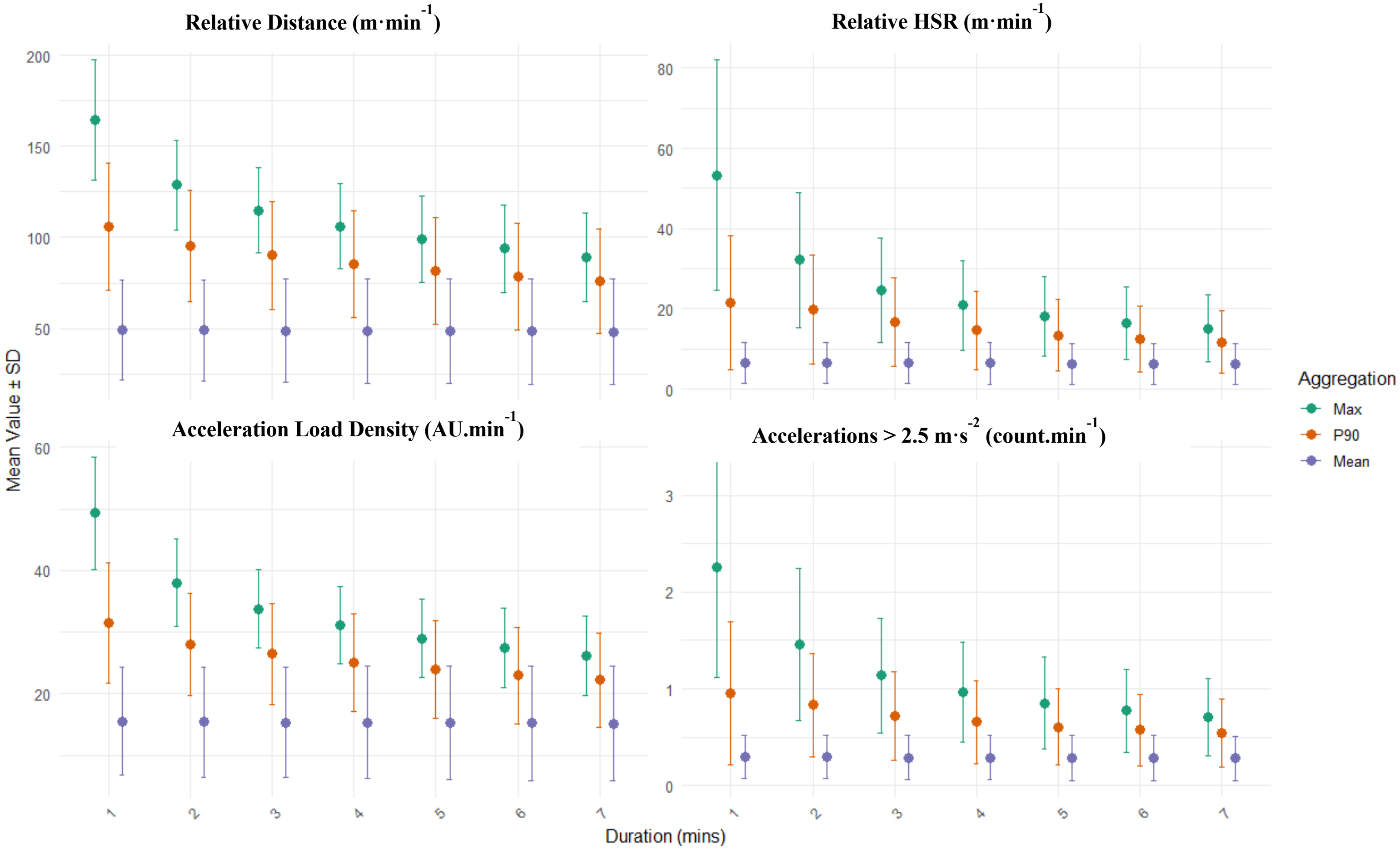

Figure 1 Rolling average by duration for all players across all matches for each GPS microtechnology metric and aggregate method.

Values expressed as mean (SD) and categorised by metric and aggregation method. Abbreviations: P90, 90th percentile; TD, total relative distance ($m \cdot min^{-1}$); HSR, relative high-speed running ($m \cdot min^{-1}$); ALD, acceleration load density ($AU.min^{-1}$); ACC, relative acceleration count ($count.min^{-1}$); AU, arbitrary units.

Slope

Relative Distance ($m \cdot min^{-1}$)

Pairwise comparisons revealed significant differences between all aggregation methods: max vs. mean (-0.28, 95% CI: -0.29 to -0.26, $p < .001$), max vs. P90 (-0.15, 95% CI: -0.17 to -0.13, $p < .001$), and P90 vs. mean (-0.13, 95% CI: -0.15 to -0.11, $p < .001$). The main effect of position, as well as the main and interaction effects of position and aggregation method, were not significant ($p > .05$). No pairwise comparisons between positions reached statistical significance ($p > .05$).

Relative HSR ($m \cdot min^{-1}$)

All pairwise comparisons were significant: max vs. mean (-0.59, 95% CI :-0.71 to -0.47, $p < .001$), max vs. P90 (-0.47, 95% CI: -0.59 to -0.35, $p < .001$), and P90 vs. mean (-0.12, 95% CI: -0.24 to -0.003, $p = .045$). The main effect of position was not significant ($p > .05$), and neither the main nor interaction effects of position and aggregation method were significant ($p > .05$). However, when using P90 values, a significant difference was observed between backs and forwards (mean difference = 0.24, 95% CI: 0.04 to 0.45, $p = .018$).

Accelerations > 2.5 $m \cdot s^{-2}$

Pairwise comparisons indicated that maximum values were greater than both mean (mean difference = -0.52, 95% CI: -0.55 to -0.49, $p < .001$) and P90 values (-0.24, 95% CI:-0.27 to -0.21, $p < .001$). Additionally, P90 values were significantly higher than mean values (-0.28, 95% CI:-0.31 to -0.25, $p < .001$), reflecting a steeper decline in PRD values with increasing duration. The main effect of position, as well as the main and interaction effects of position and aggregation method, were not significant ($p > .05$).

Acceleration Load Density ($AU \cdot min^{-1}$)

Pairwise comparisons revealed significant differences between all methods: max vs. mean (-0.29, 95% CI:-0.31 to -0.27, $p < .001$), max vs. P90 (-0.15, 95% CI:-0.17 to -0.13, $p < .001$), and P90 vs. mean (-0.15, 95% CI:-0.17 to -0.13, $p < .001$).

The main effect of position was not significant (*p* > .05); however, pairwise comparisons indicated a significant difference between forwards and UBP (unclassified backline players), with forwards exhibiting a greater decline in PRD values (mean difference = 0.02, 95% CI: 0.001 to 0.039). The main and interaction effects of position and aggregation method were not significant (*p* > .05). However, when examining P90 values specifically, significant differences were identified between backs and UBP (mean difference = -0.42, 95% CI: -0.76 to -0.01, *p* = .014), and between UBP and forwards (-0.40, 95% CI: -0.72 to -0.01, *p* = .018).

Intercept

Relative Distance (m·min^{-1})

Significant main effects were found for position (*F*(2, 1764) = 4.67, *p* = .010). Post hoc comparisons revealed that backs had significantly higher intercepts than forwards (0.08, 95% CI: 0.01 to 0.15, *p* = .029), and UBP also showed greater values than forwards (0.10, 95% CI :0.03 to 0.17, *p* = .005).

Relative HSR (m·min^{-1})

Mean values produced significantly lower intercepts than both P90 (mean difference = -1.19, 95% CI: -1.42 to -0.95, *p* < .001) and maximum values (-2.26, 95% CI: -2.49 to -2.03, *p* < .001), indicating reduced peak output at shorter durations. No other effects or comparisons were statistically significant (*p* > .05).

Acceleration Load Density (AU·min^{-1})

Significant main effects were observed for position (*F*(2, 1749) = 9.64, *p* < .001). Pairwise comparisons between aggregation methods revealed that maximum values were associated with higher intercepts than both mean (1.29, 95% CI: 1.23 to 1.36, *p* < .001) and P90 values (0.47, 95% CI: 0.41 to 0.54, *p* < .001), while P90 values were significantly higher than mean values (0.82, 95% CI: 0.76 to 0.88, *p* < .001). Between positions, backs had higher intercepts than forwards (0.13, 95% CI: 0.07 to 0.18, *p* < .001), and UBP also displayed higher values than forwards (0.09, 95% CI: 0.03 to 0.15, *p* =

.002). Using mean aggregation values, both backs (0.16, 95% CI: 0.05 to 0.26, *p* = .003) and UBP (0.14, 95% CI: 0.04 to 0.24, *p* < .001) demonstrated significantly greater intercepts than forwards.

Accelerations > 2.5 m·s^{-2}

Pairwise comparisons revealed that maximum values produced higher intercepts than both mean (mean difference = 2.21, 95% CI: 2.13 to 2.29, *p* < .001) and P90 values (0.67, 95% CI: 0.58 to 0.74, *p* < .001). P90 values were also significantly higher than mean values (1.55, 95% CI: 1.49 to 1.63, *p* < .001), indicating greater peak output at shorter durations when modelled using power law principles.

The main effect of position was significant (*F*(2, 1663) = 0.37, *p* < .001) although neither the main nor interaction effects between position and aggregation method reached significance (*p* > .05). Post hoc comparisons indicated that backs had higher intercepts than forwards (0.14, 95% CI: 0.06 to 0.21, *p* < .001), while forwards had higher values than UBP (-0.15, 95% CI: -0.22 to -0.07, *p* < .001). No other position-based comparisons were significant (*p* > .05).

Across aggregation methods, intercepts were significantly higher in maximum values compared to both mean (1.36, 95% CI: 1.29 to 1.44, *p* < .001) and P90 values (0.49, 95% CI: 0.42 to 0.56, *p* < .001), with P90 values also significantly higher than mean (0.88, 95% CI: 0.80 to 0.95, *p* < .001).

Variation

The CV% values for position and aggregation method across individual players for each GPS microtechnology metric is presented in Table 2. Inter-individual variations are shown in Figures 2 and 3, with values expressed as mean (SD). The average CV% across aggregation methods and GPS microtechnology metrics for within-individuals were as follows: TD: 17.0-49.6%, HSR: 53.1-68.2%, ALD: 15.4-51.9%, and 42.9-72.9% for intercepts. For slopes, the ranges were: TD: 35.2-578.8%, HSR: 20.5-419.9%, ALD: 29.3-354.0%, and ACC: 27.7-223.1%.

Table 1 Mean and 95% confidence intervals for intercepts and slopes across aggregation methods when calculating running demands across all matches for each positional group.

		Max		**90th Percentile (P90)**		**Mean**	
		Intercept	**Slope**	**Intercept**	**Slope**	**Intercept**	**Slope**
Relative Distance ($m \cdot min^{-1}$)	All Positions	164.8 [154.8, 174.8]	-0.32 [-0.27, -0.38]	110.3 [99.1, 121.5]	-0.18 [-0.10, -0.25]	49.9 [49.9, 49.9]	-0.05 [0, -0.09]
	Forwards	162.0 [146.4, 177.6]	-0.33 [-0.25, -0.41]	107.3 [90.2, 124.5]	-0.17 [-0.05, -0.28]	45.6 [45.6, 45.6]	-0.04 [0.04, -0.11]
	Backs	166.1 [150, 182.3]	-0.32 [-0.23, -0.41]	112.1 [94.8, 129.4]	-0.18 [-0.04, -0.32]	51.1 [51.1, 51.1]	-0.05 [0.04, -0.13]
	Utility/Ball Player	167.8 [147.7, 187.9]	-0.32 [-0.21, -0.43]	113.3 [89.3, 137.3]	-0.18 [-0.06, -0.3]	55.4 [55.4, 55.5]	-0.06 [0.04, -0.15]
Relative HSR ($m \cdot min^{-1}$)	All Positions	52.9 [42.9, 62.9]	-0.67 [-0.61, -0.73]	25.3 [19.6, 31]	-0.31 [-0.14, -0.48]	6.7 [6.7, 6.8]	-0.08 [0, -0.15]
	Forwards	46.5 [32.3, 60.7]	-0.68 [-0.59, -0.77]	21.7 [14, 29.3]	-0.31 [-0.08, -0.53]	5.4 [5.4, 5.5]	-0.07 [0.04, -0.17]
	Backs	58.4 [40.9, 76]	-0.67 [-0.57, -0.78]	27.4 [17.9, 36.9]	-0.30 [0.11, -0.71]	7.1 [7.1, 7.2]	-0.06 [0.06, -0.19]
	Utility/Ball Player	57.3 [36.8, 77.9]	-0.65 [-0.52, -0.77]	28.9 [15.8, 42.1]	-0.33 [-0.04, -0.63]	8.4 [8.3, 8.4]	-0.10 [0.05, -0.25]
Acceleration Load Density ($AU.min^{-1}$)	All Positions	49.2 [46.4, 52]	-0.33 [-0.29, -0.38]	32.4 [29.1, 35.6]	-0.18 [-0.09, -0.27]	15.7 [15.7, 15.7]	-0.04 [0, -0.08]
	Forwards	47.9 [43.6, 52.2]	-0.33 [-0.26, -0.4]	31.2 [26.2, 36.1]	-0.16 [0.03, -0.35]	14.5 [14.4, 14.5]	-0.03 [0.03, -0.09]
	Backs	50.6 [45.6, 55.6]	-0.33 [-0.24, -0.41]	34.1 [28.8, 39.4]	-0.2 [-0.12, -0.28]	16.5 [16.5, 16.5]	-0.04 [0.03, -0.12]
	Utility/Ball Player	50.0 [45, 55.1]	-0.34 [-0.24, -0.43]	32.7 [26, 39.4]	-0.2 [-0.11, -0.29]	16.8 [16.8, 16.8]	-0.05 [0.04, -0.13]
Accelerations $>2.5\ m \cdot s^{-2}$ ($count.min^{-1}$)	All Positions	2.3 [2, 2.7]	-0.62 [-0.55, -0.69]	1.2 [1, 1.4]	-0.38 [-0.25, -0.51]	0.3 [0.2, 0.5]	-0.10 [-0.02, -0.18]
	Forwards	2.2 [1.7, 2.8]	-0.62 [-0.52, -0.73]	1.1 [0.9, 1.4]	-0.36 [-0.13, -0.59]	0.3 [0.1, 0.5]	-0.09 [0.03, -0.2]
	Backs	2.4 [1.7, 3.1]	-0.62 [-0.51, -0.73]	1.3 [0.9, 1.7]	-0.39 [-0.19, -0.6]	0.3 [0.1, 0.6]	-0.10 [0.04, -0.24]
	Utility/Ball Player	2.4 [1.6, 3.3]	-0.61 [-0.46, -0.76]	1.3 [0.9, 1.7]	-0.38 [-0.18, -0.58]	0.4 [0, 0.7]	-0.12 [0.05, -0.3]

Table 2 The means, standard deviation (SD) and coefficient of variation (CV) across individual players Comparison of for intercepts and slope values for each aggregation methods for a team and positional group for relative distance, relative high-speed running, acceleration load density, and relative acceleration count > 2.5 m·s^{-2}. Values expressed as mean, SD, CV%. Abbreviations:P90, 90th percentile.

		Max				**P90**				**Mean**			
		Intercept		**Slope**		**Intercept**		**Slope**		**Intercept**		**Slope**	
		Mean (SD)	**CV%**	**Mean (SD)**	**CV%**	**Mean (SD)**	**CV%**	**Mean (SD)**	**CV%**	**Mean (SD)**	**CV%**	**Mean (SD)**	**CV%**
Relative Distance (m·min^{-1})	All positions	164.8 (26.4)	16.0	-0.32 (0.14)	-42.6	110.5 (29.4)	26.6	-0.18 (0.18)	-100.0	49.9 (27.1)	54.2	-0.05 (0.13)	-279.8
	Forwards	162 (27.6)	17.0	-0.33 (0.14)	-42.8	107.3 (30.3)	28.3	-0.17 (0.21)	-122.6	45.6 (24.7)	54.2	-0.04 (0.13)	-343.3
	Backs	166.1 (23.3)	14.0	-0.32 (0.13)	-39.5	112.8 (23.4)	20.7	-0.19 (0.14)	-71.5	51.1 (26.1)	51.2	-0.05 (0.12)	-257.4
	Utility/Ball Player	167.8 (27.1)	16.2	-0.32 (0.14)	-45.2	113.3 (32.4)	28.6	-0.18 (0.16)	-91.6	55.4 (30.2)	54.5	-0.06 (0.13)	-232.1
Relative HSR (m·min^{-1})	All Positions	52.9 (26.5)	50.1	-0.67 (0.16)	-24.4	25.4 (15.2)	59.8	-0.33 (0.36)	-110.2	6.7 (5)	74.5	-0.08 (0.19)	-252.5
	Forwards	46.5 (25.1)	53.9	-0.68 (0.17)	-24.5	21.7 (13.5)	62.5	-0.31 (0.40)	-130.4	5.4 (4)	73.3	-0.07 (0.18)	-281.3
	Backs	58.4 (25.3)	43.3	-0.67 (0.15)	-22.2	27.6 (13.5)	49.0	-0.34 (0.35)	-103.3	7.1 (4.3)	60.2	-0.06 (0.18)	-281.9
	Utility/Ball Player	57.3 (27.7)	48.4	-0.65 (0.17)	-26.2	29.1 (17.6)	60.5	-0.35 (0.31)	-86.7	8.4 (6.4)	76.1	-0.10 (0.21)	-203.9
Acceleration Load Density (AU.min^{-1})	All Positions	49.2 (7.4)	15.0	-0.33 (0.12)	-37.1	32.4 (8.5)	26.3	-0.19 (0.12)	-65.5	15.7 (8.6)	55.0	-0.04 (0.11)	-282.5
	Forwards	47.9 (7.6)	15.8	-0.33 (0.12)	-36.2	31.3 (8.6)	27.4	-0.18 (0.13)	-70.5	14.5 (8.5)	58.7	-0.03 (0.11)	-346.8
	Backs	50.6 (7.3)	14.3	-0.33 (0.12)	-36.2	34.1 (7.6)	22.3	-0.2 (0.12)	-60.6	16.5 (8.2)	49.5	-0.04 (0.11)	-250.6
	Utility/Ball Player	50 (6.8)	13.7	-0.34 (0.13)	-39.1	32.7 (9.1)	27.8	-0.2 (0.12)	-63.0	16.8 (9.0)	53.9	-0.05 (0.11)	-242.8
Acceleration Count > 2.5 m·s^{-2} (count.min^{-1})	All Positions	2.3 (1.0)	43.6	-0.62 (0.18)	-29.3	1.2 (0.5)	41.8	-0.38 (0.30)	-77.7	0.3 (0.2)	68.0	-0.1 (0.21)	-211.3
	Forwards	2.2 (0.9)	42.1	-0.62 (0.18)	-28.9	1.1 (0.5)	41.3	-0.38 (0.32)	-84.4	0.3 (0.2)	69.5	-0.09 (0.20)	-229.5
	Backs	2.4 (1.0)	41.0	-0.62 (0.16)	-25.9	1.3 (0.5)	43.0	-0.39 (0.29)	-74.0	0.3 (0.2)	64.0	-0.1 (0.20)	-206.5
	Utility/Ball Player	2.4 (1.1)	47.3	-0.61 (0.20)	-33.0	1.3 (0.5)	39.6	-0.38 (0.27)	-70.6	0.3 (0.2)	67.7	-0.12 (0.24)	-193.3

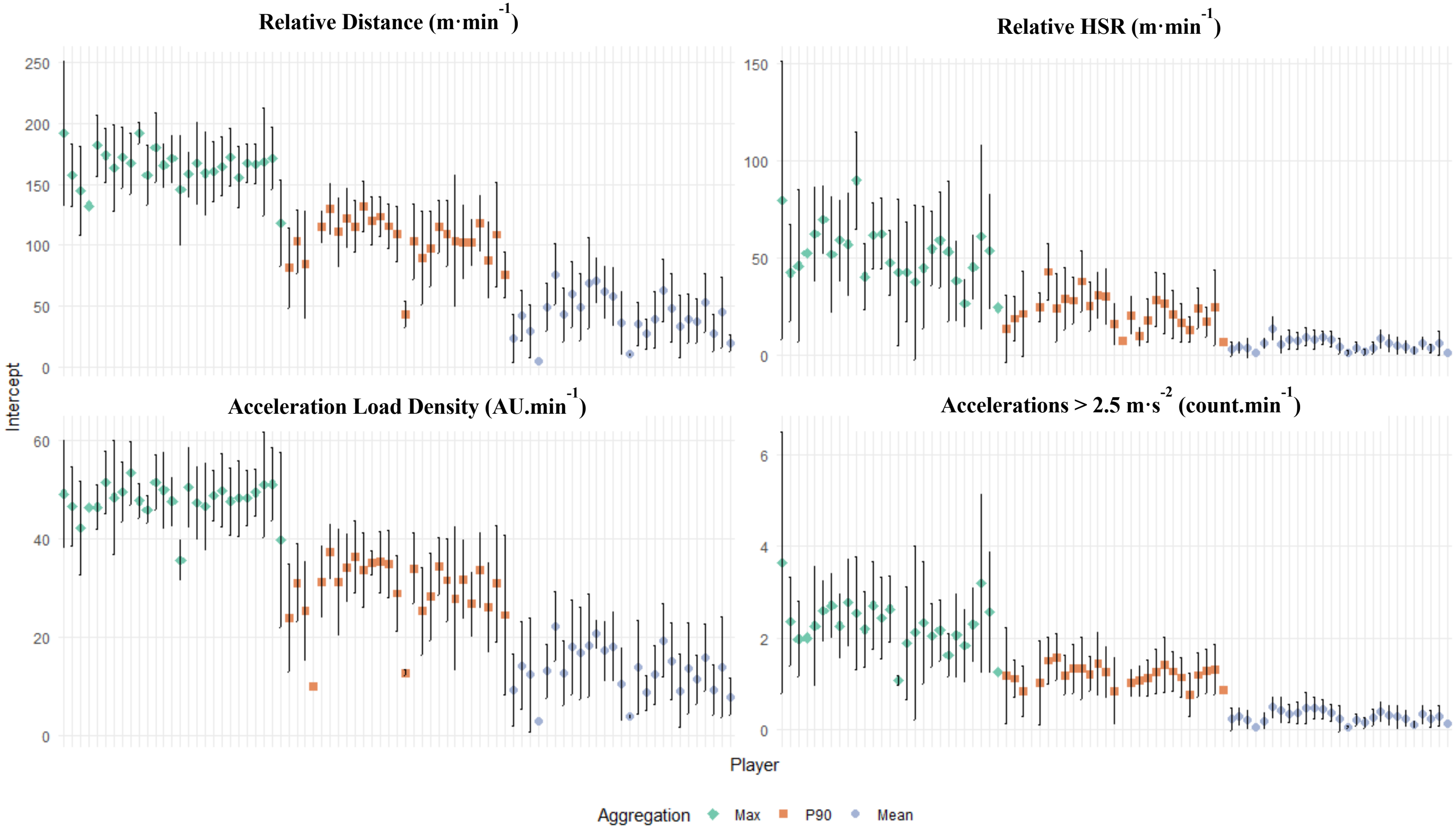

Figure 2 Distribution of intercept values for individual players.

Values expressed as mean (SD) and categorised by metric and aggregation method. Abbreviations: P90, 90th percentile; TD, total relative distance (m·min^{-1}); HSR, relative high-speed running (m·min^{-1}); ALD, acceleration load density (AU.min^{-1}); ACC, relative acceleration count (count.min^{-1}).

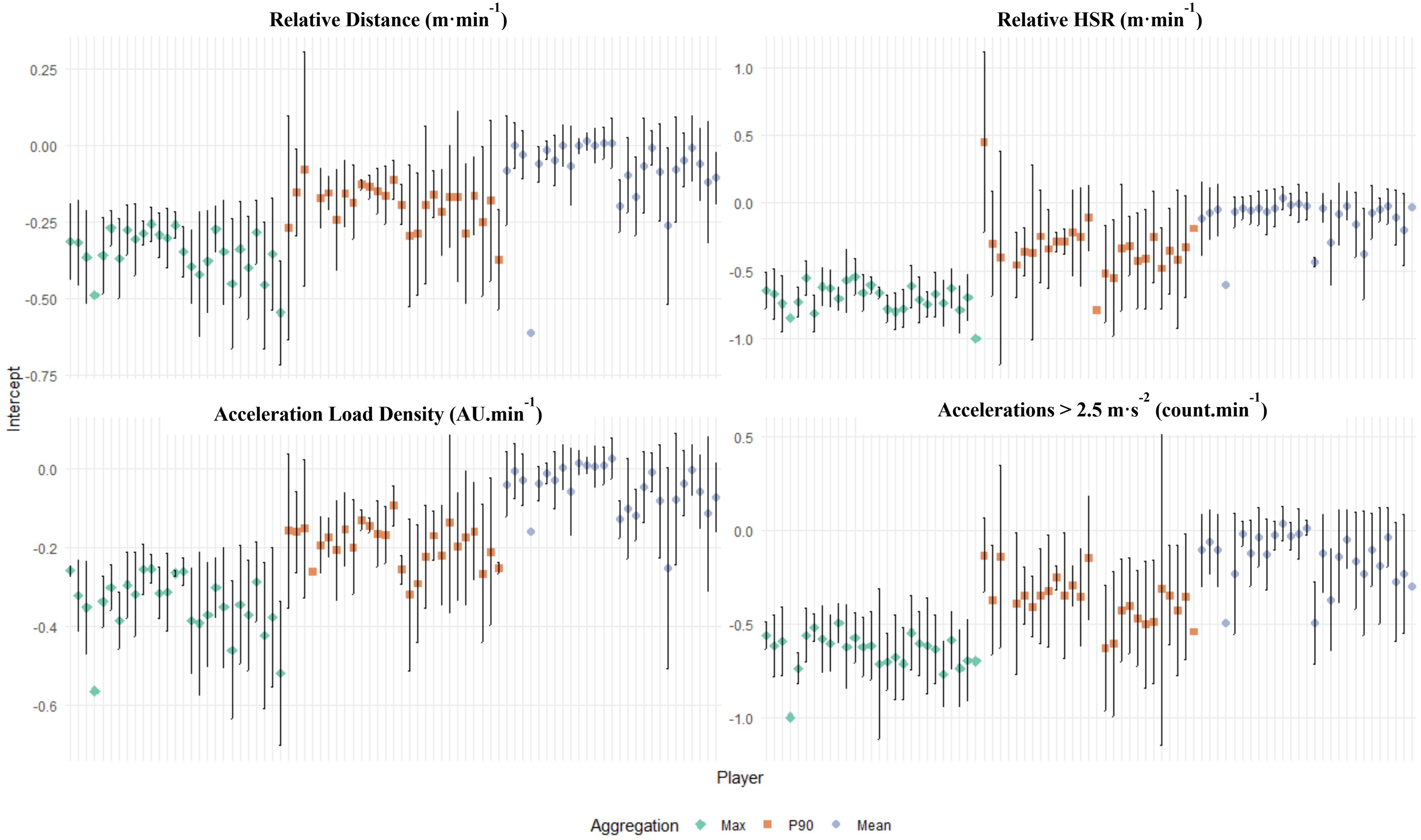

Figure 3 Distribution of slope values for individual players.

Values expressed as mean (SD) and categorised by metric and aggregation method. Abbreviations: P90, 90th percentile; TD, total relative distance (m·min^{-1}); HSR, relative high-speed running (m·min^{-1}); ALD, acceleration load density (AU.min^{-1}); ACC, relative acceleration count (count.min^{-1})

DISCUSSION

The primary aim of the present study was to analyse the peak running demands (PRD) of elite women's rugby 7s by examining the differences between aggregation methods to report PRD values. A secondary aim was to examine the reported PRD values to determine variance within squad averages, within positions, and within players. The study identified a significant difference between aggregation method values (max, P90, and mean) across intercepts, slopes, and all GPS microtechnology metrics (TD, HSR, ALD, ACC, $p < 0.01$). Furthermore, it was demonstrated that there is a wide variance among reported values when analysed across all groups (full squad, position, individuals), underscoring the dynamic and unpredictable intensities within elite women's rugby 7s competition. Variance among PRD values was non-specific to GPS microtechnology metrics, identifying that there is considerable variability of reported CV% ranging from 14.0 – 76.1% for intercepts and 22.2 – 346.8% for slope values. Max PRD values recorded lower variances between and within positional groups than P90 and mean PRD values.

Aggregation Method

The study is the first to examine the methods used to aggregate peak running demand values across matches. The results highlighted that aggregation methods used to determine intercept and slope values to calculate running intensities are unique and not specific to the GPS microtechnology metric examined. Max aggregate method values had higher intercepts compared to P90 and mean aggregate values, underscoring a single period during a match that reflects the most intense running demands is considerably larger (max vs. P90: $d = 1.99$, $p<0.001$, *very large*; max vs. mean: 4.33, $p<0.01$, *nearly infinite*) when compared to the other aggregation methods, as measured using GPS microtechnology. Similarly, the associated slopes were also higher in max aggregate values than in P90 and mean aggregate values. This demonstrates that maximal exercise intensities do not occur often and represents the transient and unsustainable nature of maximal intensity outputs over extended durations. As exercise duration increases, there is an associated decline in performance metrics, highlighting the diminishing running outputs due to accumulated fatigue.[19,20] Previous studies have identified P90 as a suitable method to categorise peak values.[16] The slope and intercept values for P90 were lower (p<.001) than max values and demonstrated slope characteristics that would indicate stable running outputs across 90% of a match with a reduced degree of decline over time (as indicated by the slope). However, the difference between max and P90 values underscores the large gap between the two aggregation methods for intercept and slope values, demonstrating that even within the top 10% of a match, there remains a substantial gap compared to values occurring only once.[3] Mean aggregate method values had slope characteristics that demonstrated consistent running intensities across all GPS microtechnology metrics throughout all durations, indicating that running intensity fluctuations are obscured and not an indicator of varying running intensities experienced in a match.

The 90th percentile (P90) was selected as the primary aggregation method for reporting peak running and metabolic demands. While maximum values capture the most extreme efforts observed, they are often influenced by outliers or context-specific actions (e.g., chasing down a breakaway), which may not be repeatable. In contrast, the P90 approach better represents typical high-intensity efforts across multiple observations, offering a more stable and generalisable metric for informing training prescription.[16] Thus, the P90 method balances specificity with robustness and aligns with current practice in elite sport for guiding sustainable load targets.

Findings were comparable when categorising intercepts and slopes between GPS microtechnology metrics examined (TD, HSR, ALD, ACC) based on the aggregation method. The GPS microtechnology metrics reported can be considered unique depending on the aggregation method utilised (max, P90, and mean) and require consideration in identifying appropriate values to use in assessments of PRD in practice. HSR displayed significantly different slope values across max and P90 (mean difference: -0.47, 95% CI: -0.59 to -0.35, $p < .001$) values but not mean aggregate methods demonstrating the large decrement of running outputs due to the metabolically taxing nature of the movements[21] compared to measures of TD and ALD. The slope value offers insight into the running decrements observed because of duration; the steeper the slope (larger negative values), the greater the magnitude of the decrement.

Interestingly, comparisons to a previously published study[16] identified comparable TD, 161 (19) m·min^{-1} (mean (SD)) compared to those presented in this study 165.1 (98.4, 231.8) (mean (95% CI)) but higher variability in reported values. ACC intercept and slopes were lower in the present study 2.3 (95% CI: 1.4, 3.3) compared to Couderc's study[16], 5 (2) n·min^{-1} (mean (SD)) possibly, identifying differences in peak values due to tactical, physical, and technical differences.[22] Differences in GPS processing between manufacturers present as another possible explanation for differences between acceleration values as inter-manufacturer differences can account for very large differences (ES ± 95% CI: -3.6 ± 0.7) when comparing two GPS microtechnology manufacturers.[23] HSR could not be examined under similar conditions due to the varying classification of HSR zones (5 m·s^{-1} vs 4.44 m·s^{-1}). The use of acceleration load density (ALD) is a novel component to the analysis of women's rugby 7s peak running demands. Acceleration load examines accelerations and decelerations that typically occur at lower speeds and are often missed when using traditional distance and high-velocity measures.[24] Similarly, the use of discrete thresholds to classify acceleration and deceleration activity, such as efforts greater than 2.5 m·s^{-2} or less than -2.5 m·s^{-2}, respectively, can underestimate total changes in speed activity that can occur at lower intensities and in confined spaces.[25] The results from this study identified a significant difference between max and P90 values and between P90 and mean values, providing practitioners insight into demands placed on players beyond the traditional distance of high-speed measures.

Interestingly, distinctions between positional groups were not always apparent in the results. When examining intercept and slope values, inter-positional variance in values was minimal ($p>0.05$) between forwards, backs, and utility/ball players (UBP) except for ALD slope measures between backs and UBP (mean difference = -0.42, 95% CI: -0.76 to -0.01, $p = .014$), and between UBP and forwards (-0.40, 95% CI: -0.72 to -0.01, $p = .018$). ACC and ALD values were significantly different across intercepts when comparing backs and UBP to forward players ($p<.001$). While there were some statistically significant differences between positions, the overall results identify the potential to utilise a combined value reflective of the squad average if practitioners choose to simplify reporting computations or reduce the burden placed when monitoring large groups of players.[26] Further distinctions between the four GPS microtechnology metrics demonstrate minimal differences between reported position values (Appendix Figures 1 and 2).

Variability of Intercepts and Slopes

Examination of the PRD revealed a high amount of variability reflecting the unpredictable nature of the sport, and further complicated by variations across metrics, positions, and individual players. Using max values as an aggregation method had the least variance between positions when examined across intercepts and slopes compared to P90 and mean aggregate method values. In general, intercepts reported less variation when compared to the variability in the associated slope value. Slopes had a high variance in reported values when examined between the squad average and position averages, with max aggregate method values displaying less variation (22.2 – 45.2%) than P90 (60.6 – 122.6%), while mean slope values had significantly higher CV% between 193.3 – 343.3%. The lower variance may be the result of similar extreme moments in game where a player would reach their peak outputs consistently across matches. Despite the intensity and the match context changing, the physical requirements are consistent, hence the lower variance. In contrast, the P90 and mean aggregation method are more sensitive to fluctuating running intensities in a match which underscores the extreme variability when using P90 and mean aggregate values to report exercise intensity. Compared to max aggregate values, use of P90 and mean in training would provide insight into overall match demands as opposed to intensified periods within a match. Low locomotive movements, such as short, repeated collision efforts in attempts to defend the try-line and scrums that are demanding but low in running requirements,[27] were not included in this study, which may differentiate matches based on P90 and mean values.

Variability did not differ significantly when examined within positions indicating that PRD values fluctuate similarly across forwards, backs, and utility/ball players. Despite the varied CV% reported between aggregation methods and GPS microtechnology measures, positional variance did not differ significantly for intercept and slope values, underscoring that positional groups may not be a predominant factor that distinguishes running performance. The lack of distinction between positions could be attributed to the influence of substitutions occurring throughout a match. While not examined in the present study, substitutions can predominantly be based on tactical or physical determinants.[28] Substitutions based on coaches' perception of fatigue may result in the rotation of players on the field to reduce the decline of running outputs, skill execution errors, and tactical plans.[28] Ball in play (BIP) analysis, which assesses GPS measures based only on 'active' periods during a match, demonstrated no differences (ES: 0.02 – 0.37, $p > 0.29$) between match-halves when identifying running decrements[1] suggesting that sustained outputs of high-intensity running are important in elite women's rugby 7s.[29] Future studies may examine the methods used in this study to identify locomotive output changes in PRD between match halves to determine whether differences occur between match halves and within positional groups.

The high inter-athlete variance in individual running outputs can differ greatly, underscoring a potential issue when applying a generic set of values aggregated into a team average. For example, two players had total relative distance PRD values of 191 (player one) and 144 $m \cdot min^{-1}$ (player two), respectively, with the whole team average of 164 $m \cdot min^{-1}$ when aggregated with remaining players. If both participated in a SSG producing 200 $m \cdot min^{-1}$, player one would achieve ~105% of their PRD, while player two would reach nearly 139%. Meanwhile, the team's average intensity would be reported as 122%. The difference in relative running outputs needs to be contextualised at an individual level, as intensities achieved by player one was equal to their maximum, while player two experienced supramaximal intensities relative to match conditions. Despite the need to accurately quantify the repeatability of PRD to draw inferences to prepare players for intensified periods of a match physically, understanding training intensity distribution is insightful but widely governed by coaching philosophy, prescription, and execution.[30,31] Optimising periodisation strategies that consider the individual responses to training stimuli should be focused on enhancing physiological adaptations rather than solely pursuing predefined intensity thresholds. Given the unpredictability of match demands, improving a player's capacity to respond to fluctuating intensities would improve the specificity of training and transfer to competition.[32]

LIMITATIONS

A limitation of the current study is that only one team was analysed, making generalisations difficult between cohorts of different playing levels (i.e., sub-elite and junior)[33], as well as between other nations that may have physical, technical, and tactical differences.[22] Additionally, the high inter-athlete variance in PRD values raises questions about the contributions of players who are substituted during games compared to those who initially start the match. While no study has been conducted in women's rugby 7s, observations in elite soccer players demonstrated that starters generally cover greater PRD total distances than substitutes and exhibited lower PRD high-speed distances over a 300-second rolling average window.[11]

FUTURE DIRECTIONS

While it has been insufficiently explained in the literature for choosing specific rolling average methods,[4] examining the effect of epoch lengths on slope values as part of rolling average analysis may raise important methodological considerations. While the present study utilises durations between one to seven minutes, smaller rolling average durations, such as 30-seconds, 45-seconds, 60-seconds and 90-seconds have been reported and may influence slope characteristics.[10] Care must be taken though when utilising windows shorter than one minute as there is the potential for temporal scaling to mislead as there is an assumption that shorter windows can be used interchangeably with longer durations when expressed as rate per minute, disregarding performance decays over time due to fatigue.

The contextual factors influencing PRD values remain poorly understood despite evidence that point differentials, match outcomes, and positional roles can affect whole-of-match GPS running outputs.[34] While the positional groups have been demonstrated not to differ for PRD intercepts and slopes, given the expansive and dynamic nature of rugby 7s, specific scenarios, such as a full-field intercept try, may elevate high-speed running metrics, potentially leading to overestimations of relative running intensities in a single match.

PRACTICAL APPLICATIONS

The present study offers novel insights into the practical implications of different aggregation methods – namely maximum, 90th percentile, and mean – used to summarise peak running demands derived from rolling average analyses. The findings demonstrate that these aggregation approaches yield distinct outputs, each of which may inform different aspects of performance monitoring. The choice of aggregation method for peak demand metrics has important implications for how training targets are prescribed and interpreted. Using the maximum (max) value represents the single highest intensity effort observed, capturing the extreme limits of physical output during competition. While useful for identifying an athlete's absolute ceiling in the context of a match, max values are highly sensitive to outliers and may reflect rare, context-specific events rather than repeatable performance thresholds. In contrast, percentile-based approaches, such as the 90th percentile (P90), offer a more robust and representative measure of typical peak performance by accounting for the distribution of efforts across multiple matches or efforts.[37] P90 values may better inform conditioning targets that are both challenging and repeatable, reducing the risk of overprescription and excessive fatigue. Coaches must therefore weigh the trade-offs between specificity and stability when selecting aggregation methods, aligning their use with the intended application—whether for benchmarking elite performance, informing worst-case scenario planning, or guiding sustainable training prescription.

The little statistically significant differences in PRD values across positional groups suggests that the use of squad averages may be a pragmatic approach for practitioners, particularly when managing large cohorts. This approach may enhance the scalability and efficiency of load monitoring protocols without substantially compromising the utility of the data at a group level.

Nonetheless, considerable variability was observed at the individual level, underscoring the necessity of retaining an athlete-centred approach to training prescription. These findings reinforce the importance of individualising load parameters in accordance with an athlete's unique physiological responses and performance capacity. As such, PRD metrics should be integrated into broader periodisation strategies that account for both the inter- and intra-individual variability, thereby supporting informed decision-making in high-performance settings.

CONCLUSION

To my knowledge, this study is the first to present findings relating to aggregation methods used to summarise peak running demands. It was demonstrated that using max, 90th percentile, and mean aggregate method values presents unique results when aggregating values obtained through the rolling average method to calculate and understand fluctuations in running intensities. There were no differences in PRD values across positional groups, suggesting that using of a squad average may suffice when utilising PRD in practice and improve the scalability of monitoring large groups of players. It should be noted that recorded values at an individual level varied greatly and should be a key consideration in its adoption in practice, emphasising the requirement to individualise training based on an athlete’s response to training stimuli as part of periodisation approaches.

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CHAPTER FOUR:

METHODOLOGY – AN EXPANDED APPROACH TO MATCH DEMANDS

BRIDGING STATEMENT

In Chapter Three, the investigation into peak running demands (PRD) using different aggregation methods revealed significant variability in the values reported through use of maximum, 90th percentile, or mean aggregation methods. This variability highlighted inconsistencies and identified a critical gap in the existing literature regarding how match demands are quantified. Many studies had aggregated data without delving into within-subject, positional, and squad-level differences, thereby leading to a shallow understanding of performance demands. Furthermore, the findings of Chapter Three examined the disparity between aggregation methods, underscoring the infrequent occurrence of maximal running intensities and therefore limiting its application as a tool to assess training demands. Recognising these gaps, Chapter Four develops a systematic method to analysing match demands.

Chapter Four builds on observations from Chapter Three to develop an expanded method to quantify match demands which emphasises a key element of rugby 7s: speed. This methodology provides a replicable and transparent approach for future researchers and practitioners, marking a significant advancement in the ability to measure and interpret match demands accurately. Researchers and coaches can utilise the framework proposed to compare findings with other teams and address limited empirical evidence in sub-elite competitions.

ABSTRACT

Objective: Chapter Four details the formulation of a methodology that expands on current assessments of match demands in elite women's rugby 7s with consideration of contextual factors including positional groups and other match-related factors. The methods described supports future research in communicating replicable methods and offers flexibility for practitioners to adapt their current analysis of match demands.

Methods: Data for 27 female international rugby 7s players were provided from major international competitions during the 2021-2022 season. Sample-by-sample GPS microtechnology data were analysed using a custom script developed by the researchers to categorise GPS microtechnology data into four separate analysis; absolute time, total time spent in each speed zone by increments of 1 $m \cdot s^{-1}$; relative time, total time spent in each percentage of maximal sped zones in increments of 10%; absolute distance, total distance in each speed zone by increments of 1 $m \cdot s^{-1}$; and relative distance, total distance in each percentage of maximal speed zone by 10% increments.

Results: Data from 52 matches were analysed. An R script was designed to automate data extraction, filter accurately, and create visualisations for preliminary analysis. The script was adapted to read multiple match files, recognise filenames, perform the analysis, and summarise data.

Conclusion: The Chapter provides an expanded methodology to quantify match demands in elite women's rugby 7s. The refined methods aim to enhance reproducibility of research and facilitate effective evidence-based practices in sport. Future research using large datasets across different populations and teams will improve the generalisability of this method. The detailed methodology will be utilised in Chapter Five.

Keywords: Rugby 7s, positional groups, contextual factors

INTRODUCTION

A scoping study examining the ratio of male and female participants in sport and exercise science research by reviewing published articles between 2014 and 2020 indicated that 34% of all participants were females, and only 6% of publications across six journals were exclusively conducted on women.[1] In an area where data and access to participants are often sparse, particularly regarding women's rugby 7s, the ability to produce reliable, generalisable results is critical. This chapter further informs the ever-growing body of knowledge with objective measures that will contribute to coaching, athlete development, and competition preparation as an area of practice within a translational gap.[2]

Findings from Chapter Two and Chapter Three highlight a methodological gap in the examination of peak running demands (PRD). Existing studies report on single peak values that can be highly variable and may not occur under every match context. Solely utilising peak values to analyse match demands overlooks important contextual factors that influence reported running outputs, including aggregating intra-positional and squad data. Aggregations may mask meaningful differences observed between individuals and hinder the ability to individualise training modalities and monitor loads appropriately based on load monitoring practices.[3]

Furthermore, findings from Chapter Two underscore the minimal differentiation between playing positions, suggesting that women’s rugby 7s athletes are more homogenous than their male counterparts. Brosnan and colleagues (2024) identified the need to differentiate backs into further sub-categories due to their unique tactical roles.[4] While the study did not address the physical and physiological differences between positions, there were significant differences when comparing positions between the domestic and international competition levels. The lack of distinction between positions can be further compounded by the limited knowledge of contextual factors affecting running demands. Current studies have examined how match outcomes, including winning or losing, score differentials, and margins of victory or defeat can influence GPS microtechnology outputs. The results are often generalised as an overall team-reported value.[5,6] The differences in tactical and technical ability between rugby 7s playing nations are important as technical and running performance have been strongly associated with winning match outcomes, favourable points differentials, and favourable weather conditions.[7]

Load monitoring research has typically utilised aggregations to report speed zones, which can simplify reporting structures but may introduce a challenge in identifying the most relevant zones to accurately quantify external load.[8] Traditional speed zones rely on fixed thresholds, potentially oversimplifying an athlete's exposure and failing to account for differences in physical and physiological capacity.[9] Absolute speed zones have been the more common tool to report and determine thresholds for high-speed running (HSR) and sprint exposures, but the methodology does not consider the individual athlete when assigning these zones.[8,10] In contrast, relative speed zones determine thresholds based on an individual's maximal velocity, ensuring inter-athlete comparisons are contextual to the disparity in physical attributes.[11,12] Additionally, physiological speed zones integrate metabolic considerations, offering insight into energy system contributions during competition and providing a more holistic representation of an athlete's exposure.[13]

Given the multitude of methodological considerations encountered, a multi-layered approach can enhance reproducibility, allowing future research to leverage large datasets to replicate methodologies across various contexts. Accurate replication would improve the generalisability of findings and facilitate transference into practice. As Dźwigoł (2020, p. 6)[14] notes, "Research can indeed contribute to the discovery of a new truth, but it can also lead to the modification of a known state or process or the improvement of what is already there." This sentiment underscores the broader goal of extending evidence-based practices[14] into women's sports, which has been significantly underrepresented in sport and exercise science research.[15]

Therefore, this Chapter aimed to develop a unique method to enable the quantification of match demands in elite women's rugby 7s in relation to contextual factors, specifically individual variance, positional groups, and other match-related factors. The significance of this method is that it can be implemented readily in practice, while offering the flexibility to adapt specific zones based on practitioner choice.

METHODS

Research Approach

A longitudinal retrospective cohort study design was employed in this research to provide a snapshot of data across points in time, enabling the researchers to analyse specific variables and their relationships within defined subgroups.[16] In this context, the study involves repeated observations from individual athletes and position groups across nine international tournaments of the 2021 Olympic Games and 2021-2022 HSBC World Sevens Series, offering a robust approach to quantify physical performance metrics and explore factors influencing running demands such as changes and assessments of cumulative effects throughout a season in rugby 7s, where fatigue, the amount of contextual performance variability in matches,[7] and exposure progression are factors requiring consideration.[15]

Participants

This study involved 27 female rugby 7s players (aged 22.6 ± 4.1 years) competing in international competitions between 2021-2022. The team was ranked 1st at the end of the 2021-2022 World Sevens Series as well as finishing in 5th place at the 2021 Tokyo Olympic Games. Teams that competed during these competitions include Belgium, Brazil, Canada, China, Fiji, France, Ireland, Japan, Mexico, New Zealand, Russia, South Africa, Spain, and USA.

Data Collection

Data was collected using GPS microtechnology devices (Vector, Catapult Sport, Australia) to quantify running demands during matches. Devices were sampled at 10 Hertz (Hz) (i.e., 10 data points per second) and accelerometer data sampling at 1 kHz and provided at 100 Hz.

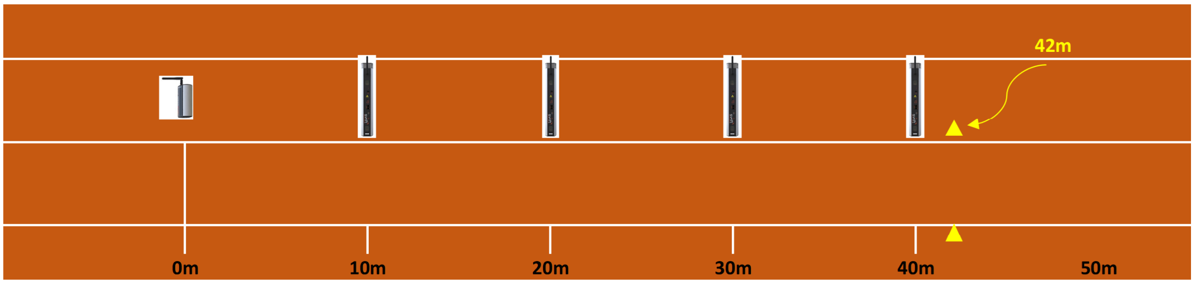
GPS microtechnology data was tracked live using a single receiver that relayed data to a portable device (iPad, Apple Inc. California, United States) in which the commencement of a match was aligned to ‘ball drop’ for both halves. Ball drop is defined as when the ball is in contact with the ground during a drop-kick to start or restart the game. This action is used in practice as a timestamp to align analysis being performed by the team analyst relating to match statistics such as ball in play and coding event sequences such as phases, tackles, and ball carries[17] with video footage or in this case the commencement of the match for analysis. Pre-game match warm-ups and any match warm-ups during the game were tagged live for load monitoring but were excluded from analysis as part of the purpose of the study to examine match demands. Devices were allocated to a single athlete throughout the data collection period to limit inter-device variability.[18] Data collection and analyses (tagging) were standardised and aligned with the data collection protocols stipulated by the governing body. Standardisation enhances the reliability and validity of findings, ensuring replicability across similar teams and contexts.[19] To prepare for data analysis, sample-by-sample 10 Hz data in comma-separated values (CSV) in Excel format were retrieved for each athlete across matches and tournaments.

The quality of positional data was assessed for each match and tournament through horizontal dilution of precision (HDOP) and the number of satellites reported. As part of obtained from the GPS microtechnology devices, HDOP of sample-by-sample data was reported as 1.07 ± 0.41 (mean ± SD) and the number of satellites as 12.0 ± 2.16, which are both deemed ideal.[22,23]

Maximal Speed

Assessments of maximal speed were used to reference relative metrics. Measures of maximal velocity were obtained as part of the organisation's standardised testing battery on all contracted athletes conducted indoors on hardwood floors. Testing indoors helped to mitigate the variability of surfaces and environmental conditions experienced when conducting testing outdoors.[20] A dual-beam electronic timing gate system (Swift Performance Equipment, Lismore, Australia) was utilised over a 40-m length with timing gates set at 10-metre intervals. A front-foot switch was utilised as a part of assessments which showed a decrease in overall sprint times (5-metres) in comparison to other methods (first move, rear-foot switch).[21]

A standardised warm-up was completed before performing a minimum of two trials, with an optional third trial to establish maximal speed ($m \cdot s^{-1}$). The fastest split over a 40-metre length was utilised as the reference average maximal velocity during the study. A visual schematic of the setup of speed testing is presented in Figure 1. One testing session was completed throughout the study because of the inability to complete a re-assessment due to the extended leave after the Olympic Games and the shortened preparation block before the commencement of the 2021-2022 HSBC 7s Series.



Foot positioned so that the mid foot breaks foot switch beam - Base of 5th Metatarsal

Cones to mark finish line 4m after last Gate (42m)

Figure 1 Testing setup during a 40-metre sprint test utilising a front footswitch.

Data Preparation

Match files were categorised into their respective tournaments and individual match folders to aid in managing data (University of York, n.d.). Playing positions were represented as forwards, backs, and utility/ball players. Positional groupings were determined through consultation with the head coach on accurate descriptions and allocation of players.

Throughout the 2021-2022 HSBC World Sevens Series, points were awarded based on rankings at each tournament, where a first-place finish awards 20 points to one point for a 12th-place finish. Final placings after the Toulouse tournament determined opponent rankings.

Data for the analysis was then prepared using the following criteria:

- Match files in which an individual did not participate were excluded
- Participants who played very low match minutes were excluded

- Periods of match warm-up, as well as any in-game warm-ups conducted were excluded
- Individual matching of first-half and second-half periods

Data Analysis

During the research process, preliminary analyses were conducted to identify the most appropriate methods for examining and visualising match demands. These informed both the descriptive reporting of intensity and the applied interpretation of how such data could inform training design.

Stage 1: Use of rolling average durations

The findings from Chapter Three examined the use of rolling average durations to identify peak running intensities experienced during a match. The brevity of rugby 7s presents unique challenges compared to sports like soccer or rugby league, as peak demands often occur over shorter durations. This highlighted the need for accurate representation of such moments, which is often lacking when using traditional match analysis methods. Selecting the appropriate durations for peak running demands (PRD) analysis is critical for actionable training insights and physical preparedness.

However, the rationale for utilising specific rolling average windows is often insufficiently explained in the literature. Durations of one minute are commonly cited as appropriate and interpretable for PRD analysis, although there is possibility of justifying shorter periods. Examining the duration specific running intensities displayed in Figure 2 raises the notion that PRD would be more meaningful should values be presented in absolute terms. For instance, a player covering a relative distance of 272.4 $m \cdot min^{-1}$ only covers 68.1 metres when considering the duration of the activity and expressed in metres. Additionally, representations of relative distance can be interchanged with measures of average speed which depicts the PRD as running at an equivalent average speed of 4.54 $m \cdot s^{-1}$, raising questions on the suitability of this intensity as an optimal physiological stimulus to induce adaptation when being applied in practice. Coaches attempting to replicate "peak intensity" periods in training could mistakenly prescribe sessions at this level, assuming it represents a high neuromuscular or metabolic load. Thus, this stage of the analysis underscores the importance of expressing PRD values in both relative and absolute terms to enhance interpretability and training transfer.

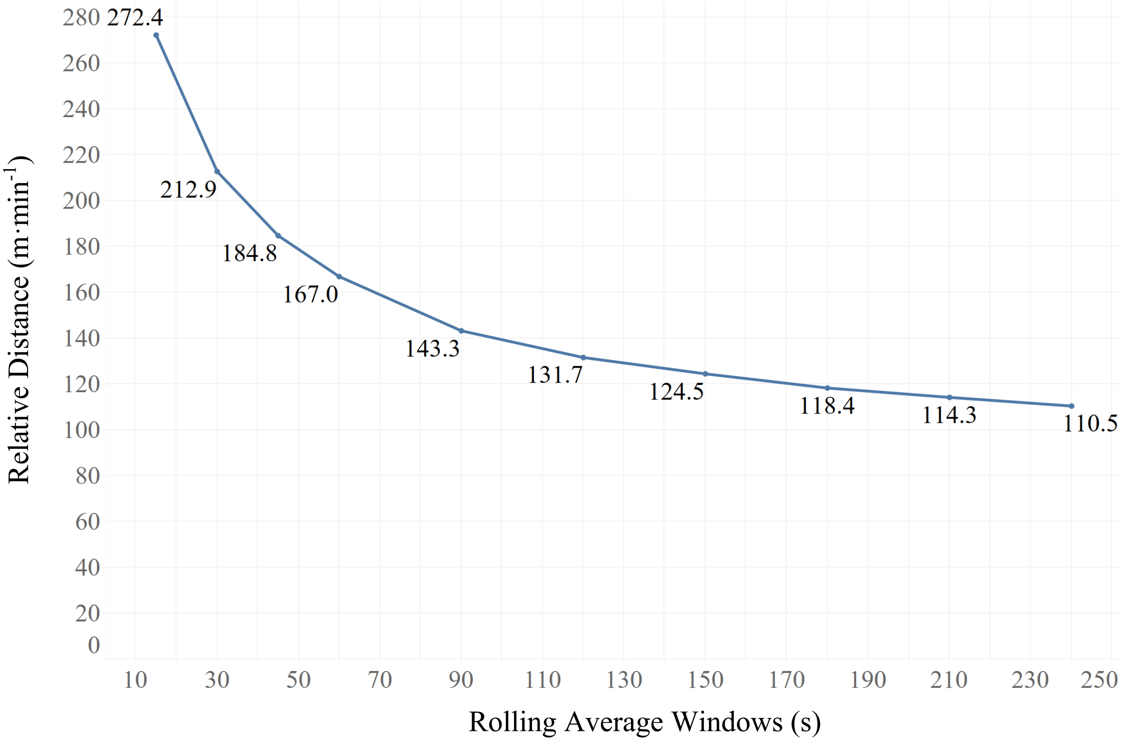


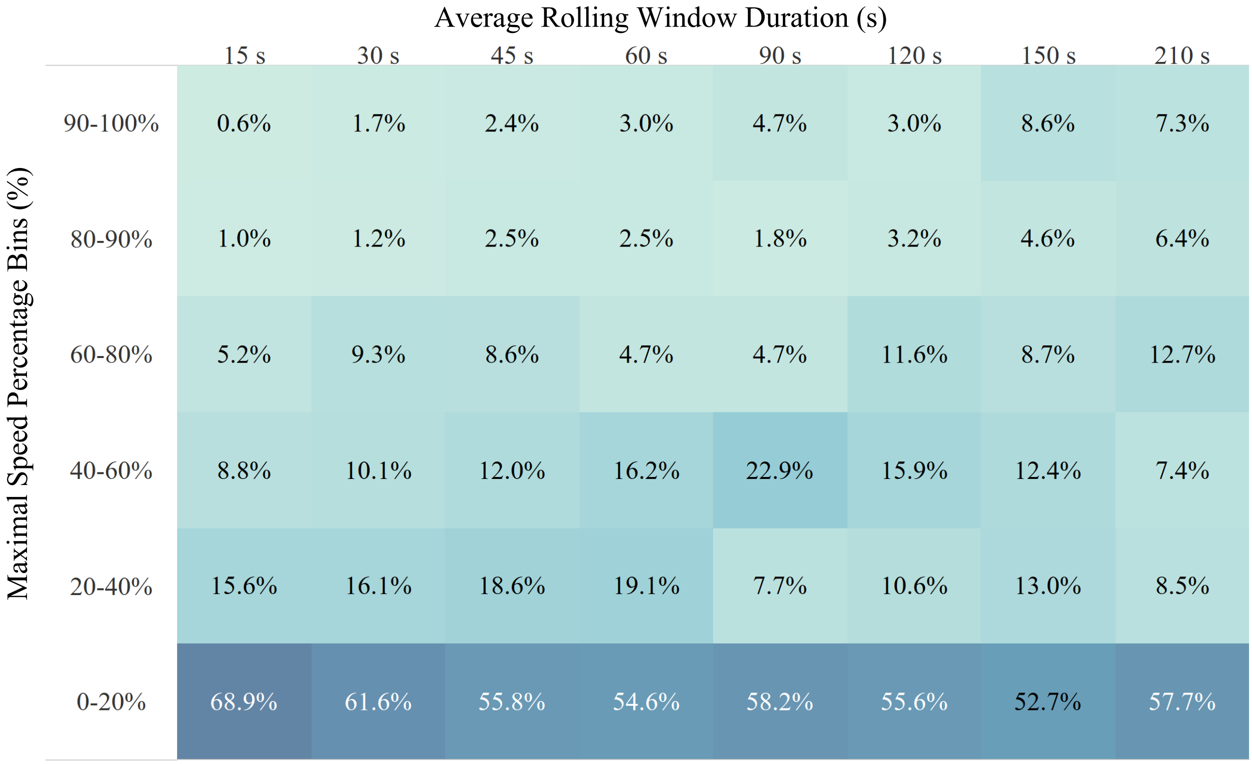
Figure 2 Relative distance (m·min^{-1}) against rolling average window durations (s) for one player during one match.

Stage 2: Examining the equivalent average speed

To improve interpretability, the second stage introduced an approach that converted rolling average values into an equivalent average speed, which was then compared to an individual's maximal sprint capacity. Time spent in different percentage bands of maximal speed (e.g., 60–70%, 80–90%) was quantified, providing a new lens through which to understand the *relative* intensity of match-play, accounting for individual capacity.

This approach added an important layer of individualisation, particularly in differentiating players who may produce similar absolute speeds but differ significantly in relation to their maximal capabilities. However, the analysis also revealed high variability in the derived peak values across different durations, reflecting not only physical output, but the tactical and contextual nature of the game. For instance, prolonged exposure to 70–80% Vmax may reflect prolonged defensive pressure or covering space rather than meaningful sprint exposure.

Compared to Stage 1, this method moved closer to understanding whether athletes were operating near their performance ceiling. However, it was still limited in that it was tied to the arbitrary selection of rolling average durations and did not account for actual time or distance spent at each intensity, both of which are crucial for training prescription.



	15 s	30 s	45 s	60 s	90 s	120 s	150 s	210 s
90-100%	0.6%	1.7%	2.4%	3.0%	4.7%	3.0%	8.6%	7.3%
80-90%	1.0%	1.2%	2.5%	2.5%	1.8%	3.2%	4.6%	6.4%
60-80%	5.2%	9.3%	8.6%	4.7%	4.7%	11.6%	8.7%	12.7%
40-60%	8.8%	10.1%	12.0%	16.2%	22.9%	15.9%	12.4%	7.4%
20-40%	15.6%	16.1%	18.6%	19.1%	7.7%	10.6%	13.0%	8.5%
0-20%	68.9%	61.6%	55.8%	54.6%	58.2%	55.6%	52.7%	57.7%

Figure 3 Percentage of total match time spent (%) in each speed percentage bin based against average window duration (s).

Stage 3: Absolute and Relative Bins

The final data structure used in the following Chapter grouped match running outputs into four categories: absolute time, relative time, absolute distance, and relative distance spent in discrete speed bins. This approach allowed for detailed comparisons of match intensity within and between players, while accounting for individual speed profiles derived from maximal velocity testing.

This methodological development provides a direct link to training design. For instance, if analysis reveals that an elite back spends 90 seconds above 7 $m \cdot s^{-1}$ in a match (Bin 7–8 $m \cdot s^{-1}$), coaches can design drills (e.g., repeated 30-m accelerations or sprint-repeat efforts) that match or slightly exceed this exposure. Similarly, if relative distance covered in the >90% Vmax bin is minimal, this may highlight a gap in stimulus for top-speed running, therefore prompting integration of maximal sprint exposures within weekly microcycles.

Additionally, by including relative bins (>100% Vmax), the method accounts for GPS or testing anomalies and allows coaches to detect sprint exposures beyond tested values—useful in evaluating both performance progression and risk.

These insights are not just statistical refinements; they shift how practitioners interpret match demands. Rather than training to generic high-speed thresholds (e.g., >5.5 $m \cdot s^{-1}$), which may be appropriate for some but under-stimulating for others, the use of relative bins allows for truly individualised high-speed running targets. In this way, the methodological choices made in the thesis have tangible consequences for monitoring load, identifying training gaps, and optimising athlete development.

Data were grouped into four categories to analyse match demands.

- Absolute time – Total time spent in each speed zone by increments of 1 $m \cdot s^{-1}$ (i.e. 0-1 $m \cdot s^{-1}$, 1-2 $m \cdot s^{-1}$, 2-3 $m \cdot s^{-1}$, 3-4 $m \cdot s^{-1}$, 4-5 $m \cdot s^{-1}$, 5-6 $m \cdot s^{-1}$, 6-7 $m \cdot s^{-1}$, 7-8 $m \cdot s^{-1}$, 8-9 $m \cdot s^{-1}$, 9-10 $m \cdot s^{-1}$). Each increment was termed a bin, giving 10 bins in total.

- Relative time - Total time spent in each percentage of maximal speed zones in increments of 10% (i.e., 0-10%, 10-20%, 20-30%, 30-40%, 40-50%, 50-60%, 60-70%, 70-80%, 80-90%, 90-100%,>100%). Each increment was termed a bin, giving 10 bins in total.
- Absolute distance - Total distance in each speed zone by increments of 1 $m \cdot s^{-1}$
- Relative distance - Total distance spent in each percentage of maximal speed zone in increments of 10%

Relative measures (time and distance) utilised individual maximal velocities derived from the maximal speed testing of each individual player.

Sample-by-sample data was analysed in R (RStudio, Version 4.4.1, Boston, USA) using a script that was specifically designed to ensure consistency and improve the efficiency in analysing match demand data.

RESULTS

The researchers were provided data from a total of 27 elite women's rugby 7s athletes from a single team competing at the 2021 Olympic Games and 2021-2022 HSBC World Sevens Series a total of 52 matches (600 match-observations).

Sample-by-sample data were analysed in R using an R script designed by the researcher (MK) to analyse multiple CSV data generated from GPS microtechnology devices. While multiple revisions were required to analyse the data, the final script was seen to automate data extraction, filter accurately, and create insightful visualisations to aid communicate findings. The script (see Appendix 3) performs the following functions:

- Data Import and Pre-processing: Reads multiple CSV files and extracts relevant information.
- Data Matching: Filenames had consistent naming conventions of "Year – Tournament – Player Name" which allowed the script to recognise filenames, player names, and match corresponding maximal velocity data (relative distance and time).
- Filtering: Excludes non-relevant periods, such as half-time breaks

- Velocity Bins: Utilises velocity bins (m·s^{-1} and %) to determine the total distance and time spent in each bin.
- Summary: Data relating to output value (time or distance) is summarised for each player match file.
- Data Export: Aggregates analysed data into a single CSV file in a long-format structure for further statistical analysis and visualisation.
- Data Visualisation: A bar plot visualises individual velocity distribution for each player and compiles each match file into a single PDF for review.

Associated visualisations are presented in Figure 2 and display individual match outputs for a player. The graph represents total distance (m) covered in specific percentages of maximum velocity bins as determined by 40m speed testing specified in the methods. There is a distinct skew right shape for most graphs demonstrating the higher contribution of distance covered at lower percentages. Interestingly, in certain graphs a bimodal distribution emerged between 40-50% bins which highlights unique distributions in running intensities between individuals.

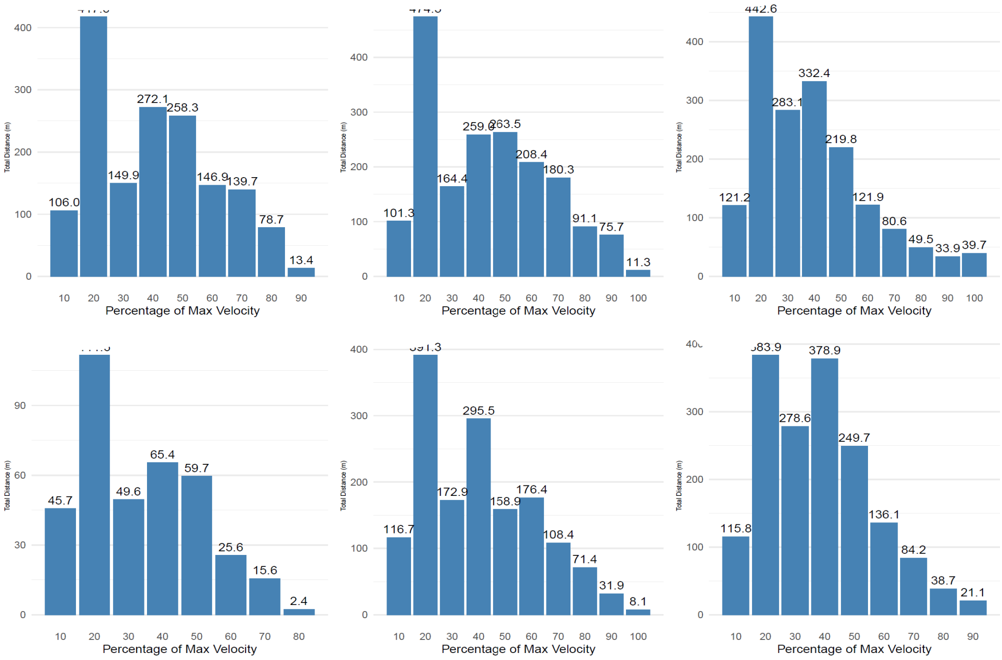


Figure 4 Visualisations of various players in a single match. Values represent total distance (m) covered in specific percentage of maximum velocity bins.

DISCUSSION

This Chapter aimed to develop a method to quantify match demands that accounted for match-related factors, positional groups, and individual variance. Currently, contextual factors have not prominently been examined in relation to match running performance.[5,7,22] The coupling of physical and contextual factors presents an area that should be understood at both a team and individual level, as accounting for potential running loads that can be experienced in a match has implications on subsequent load monitoring interventions and the training prescription process.[24]

While it has been indicated that match outcomes can significantly impact match running outputs,[7] contextual factors can differ markedly between cohorts despite playing at a similar competition level. Studies conducted in rugby league have determined differences when examining competition levels, age grades, and positions.[25,26] Despite the current methodology examining the longitudinal effects of tournaments and opponent ranking on match running demands, understanding contextual factors in team-based sports presents an infinite number of factors available for analysis.[27] The tournaments and opponent rankings presented in this methodology have been examined under the context of positional variance, as there have been mixed results in the literature when determining the effect of positional groups on running demands.[5,22]

A secondary aim of Chapter Four was to detail a methodology that allows for replication while offering the flexibility to adapt the analysis to implement in a practitioner's environment. When examining demands in the literature, a key consideration is the disparate speed zones reported that can limit comparative analyses.[4] There is the potential for criticism of the selected bins and underlying analyses employed in this Chapter, as GPS manufacturing companies already provide a similar method. However, the researcher carefully considered the methods presented as they can address both the interpretation of match demands and addresses common practical implications such as large-scale data re-processing.

The increments described (both absolute and relative) are aimed at improvements of previously reported velocity zones[14] by providing practitioners a comprehensive spectrum from which to extract insights tailored to their athletes' preparation needs. The method offers the ability to analyse data at a more granular level than those that are software provided and require aggregation of zones, potentially masking interactions at match level.

High-speed running (HSR) thresholds were individualised using a percentage of each athlete's maximum observed velocity during competition (e.g., >70% max velocity), rather than applying a fixed absolute speed (e.g., >5.0 $m \cdot s^{-1}$). This approach accounts for inter-individual differences in physical capacity and better reflects relative intensity demands experienced by each player. Fixed thresholds may under- or overestimate the actual demands on slower or faster athletes, respectively.[6,11] By scaling HSR thresholds to individual capacity, the resulting outputs offer a more ecologically valid basis for performance profiling and training design.

Analysis of demands can be more customisable to address the varied thresholds reported in the literature and provide a method to ensure consistency of reported velocity bins for research alignment. For example, Chapter Two identified ranges in absolute speed bins (see Appendix 1) with HSR predominantly reported as 5 $m \cdot s^{-1}$ with the next closely reported values of 3.9 $m \cdot s^{-1}$ [28] and 4.4 $m \cdot s^{-1}$.[22] While sample-by-sample processing of data may present as a laborious process[29], it is not uncommon to derive GPS microtechnology measures through sample-by-sample data manipulation[30-32] outside of software-provided categorisations and may be a solution to ongoing challenges of disparate speed bins.

PRACTICAL IMPLICATIONS

A key strength of this methodology is the multi-layered approach aimed to enhance reproducibility. The methodology allows future research to leverage this framework to analyse large datasets across different populations, improving generalisability and informing training practices at various levels of competition. The current methodology affords practitioners the ability to process large amounts of data without needing to change current GPS reporting practices and utilise tools such as R (RStudio) to aid in analyses.

The adoption of additional or updated velocity bins can be common practice but may warrant preliminary analysis to determine its appropriateness in each context, including sport,[33,34] playing level,[35] and gender.[36] Methods to replicate match demands have been encouraged as a prescriptive tool to optimise training specificity with activity duration, duration in various velocity bins, and the interplay of work-to-rest periods being identified as critical elements in the training process.[37,38] Integrating overlapping thresholds derived from physiological measures could complement existing reporting zones and enhance training prescription as measures such as maximal aerobic speed[39] have demonstrated correlations to changes in aerobic fitness based on time spent in this bin.[40] Similarly, the methodology presented in this Chapter provides the opportunity to enhance the broader literature on speed zones that consider the female athlete,[41] a consideration rampant in current literature.

LIMITATIONS

Compared to other studies conducted on match demands, a limitation of the methodology is that data was not segmented by stages that occur within a tournament, such as pool matches, semi-finals, and finals, which may offer more context on the variability of matches experienced within a single tournament.[41] Furthermore, whilst this study focuses primarily on distance as a measure of external exposure, future studies may apply this methodology to understand match demands across metrics such as acceleration, deceleration, metabolic power, and contacts. The requirement to perform a separate maximal speed test for individuals may present as a practical limitation as it requires a dedicated session to perform this testing, which may not always be feasible.

It is also important to acknowledge that objective performance measures alone do not capture performance's subjective and contextual aspects. Factors such as perceived fatigue, psychological readiness, and tactical decision-making play a role in match demands. While this Chapter does not include internal measures, this limitation presents an opportunity for future research to incorporate qualitative methodologies for a more holistic understanding of performance.

CONCLUSION

This Chapter aimed to develop and provide an expanded methodology to quantify match demands in elite women’s rugby 7s. The Chapter identifies the importance of accounting for key contextual factors including positional groups and match-related factors when reporting match demands. The findings contribute to the growing body of knowledge by addressing conventional approaches to aggregating velocity bins and aims to enhance the reproducibility of research and facilitate effective evidence-based practices in the sport. The refined methods presented in this Chapter will be investigated across multiple tournaments with elite women’s rugby 7s players.

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CHAPTER FIVE:

MATCH DEMANDS IN WOMEN'S RUGBY 7s – AN EXPANDED APPROACH

BRIDGING STATEMENT

Chapter Two identified a key challenge when analysing and reporting match demands as the aggregation of speed thresholds can vary greatly. While there is still much debate to assign appropriate thresholds for female athletes, the generalisability of previous findings is limited as varying thresholds will affect our assessments of running demands. Similarly, the findings from Chapter Three highlighted both the high intra-athlete variance (i.e., fluctuations in an individual's running intensity across matches) and inter-athlete variability in reported values. These findings suggest that peak running outputs may occur infrequently and inconsistently, which presents a limitation when interpreting these data to monitor training volume and intensity.

The methodology introduced in Chapter Four serve as the basis for the original investigation detailed in Chapter Five. Adopting an approach that more accurately captures match demands through refined aggregation and analysis, allows a deeper and generalisable exploration into a specific analysis technique. In Chapter Five, the methods utilised have examined high-level international competitions such as the Olympic Games and HSBC World Sevens Series. The study quantifies overall intensity but also dissects individual movement patterns contribution to understanding how cumulative speed affect performance. This comprehensive analysis fills a critical gap in the existing literature by linking granular, individual-level data to broader team and match outcomes. Moreover, this study provides detailed insights into how match factors, such as tournament context and opponent rankings, influence physical demands.

ABSTRACT

Objective: This study aims to examine a novel method to quantify match intensity based on individual variance and positional group. A secondary aim examines the interaction of match factors, such as tournaments and opponent rankings, to determine whether there is an effect on cumulative changes in speed demands in women's rugby 7s.

Methods: This was a retrospective cohort study using elite women's rugby 7s players (n=27) from one international rugby 7s team participating in the 2021 Olympic Games and HSBC World Sevens Series (seasons 2021-2022). A global positioning system (GPS) microtechnology device was used to quantify demands during a match. The GPS microtechnology units (Vector, Catapult Sport, Australia) samples at 10 Hz with accelerometer data sampling at 100 Hz. GPS data were grouped into four categories: absolute time, total time spent in each speed zone by increments of 1 $m \cdot s^{-1}$; relative time, total time spent in each percentage of maximal sped zones in increments of 10%; absolute distance, total distance in each speed zone by increments of 1 $m \cdot s^{-1}$; and relative distance, total distance in each percentage of maximal speed zone by 10% increments.

Results: Across all analyses, bin percentage (relative) and velocity bin (absolute) consistently emerged as a significant factor influencing both distance and time. Positions significantly influenced absolute time spent in velocity bins with back spending less time at 2.0 $m \cdot s^{-1}$ than utility/ball players but more than forwards. Absolute distance demonstrated greater distances covered by utility/ball players than other positions, which was also observed for relative distance. No overarching trends were identified when examining the main and interaction effects of tournaments on match running outputs.

Conclusion: The study provides a multifaceted understanding of elite level competition and underscores the necessity to manage physical preparedness and adapt to the dynamic demands of rugby 7s. Analysis of velocity zones revealed a substantial contribution of low-speed activities such as walking and jogging to overall match loads.

Keywords: global positioning system, velocity, intensity, bin

INTRODUCTION

The introduction of the women's rugby 7s game has generated new challenges for understanding the physical demands for females participating in the sport. The high-intensity nature of the game, combined with the need for players to cover significant distances on the field, makes it imperative to characterise the physical demands of the game. The development of the sport has led to investigations of the physical demands experienced during both training and matches, routinely using GPS micro-technology.[1-3]

Female rugby players cover an average distance of 1,474 meters per game,[4] with a range of 1,060 to 1,728 meters.[5,6] Additionally, players reached a peak speed of 8.05 meters per second, with a mean speed of 1.6 meters per second.[4] Forwards and backs covered similar distances during the match, averaging 1,601 meters vs an average of 1,527 meters, respectively. However, backs had a higher number of high-intensity efforts, including sprints greater than 90% maximal velocity and number of high-speed running metres compared to forwards. In addition to providing insights into the physical demands of the game, GPS micro-technology has also been used to monitor player exposure and fatigue. A notable reduction in outputs between halves across distance-based metrics in varying categories (low, moderate, high, sprint) has also been observed.[7]

While these studies provide valuable insights into the overall running demands of women's 7s rugby, they represent only a snapshot of the game. Information that examines the fluctuations of running intensity may offer another method to contextualising these match demands and offer direct application to training modalities as part of ensuring physical preparedness. Utilising sample-by-sample GPS microtechnology data, a rolling-average approach has been utilised to capture intensified periods within a match. This method utilises pre-define periods; for example, a 2-minute window to identify consecutive data points and report the cumulative max or average across a given GPS microtechnology-derived performance metric. For instance, when sampling data at 15 Hz (i.e., 15 samples/s for 60 seconds), a 2-minute window would involve 1800 consecutive samples to determine relative distance over that time. Furlan and colleagues (2015) identified that a rolling average value of

2-minutes over this period was statistically higher than both the preceding and ensuing 2-minute period, thereby highlighting that whole of match reporting may lead to underestimations of ‘peak’ demands.[8]

Reporting of the worst-case scenario (WCS) can be highly variable depending on the chosen duration examined as well as the context of the sport. Fereday and co. (2015) examined the effects of a fixed duration compared to a rolling duration when examining the WCS and observed a significant underestimation of total distance and high-speed running (HSR) demands when comparing the fixed to rolling method in elite male soccer players.[9] This element was also exhibited in elite rugby union players across varying position groups that reported underestimated values of relative distance and relative HSR by 11-12% when comparing the same methods.[10] Moreover, appropriate epoch lengths need to be considered for rugby [11] as durations exceeding 5-minutes offer little practical benefit [11] as the average duration that a ball is in play (BIP) in international rugby is between 50 to 55 seconds.[12]

The adoption of the WCS to assess match demands has become well documented and has been advocated for its use in training practices. However, practitioners should still exercise caution in using this as a primary method to analyse match demands and replicate training intensity as peak positional periods of 1-minute may only constitute 5% of overall match play.[11] Therefore, the aim of the study is to examine a novel method to quantify match intensity based on intra-athlete variance, inter-athlete variance and positional group. A secondary aim examines the interaction of match factors, such as tournaments and opponent rankings to determine whether there is an effect on cumulative changes in speed demands in women’s rugby 7s. It is hypothesized that there will be differences when comparing positional groups as well as a difference in distance covered between positional groups based on individual percentages of maximum velocity. Secondly, the interactions of tournament will not have an effect on performance measures but will be evident when examining opponent rankings.

METHODS

Study Design

This was a retrospective cohort study using elite women's 7s rugby players (n= 26) from one international rugby 7s team (age: 22.6 ± 4.1 years, stature; 169.4 ± 4.1 cm, body mass; 73.3 ± 5.7 kg) participating in the 2021 Olympic Games and HSBC World Sevens Series (seasons 2021-2022). The team was ranked 1st at the end of the 2021-2022 World Sevens Series as well as finishing in 5th place at the Olympic Games. The teams represented include Brazil, Canada, China, Fiji, France, Great Britain, Japan, Kenya, New Zealand, Russia, USA.

Players were categorised into the following groups to allow for inter-positional comparisons; forward, utility/ball player, and back. Opponent teams were ranked as Invitational, Bottom Four, Middle Four, Top Four and were classified based on final placings at the end of the 2021-2022 HSBC World Sevens Series. The study was approved by The University of Sydney Human Research Ethics Committee (Protocol 2024/HE001488) in accordance with the Declaration of Helsinki.

Match Demand Outcome Measures

A global positioning system (GPS) microtechnology device was used to quantify running demands during a match. The GPS microtechnology units (Vector, Catapult Sport, Australia) were placed between the scapulae of the players in bespoke pouches housed on the playing jersey. Units sampled at 10 Hz with accelerometer data sampling at 100 Hz. At the end of each match, data were downloaded using the company-provided software (OpenField, version 3.4.0) from which game time was included in the analysis and any other periods (half-time and warm-up) excluded from the analysis. GPS data were grouped into four categories:

- Absolute time – Total time spent in each speed zone by increments of 1 $m \cdot s^{-1}$ (i.e. 0-1 $m \cdot s^{-1}$, 1-2 $m \cdot s^{-1}$, 2-3 $m \cdot s^{-1}$, 3-4 $m \cdot s^{-1}$, 4-5 $m \cdot s^{-1}$, 5-6 $m \cdot s^{-1}$, 6-7 $m \cdot s^{-1}$, 7-8 $m \cdot s^{-1}$, 8-9 $m \cdot s^{-1}$, 9-10 $m \cdot s^{-1}$).

- Relative time - Total time spent in each percentage of maximal speed zones in increments of 10% (i.e., 0-10%, 10-20%, 20-30%, 30-40%, 40-50%, 50-60%, 60-70%, 70-80%, 80-90%, 90-100%,>100%).
- Absolute distance - Total distance in each speed zone by increments of 1 $m \cdot s^{-1}$
- Relative distance - Total distance spent in each percentage of maximal speed zone in increments of 10%

Maximal speeds used to reference relative metrics were recorded prior to a final preparation block to the Olympic Games and were obtained through dual-beam electronic timing gates set at 10 metre intervals (Swift Performance Equipment, Lismore, Australia). Maximal speed was attained from the best split over a 40-m length and defined as the running speed obtained from this period.

Statistical Analysis

A linear mixed models' analysis was conducted to investigate the factors affecting distance travelled in both absolute and relative terms, as well as time spent relative to game time. Separate analyses were conducted on fixed effects of position (backs, forwards, halves/utility), opponent ranking (Invitational, Bottom four, Middle four, Top four), tournament and discrete bins: percentage of player's maximal speed: and player's absolute speed. The player was included as a random intercept to account for repeated measures within individuals. The model assessed both the main effect of these variables and their interaction effects. Pairwise comparisons were conducted to identify statistically significant differences between specific effects. The estimated marginal means were calculated to provide adjusted averages for each factor level after accounting for other variables in the mode. Interaction effects, where applicable, were further examined to identify meaningful differences in subgroup performance. Significance set at $p < 0.05$. Analysis was performed using SPSS V29.0 (Armonk, New York, United States).

RESULTS

Participants

A total of 27 participants (mean age: 22.6 ± 4.1 years, stature; 169.4 ± 4.1 cm, body mass; 73.3 ± 5.7 kg) participated in the study (forward: n = 11, back: n = 7, utility/ball player: n = 8). A total of 52 matches were analysed for a total of 600 match-observations (players x matches). To enhance transparency and support the interpretation of findings, the number of observations is provided across each level of analysis. Data were drawn from 9 international tournaments for a total of 600 match files being included with 27 unique players comprising the match files. When stratified by playing position, the sample comprised 7 backs and 11 forwards, and 8 utility/ball players with 163, 260, and 177 match observations per positional group, respectively.

Across all analyses, bin percentage (relative) and velocity bin (absolute) consistently emerged as a significant factor for both distance (absolute: $F(9, 4596) = 95.04$, $p < 0.001$; relative: $F(11,5405) = 239.06$, $p < 0.001$) and time (absolute: $F(9, 4603) = 1016.66$, $p < 0.001$; relative: $F(11, 5410) = 981.51$, $p < 0.001$). This indicates that the distance or time in each bin was different and will not be commented on further.

Absolute Time

Position

The mixed-model analysis indicated the interaction effect of position was statistically significant for absolute time spent in velocity bins ($F(2, 4603) = 4.334$, $p = 0.013$). At a velocity of 1.0 - 2.0 $m \cdot s^{-1}$, backs also spent less time compared to utility/ball players (-23.2 s, 95% CI: -44.9 to -1.4, $p = 0.032$), but more time compared to forwards (19.8s, 95% CI: 0.3-39.3, $p = 0.045$). Utility/ball players also spent more time than forwards in this zone (43.0 s, 95% CI: 22.7-63.3, $p < 0.001$) (Figure 1).

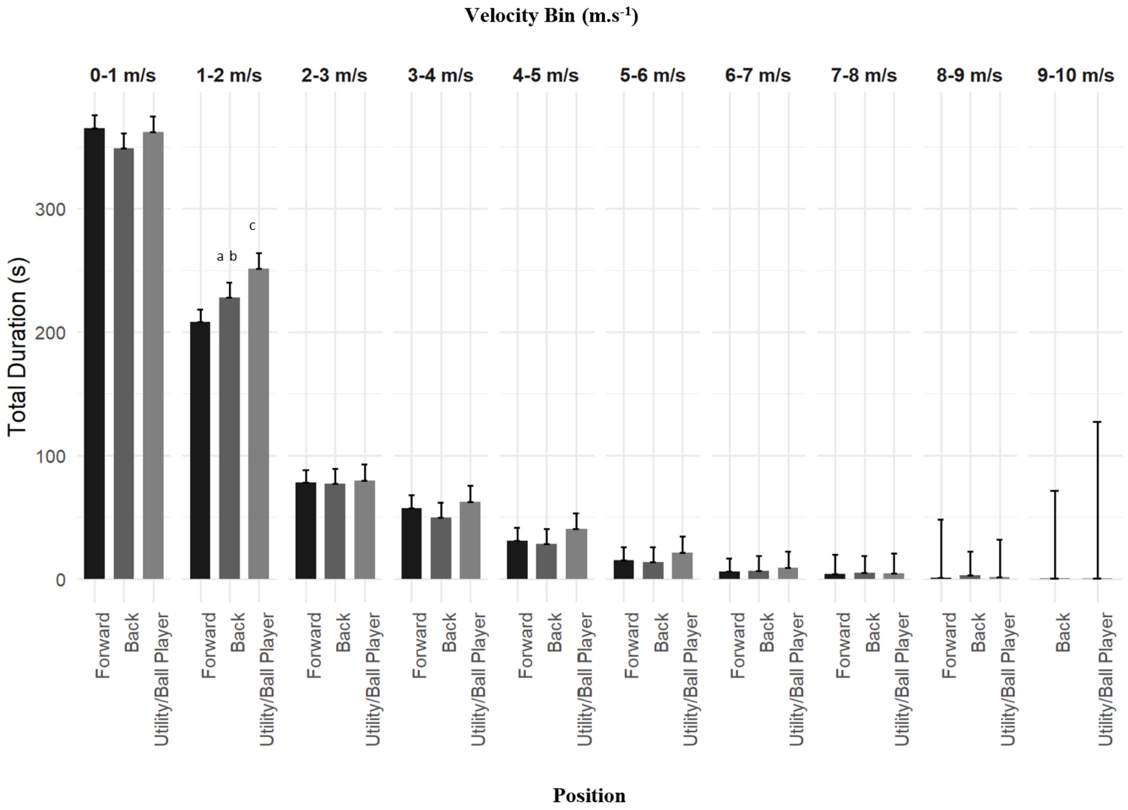

Figure 1 Mean total duration (s) spent in individual velocity bins and grouped by positions. Error bars depict 95% confidence interval. a: Significant difference between backs and forwards ($p \leq 0.05$); b: Significant difference between utility/ball players and backs ($p \leq 0.05$); c: Significant difference between utility/ball players and forwards ($p < 0.001$)

Opponent ranking

There was a significant interaction effect between velocity bin and opponent ranking (F(25, 4603) = 1.645, p = 0.023). At 1.0 m·s^{-1} bottom four teams typically spent less time in this zone compared to invitational (-57.9 s, 95% CI: -90.2 to -25.6, p <0.001), middle four (-57.4 s, 95% CI:-89.9 to -24.9, p <0.001), and top four teams (-73.73 s, 95% CI: -104.8 to – 42.7, p<0.001). Main and interaction effects for position and opponent ranking were not significant (F(6,4603) = 0.52, p=0.79).

Tournament

The main effect of tournament was significant (F(68,4627) = 4.260, p < 0.001). When comparing differences between two Dubai tournaments and the Olympic Games the time spent in each velocity bin in a match was significant (Dubai One v Olympic Games: -19.6s, 95% CI: -34.9 to -4.3, p = 0.002; Dubai Two v Olympic Games: -15.5s, 95% CI: -30.6 to -0.5, p = 0.036). The interaction between tournaments and velocity bin was significant (F(8,4627) = 3.454, p <0.001) with differences at 1 $m \cdot s^{-1}$ between Dubai One (p<0.001) compared to the following tournaments: Oceania (-141.6 s, 95% CI:-177.7 to -105.5), Olympic Games (-131.2 s, 95% CI: -168.3 to -94.3), Trans-Tasman (-116.9s, 95% CI: -152.4 to -81.4), Langford (-108.3s, 95% CI: -144.5 to -72.1), Malaga (-103.6s, 95% CI: -140.2 to -67.1), Seville (-96.1s, 95% CI: -132.5 to -59.7), Toulouse (-94.1s, 95% CI: -130.3 to -57.9).

Relative Time

Position

A significant interaction effect was observed between playing position and velocity bin percentage (F(20, 5410) = 3.932, p = .001), indicating that the amount of time players spent within each velocity bin varied depending on their positional role. Comparisons between time spent in bins showed that forwards ran more than utility/ball players in the 0-10% bin (21.58 s, 95% CI: 3.3-39.8, p = 0.014) and 10-20% maximal speed percentage bin between backs with forwards (30.1 s, 95% CI: 13.0-47.2, p<0.001), utility/ball players with backs (32.78 s, 95% CI: 13.7-51.8, p< 0.001), and utility/ball players with forwards (62.9 s, 95% CI: 45.1-80.7, p< 0.001) (Figure 2). Other pairwise comparisons did not reach statistical significance (p>0.05).

Opponent ranking

There was no statistically significant main effect of opponent ranking (F(3, 5410) = 0.152, p = .929) nor an interaction between percentage bins and opponent rankings (F(30, 5410) = 1.39, p=0.076).

Tournament

Main and interaction effects were significant when assessing tournaments (F (8, 5441) = 2.41, p=0.013) and between percentage bins and tournaments (F(8, 5441) = 4.00, p<.001).

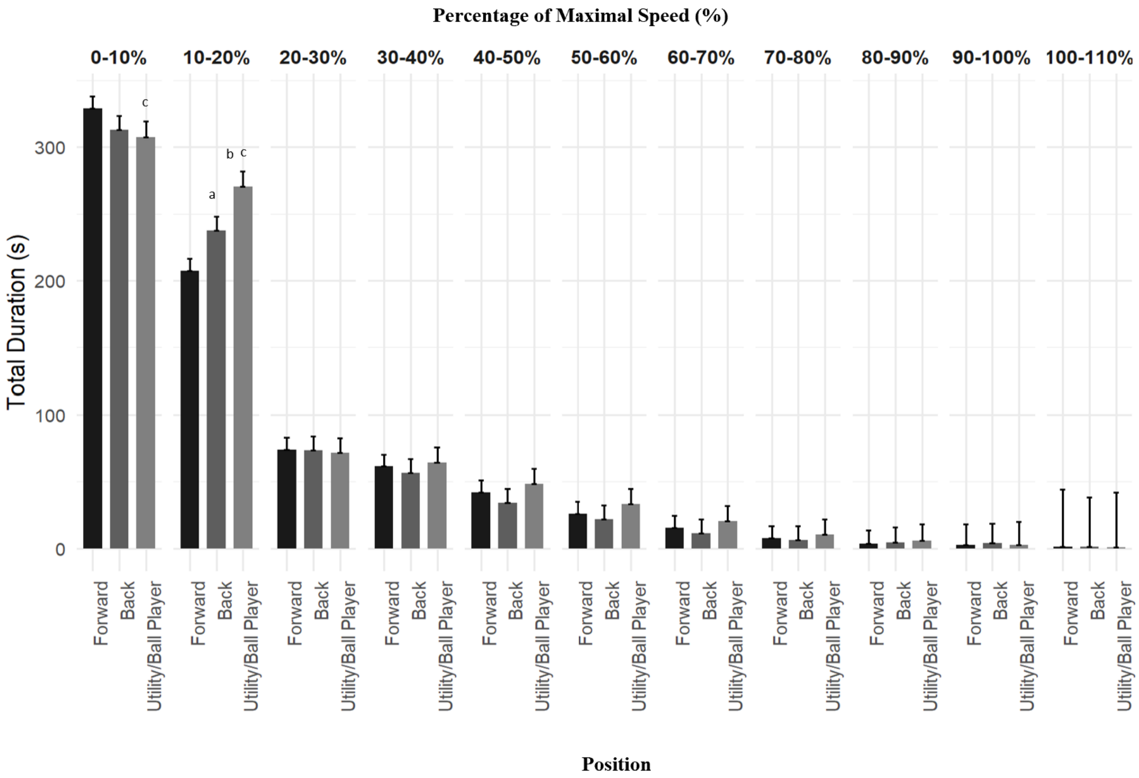

Figure 2 Mean total duration (s) spent in percentage bins based on individual maximal velocity further grouped by position. error bars depict 95% confidence intervals. a: Significant difference between backs and forwards ($p \leq 0.05$); b: Significant difference between utility/ball players and backs ($p \leq 0.05$); c: Significant difference between utility/ball players and forwards ($p \leq 0.05$)

Absolute Distance

Position

Main effect of position was significant (F(3,4596) = 10.83, $p < 0.001$) as well as interaction of position and velocity bin (F(23, 4596) = 1.76, p = 0.014). Utility/ball players covered more distance when compared to backs (27.3 m, 95% CI: 13.3 to 41.4, $p < 0.001$) and forwards (22.6 m, 95% CI: 7.7 to 37.5, $p < 0.001$). Velocity bins (Figure 3) showed differences when evaluating distances covered at 4 $m \cdot s^{-1}$ when comparing forwards to backs (-27.2 m, 95% CI: -54.3 to -0.1, p =0.049) and backs to utility/ball players (-47.4 m, 95% CI: -77.62 to -17.2, $p < 0.001$). This was also evident at 5 $m \cdot s^{-1}$ and 6 $m \cdot s^{-1}$ when comparing utility/ball players to backs (5 $m \cdot s^{-1}$: 55.1 m, 95% CI: 24.8 – 85.3, $p < 0.001$;

6 m·s⁻¹: 42.3 m, 95% CI: 12.0 – 72.6, $p < 0.001$) and forwards (5 m·s⁻¹: 43.5 m, 95% CI: 15.2 – 71.8, $p < 0.001$; 6 m·s⁻¹: 34.4 m, 95% CI: 6.0 – 62.8, $p < 0.009$). There were no other significant findings between other velocity bins ($p > 0.05$).

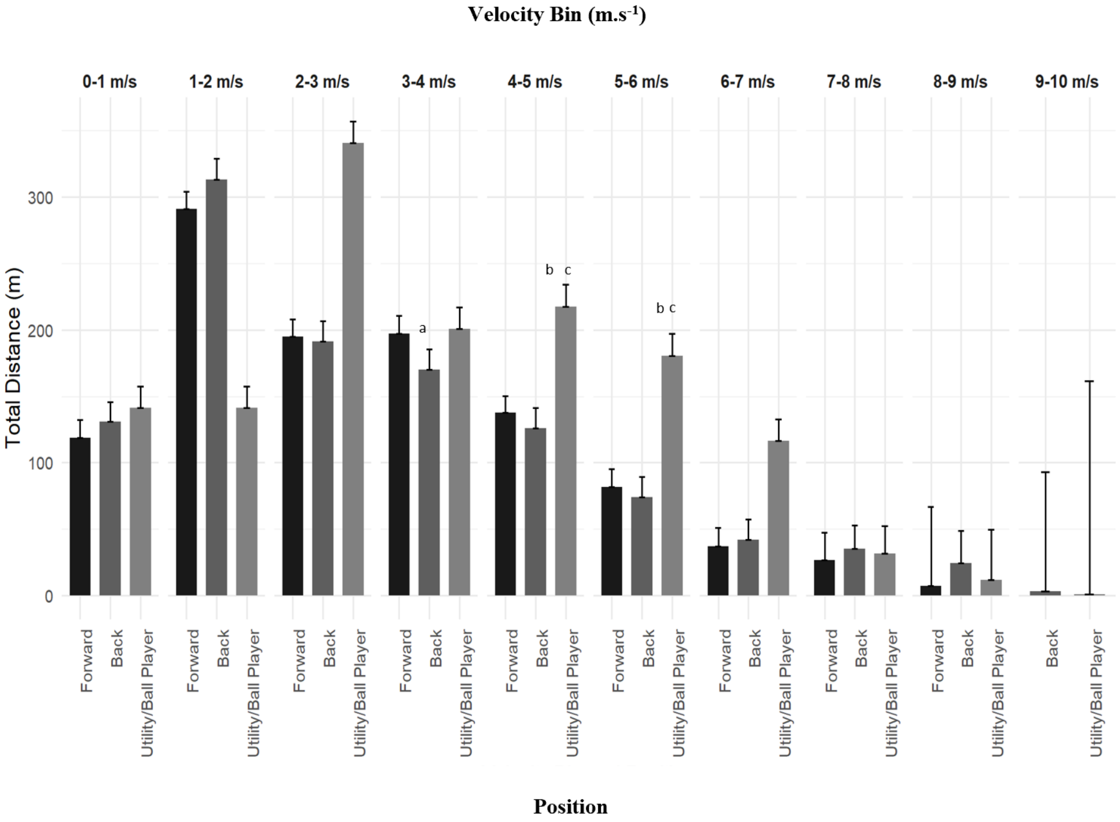

Figure 3 Mean total distance (m) covered at individual velocity bins across positions. Error bars depict 95% confidence interval. a: Significant difference between backs and forwards ($p \leq 0.05$); b: Significant difference between utility/ball players and backs ($p \leq 0.001$); c: Significant difference between utility/ball players and forwards ($p \leq 0.05$)

Opponent rankings

The main effect for opponent rankings (F(3,4596) = 1.32, p = 0.27) and interaction effect for opponent rankings and velocity bin were not significant (F(25, 4596) = 0.78, p = 0.77).

Tournament

Main effects of tournament were significant (F(8, 4627) = 3.137, p = 0.002) with comparisons between tournaments showed a significant difference between the Olympic Games and Seville (28.85 m, 95% CI: 9.48-48.22, p <0.001). No interaction effect were observed for velocity bin and tournament (F(68,4627) = 0.94, p = 0.61).

Relative Distance

Position

The main effect of position (F(2,5405) = 6.31, p = 0.002), and main and interaction effect of bin percentage and position (F(20,5405) = 3.17, p <0.001) were significant. Comparisons showed that utility/ball players covered more distance than backs and forwards (15.3 m, 95% CI: 3.7-26.8, p=0.005; 19.8 m, 95% CI: 8.5-31.1, p<0.001, respectively). This was also evident across bin percentage zones of 10-20%, 40-50%, 50-60%, 60-70% (Figure 4).

Opponent rankings

Opponent rankings did not show significance to distance covered (F(3, 5405) = 2.20, p = 0.086). No other main and interaction effects were observed to be significant (p >0.05).

Tournament

No main effects were observed for tournament (F(8, 5436) = 1.73, p=0.086) or interactions between percentage bins and tournament (F(81, 5436) = 1.01, p=0.465).

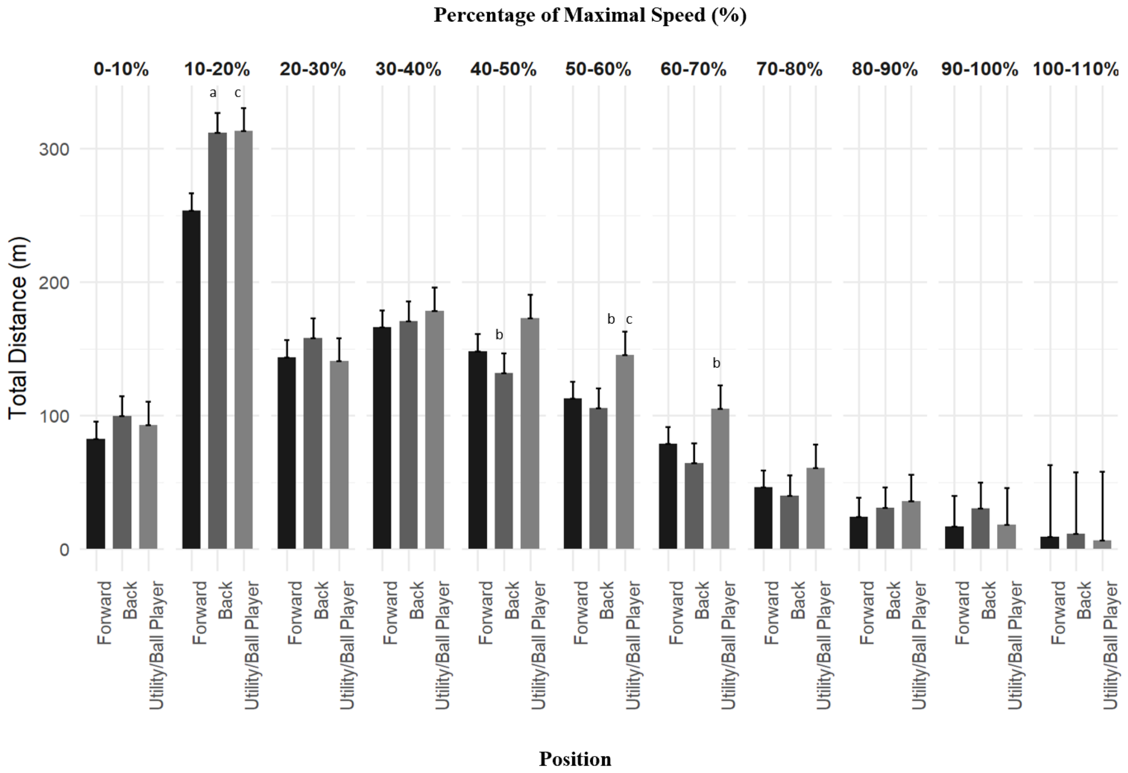

Figure 4 Mean relative Distance (m) covered at percentage maximal speed grouped by percentage bins and position groups. Error bars depict 95% confidence interval. a: Significant difference between backs and forwards ($p \leq 0.05$) b: Significant difference between utility/ball players and backs ($p \leq 0.05$); c: Significant difference between utility/ball players and forwards ($p \leq 0.05$).

DISCUSSION

The present study examined the demands of women's rugby 7s by analysing the distance covered and time spent within defined velocity zones, contextualised by positional roles, tournament stages, and match-specific variables such as opponent rankings. These findings offer a comprehensive view of the physiological demands encountered in elite-level competition and highlight the importance of managing physical preparedness in response to the fluctuating intensity inherent to the sport. The distribution of movement across velocity zones demonstrated a substantial contribution of low-speed activities, such as walking and jogging, to overall match loads. This finding reinforces the intermittent nature of rugby 7s, where high-intensity efforts are frequently interspersed with lower-intensity periods that function as active recovery.

From a practical perspective, these results underscore the necessity of designing training programmes that reflect the game's fluctuating intensity profile. Conditioning drills should incorporate both high-speed efforts and strategically integrated recovery periods to reflect the demands of match play. Moreover, given that velocity zone distributions varied by positional group, position-specific conditioning strategies may be warranted to ensure that training loads are representative of individual match demands. Although an in-depth analysis of in-game recovery phases was beyond the scope of this investigation, the current findings lay a foundation for further work that may inform the development of more nuanced pacing strategies and targeted training interventions.[13]

The categorisation of positions (utility/ball players (UBP), forwards, and backs) affirms the inherent diversity of rugby 7s previously examined[2,4,6] and serves as a key component in understanding match running loads and positional roles. The addition of utility/ball players as part of positional analysis is novel when examining match demands in women's rugby 7s. One other study had examined a third position group (speed-edge)[4] and demonstrated significant findings for speed exertion—an arbitrary unit (AU) calculated by another GPS-microtechnology manufacturer based on the accumulation of maximal speed- and acceleration-based indices—with a mean difference (standard error) of 4.12 AU (1.46), $p = .01$, and for maximal acceleration with a mean difference (standard error) of 0.2 $\mathrm{m \cdot s^{-2}}$

(0.10), *p* = .03, when comparing international and domestic level players. In the current study, UBP consistently exhibited the highest distance outputs (m) especially during absolute speed zones of 4 $m{\cdot}s^{-1}$, 5 $m{\cdot}s^{-1}$, and 6 $m{\cdot}s^{-1}$ with mean differences being ~28%, 44%, and 47% higher when comparing UBP to backs, respectively. This finding highlights a distinction in this hybrid role that requires a high aerobic capacity and refined qualities of speed, often requiring sustained high-intensity outputs across both halves of play[14] to maintain the game's attacking and defensive tempo.

Forwards, while contributing significant distances, played less time at higher velocity zones, reflecting their role that is prominent in defensive ruck activities, restarts and ball carries into contact which make traditional locomotor measures underreport actual match demands for this position.[15,16] Backs, in contrast, consistently demonstrated running outputs at high speed, highlighting the critical role of repeated sprinting and high maximal velocity traits in exploiting space during counterattacks or line-breaks. Despite, the mean differences between backs and other positions at speeds exceeding 8 $m{\cdot}s^{-1}$ not being statistically significant, this is likely a reflection of the limited opportunities for backs to reach such velocities during matches. Similarly, no speeds above 9 $m{\cdot}s^{-1}$ were recorded for forwards, aligning with the physical and tactical demands of their position and potentially indicating limitations in reaching velocities greater than 9 $m{\cdot}s^{-1}$.

Chapter Five presents the first study in women's rugby 7s to examine the contribution of relative running velocities in relation to an individual's maximal velocity. While no significant differences were observed, particularly in zones exceeding 80% of maximal speed there were distinctions between UBP and the other two position groups at various relative speeds. There were significant differences between UBP and backs at 40-50%, 50-60%, and 60-70% emphasising the role-specific variability when classifying 'backs', while demonstrating the need for a refined, granular approach to match analysis. The more common method to report velocity bins uses larger aggregations that may mask meaningful differences that would otherwise be grouped together and limit the ability to replicate the mechanical load demands unique to each position.[4,5,18]

Examining tournaments revealed insight into analysing match demands across diverse contexts. While there were limited findings when examined across four types of analysis categories (absolute time, relative time, absolute distance, relative distance) the consistent running outputs suggests that there is a high level of physical readiness and resilience among the athletes. There is a necessity to peak physically for pinnacle events[19] despite the cumulative fatigue inherent in multi-match tournaments across a full season. This observation places emphasis on the efficacy of periodised training programs but also emphasises the importance of recovery protocols and psychological preparation in sustaining performance under pressure.[20]

For coaches and practitioners, the consistency in match running outputs emphasises the need to tailor training based on tournament timing and player readiness. Leading into pinnacle events like the Olympics, the focus should be on optimising peak physical capacity and psychological resilience, whereas early-season tournaments may necessitate a greater emphasis on gradual integration of high-intensity blocks. Furthermore, the introduction of scrimmages to aid transitioning between pre-season blocks to competition phases, as well as ensure continuity of 'match rhythm'.[19] Scrimmages defined as structured, game-representative training scenarios that can be utilised during transitional periods between pre-season and competitive phases, as well as periodically throughout the season, may play a critical role in supporting both short-term readiness and long-term performance sustainability. In the short term, scrimmages provide a contextually rich stimulus that closely replicates the perceptual, cognitive, and physical demands of competition, thereby facilitating the transfer of training adaptations into match-specific performance.[21] This form of practice enhances the reactivation of decision-making processes, tactical coordination, and neuromechanical responsiveness that may diminish during non-competitive periods.[22] Moreover, when introduced during preparatory blocks, scrimmages allow players to progressively re-acclimate to match intensity under controlled conditions, reducing the performance volatility often observed in early-season fixtures.[23]

From a long-term perspective, the periodic use of scrimmages contributes to the preservation of sport-specific physical qualities, including high-intensity running capacity, acceleration-deceleration load, and collision tolerance—characteristics that are difficult to replicate through isolated drills.[24] Additionally, regular exposure to competition-like scenarios supports neuromuscular robustness and may mitigate injury risk by maintaining familiarity with the dynamic loading patterns inherent in match play.[23,25] This approach aligns with the principles of training specificity and contextual interference, suggesting that athletes benefit most from practice environments that closely mirror the constraints of actual performance.[26] Consequently, the deliberate use of scrimmages can be viewed not only as a short-term preparatory tool but also as a long-term strategy to maintain competitive readiness, optimise adaptation retention, and reduce detraining during periods of limited match exposure.

The nuanced relationship between opponent ranking and match demands challenges simplistic interpretations of match intensity. Despite no overarching trends being observed, there is a distinct difference when playing bottom four teams as there is greater absolute time spent at 1 $m \cdot s^{-1}$ suggesting that tactical dynamics such as, increased possession or dominant territorial play, significantly shape match exposures. This aligns with previous research emphasising the context-dependence of running demands, where factors like scoreline pressure, tactical intent, weather, and opposition behaviour dictate intensity.[15]

Physical performance measures, such as repeat sprint ability, have also been linked to increases in technical performance even under fatigue,[27] benefiting from longer playing durations and match ups against lower-ranked opponents.[15] A finding of interest in the analysis is the lack of statistically significant difference when playing invitational teams. It was common during tournaments for two teams to be invited to compete on the HSBC World Sevens Series based on prior qualification in a separate tournament which resulted in seven different nations being included in the analysis. This may potentially mask relationships within this sub-group due to the high variance in tactical, technical and physical demands but also the limited match time competing against these teams, compared to those that are regularly on the World Sevens Series.

While it has been previously reported that there are statistically significant ($p<0.05$) differences in measures of total distance, moderate-speed distance and high-speed distance [2] when competing against top four opponents compared to bottom four opponents, the findings from this study may suggest that there is less of a disparity in tactical and physical abilities across teams and nations. A possible explanation would be the increased fatigue tolerance and ability to handle increases in volumes of repeated high-intensity activity,[28] which have been examined previously as being more prominent when playing higher ranked, more successful teams. The ability to execute core skills at speed under such conditions further underscores the critical interplay between physical and tactical demands during international competition.

The study contributes to the growing body of literature on rugby 7s, and in particular women's sport by offering a longitudinal, multi-tournament perspective on match demands. Unlike prior research focusing on isolated tournaments, this approach captures the temporal and contextual variability inherent in elite competition. The provision of more granular velocity bin analysis carries distinction between absolute and relative velocity measures to provide coaches with a dual lens to evaluate performance. Absolute metrics quantify overall exposure, critical for monitoring fatigue and long-term adaptations, while relative metrics capture efficiency and context-specific effort. Moreover, the findings underscore the critical interplay between high-intensity activity and low-intensity activity in determining total match demands. Future research should also integrate non-locomotor metrics, such as tackle counts, ruck engagements, and scrummaging loads, to offer a holistic understanding of player demands thereby facilitating the development of composite exposure models, blending physical, tactical, and technical data to enhance training specificity.

LIMITATIONS AND FUTURE DIRECTIONS

While the study offers valuable insights, certain limitations warrant consideration. One such limitation is the exclusive use of GPS data from a single team. Although data were collected from matches involving two opposing teams, the absence of GPS data from both sides restricts the ability to fully understand the complex, interactive dynamics of match play. Including data from both teams in future research would offer a more comprehensive perspective on the tactical and physical interplay that influences performance outcomes. The absence of significant changes in running demands across the season may reflect the homogeneity of elite-level competition, where marginal gains define success.[29] However, the stability could also mask underlying fatigue or micro-adjustments in team tactics that are not captured by velocity metrics alone. A practical limitation of this chapter is the use of 40-metre sprint testing to determine the maximal average sprint velocity, which required players to complete additional testing sessions separate from their normal training schedule. This approach may not be feasible in high-performance environments where time constraints, athlete fatigue, and scheduling demands limit the opportunity for supplementary assessments. Moreover, conducting testing outside of routine training contexts could influence player readiness and motivation, potentially affecting the accuracy and consistency of the results.

A potential limitation of the current study is the reliance on discrete velocity bins to quantify movement demands. Although widely used in analyses, velocity thresholds are inherently arbitrary and may not fully capture the individualized physiological demands of players with differing aerobic and anaerobic capacities. Future research could adopt individualised speed zones, based on measures such as critical speed, anaerobic speed reserves or maximal aerobic speed [30-33] to enhance the precision and of exposure quantification to physiological adaptation. Additionally, the integration of other GPS microtechnology-derived performance measures such as acceleration, deceleration and metabolic load may offer a more comprehensive picture of in-game intensity.[3,4,34]

This study specifically examined elite-level women's rugby 7s competition, which inherently limits the generalisability of the findings to players competing at sub-elite or recreational levels. It is well established that physiological demands and tactical approaches can vary considerably across different tiers of competition, and influenced by factors such as athlete experience, fitness, and game pace. Consequently, extending research to include lower competitive levels could provide valuable insights into the developmental pathways that underpin progression to elite performance. Understanding how match demands evolve from youth or amateur levels through to professional levels may also inform training prescription to support athlete adaptation and long-term athletic development. Future investigations should therefore consider a broader spectrum of competitive contexts to comprehensively map the interaction between physiological capacity, tactical behaviour, and performance outcomes across the rugby 7s continuum.

The influence of extrinsic factors, such as environmental conditions, travel schedules, and psychological stress, on match demands remained underexplored. For example, international tournaments often require teams to adapt to rapid time zone changes and climatic variability, which can influence match performance.[35,36] These externalities represent critical areas for future investigation, especially in the context of global rugby 7 tournaments.

PRACTICAL APPLICATION

The findings from this Chapter provide several practical implications for coaches and performance staff aiming to align training content with the match demands observed in elite women's rugby 7s. The high proportion of movement in low-speed zones, interspersed with short bursts of high-speed activity, reaffirms the intermittent nature of the sport. Conditioning drills should therefore reflect this fluctuating intensity, integrating both maximal efforts and periods of low-intensity locomotion to better replicate the metabolic and mechanical requirements of match play.

Position-specific programming is also warranted given the distinct locomotor profiles observed across playing groups. The introduction of the utility/ball player (UBP) category provides new insight into a hybrid role that demonstrated the highest outputs in high-speed zones, highlighting the need for programming that concurrently develops aerobic capacity and repeated high-speed efforts. Backs, who rely more on acceleration and top-end speed, may benefit from sprint profiling and overspeed exposures, while forwards, whose movement patterns are less represented in traditional velocity-based load models, may require alternative methods of quantifying and training for match-specific outputs.

Velocity binning using relative thresholds to individual maximum velocity introduced an additional layer of nuance in evaluating running output. Coaches are encouraged to adopt both absolute and relative thresholds to more precisely tailor load prescriptions and assess progression over time. The distinction between UBP and backs across moderate relative speed zones also suggests a need to move beyond binary or overly broad positional groupings, as these may mask meaningful differences in physical contributions during match play.

The relative consistency in match outputs across tournaments, despite changing contexts and opposition, supports the use of standardised locomotor benchmarks to monitor performance trends. However, differences observed when competing against bottom four teams suggest that match flow and tactical dominance (e.g., increased possession time) can influence the volume of low-speed work performed. Such variability should be factored into post-match analysis when using match data to inform conditioning loads.

Finally, the multi-tournament scope of this study offers a more comprehensive understanding of the competitive landscape in women’s rugby 7s. Coaches and analysts are encouraged to move beyond single-tournament insights and adopt longitudinal monitoring to better capture temporal changes in physical output. This may allow for refinement of periodised training strategies that more accurately reflect the evolving physical profile of elite competition.

CONCLUSION

This study provides a comprehensive analysis of the movement demands in elite women’s rugby 7s, highlighting the influence of positional roles, velocity bins, and opponent tanking on match outputs. Across all metrics, absolute and relative distance and times, player positions emerged as a critical factor, with utility/ball players consistently covering more distance and time in higher velocity bins compared to backs and forwards. The findings underline the nuanced physical demands placed on difference positions, with utility/ball players exemplifying versatility and contributing significantly to the overall team performance.

The role of match contexts, such as tournament stages and opponent rankings, adds another layer of complexity. While opponent rankings alone did not consistently affect performance, their interactions with player positions and velocity bins must still be considered as match-related factors. The tournament-to-tournament analysis further demonstrated consistent performance outputs despite the demanding schedule, with subtle variations linked to factors such as the timing within the season or the prestige of the event, as seen in the Olympic Games and Dubai tournaments. Furthermore, the inclusion of detailed velocity zones allows for a more precise understanding of physical demands, moving beyond traditional broad-speed thresholds to better capture the locomotor characteristics of the game.

In summary, this study advances the understanding of the elite women’s rugby 7s by identifying key factors influence match demands. The findings provide valuable insights for coaches, performance analysts, and sports scientists, enabling the developing of targeted training and tactical strategies. Future research should build on these foundations by investigating the impact of substitutions, competition levels, and team cohesion to elevate the understanding and application of performance metrics in women’s rugby 7s.

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CHAPTER SIX:

DISCUSSION

Understanding match demands has become commonplace to enable profiling in sports and translate this knowledge into practice to adequately prepare for the demands of the game, tournament, and season. GPS microtechnology has been a prolific tool used to understand match loads, although the literature has been scarce in examining elements of a match such as the peak locomotor periods in rugby 7s, most notably in the women's game. This thesis examines elite players representing at the highest international level across major international tournaments including the Olympic Games. The thesis introduces a methodological perspective on identifying peak locomotive demands and development of an expanded analytical approach to address the limitations of existing assessment techniques as well as providing empirical evidence for the novel method to analyse match demands with particular emphasis on a key element of the game, speed.

SUMMARY OF FINDINGS

This thesis presents four key chapters that address the specific aims as outlined in Chapter One: 1) conduct a scoping review to evaluate the current literature to identify peak and match demands in women's rugby 7s; 2) investigate the contemporary analysis of peak match demands with current international 7s players; 3) propose a novel methodology to quantify match demands that incorporate individual player variability, positional distinctions, and tournament-specific contexts; and 4) conduct a retrospective study to identify associations of player, position, and tournament to match demands in women's rugby 7s.

Key Findings

This thesis aimed to enhance the understanding and application of match and peak running demands in women's rugby 7s through a series of interconnected studies. Collectively, these findings advance the methodological approaches used to quantify physical match demands and offer applied insights into performance monitoring across player roles, competition phases, and contextual conditions.

A key contribution was the identification of variability in how peak running demands are aggregated and interpreted. While maximum values remain common in practice, this thesis demonstrated that using percentile-based approaches (e.g., 90th percentile) offers a more stable and representative marker of performance intensity across matches. This nuance is critical when modelling power-law relationships, as intercepts and slopes are influenced by the choice of aggregation method, impacting the way training targets are prescribed.

Positional comparisons revealed no significant differences in peak running demands when expressed through intercepts and slopes across key GPS-derived metrics (e.g., relative total distance, high-speed running, acceleration counts). The lack of distinction between positional groups suggests that, from a peak exposure perspective, squad averages may be useful for simplifying data processing in applied environments. However, this finding should be interpreted cautiously, as individual variability was still evident.

Rolling average methods, commonly used to identify peak periods, were found to produce high variability due to the intermittent and chaotic nature of rugby 7s. This variability challenges the practicality of applying fixed thresholds or uniform peak metrics across players or positions. Instead, practitioners may need to tailor peak thresholds by position or use relative metrics to improve accuracy.

Utility or ball-playing backs consistently exhibited the highest total running distances and spent more time operating within higher relative velocity zones compared to both forwards and traditional backs. This finding reflects the hybrid role within the game, which often necessitates both high-intensity contributions and repeated transitions between roles in attack and defence. Importantly, the high-speed outputs were interspersed with substantial volumes of low-speed activity (e.g., walking and jogging), reaffirming previous observations that low-speed movements make a significant contribution to overall match loads in rugby 7s.[1,2] The distribution of effort, particularly the interdependence between low- and high-intensity actions, aligns with the stochastic nature of the sport and mirrors the patterns identified in peak demand analyses.

Contextual factors such as competition type and opponent ranking appear to significantly influence running outputs. Matches played during the Olympic Games demonstrated relatively stable running profiles, while opening tournaments of new seasons (e.g., Dubai) were associated with elevated distances in lower-velocity zones, possibly reflecting early-season variability in game tempo or player readiness. Additionally, higher volumes of high-speed running were observed against lower-ranked opposition, suggesting that opposition quality, including technical proficiency, tactical structures, and physical capacity—can impact match intensity.[3,4]

From a methodological standpoint, the aggregation of velocity zones into broad categories (e.g., all speeds >5 $m \cdot s^{-1}$) may obscure critical differences in sprinting demands. Given the importance of maximal and near-maximal sprinting efforts in rugby 7s, more granular approaches to velocity binning are warranted to distinguish between moderate- and high-intensity running outputs. This approach enhances the sensitivity of performance profiling and allows for more targeted training interventions.

Notably, Chapter Five provides the first analysis in women's rugby 7s to quantify running outputs across the full spectrum of relative velocity bins (expressed as a percentage of individual maximal velocity). No statistically significant positional differences were observed in the upper velocity bands (>70% V_{max}). However, utility/ball players accumulated more distance in the 50–60% velocity bin, suggesting a distinct movement profile characterised by frequent engagement in moderate-intensity efforts, perhaps reflecting their hybridised tactical role.

Tournament comparisons revealed some statistically significant differences in time spent across relative velocity bins. Specifically, between-tournament variations were observed in the 10–20% and 50–60% bins in Seville, the 40–50% bin across Seville, Oceania, and the Olympic Games, and the 30–40% bin in Langford. While some differences emerged, the relative consistency across most tournaments supports the notion that women's international rugby 7s matches are underpinned by stable locomotor demands when evaluated using relative velocity-based methods. This has implications for monitoring and preparing athletes for the physical consistency required across a competitive season.

DISCUSSION

Chapter Two reflects a comprehensive examination of match demands in female rugby 7s players across all reported external metrics derived from GPS microtechnology. A previous systematic review into match demands of women's rugby 7s have recently been examined across multiple women's sports[5] including rugby 7s, involving a scope being more closely comparable to Chapter Two, [6] albeit GPS microtechnology-derived metrics were secondary to findings that examined anthropometric and physical qualities. This distinction marks a significant contribution of the current chapter, which provides a more focused evaluation of GPS-based running demands, reflecting recent advancements in wearable technology applications in team sports.[7]

The findings from Chapter Two highlighted a decrease in total distance demands during international competitions whereas national competitions remaining unchanged when comparing results presented by Sella and colleagues (2019).[6] Measures of high-speed running were somewhat similar when comparing the multiple competition playing levels, suggesting that there may be less of a physical disparity in running volumes experienced in a match when transitioning between junior, senior, and elite rugby 7s. This observation aligns with recent findings in other team sports, such as elite female soccer and Australian Football, which show that tactical and game-related factors may outweigh physiological differences across levels.[8] Progressions through competition levels may be better spent in developing tactical and technical abilities while improving the overall resilience of athletes to compete at higher playing standards.[9]

Inconsistencies in the reporting of thresholds made it challenging to directly compare all studies under a unified speed zone, which may result in the underreporting of HSR. No studies have examined the use of relative velocity zones to assess match demands, contributing to the debate as to what constitutes appropriate speed zones within the women's sports, an ongoing dilemma in the literature over many years.[10-12] The varying classification of speed thresholds is not unique to rugby 7s and mirrors trends in men's and women's rugby union and league, where relative thresholds are increasingly advocated for individualisation.[13,14] This gap highlights the need for a more standardised approach to speed zone classification that accounts for individual player capacity. Implementing relative thresholds, based on metrics such as maximal sprint speed or fitness test outcomes, may enhance the accuracy and comparability of match demand data in women's rugby 7s. Future research should explore and validate these methods to better inform training prescription and ensure that HSR demands are not underestimated.

Participants were predominantly represented at an international level, with few studies examining sub-elite players (junior and domestic). Maximal velocity was typically higher at international level when expressed relative to an individual's maximal velocity (%), but both the international and domestic level players experienced similar absolute maximal speeds within a match. On the other hand, acceleration counts across all zones were higher at an international level across a match. The scoping review also identified that measures of deceleration and metabolic power were heavily underreported in the literature and underscores the need for future studies to examine these metrics to better understand these specific loads as part of load management match load profiling strategies. This is particularly relevant as recent work across multiple sports has shown that accelerations and decelerations require comparable exposure to those experienced in a match to ensure athletes are optimally prepared.[15]

Chapter Two presented as the first review to examine the use of peak running demands in women's rugby 7s[16,17] with findings demonstrating that peak running demands reported higher physical demands than match averages.[18] Comparisons between rugby union and rugby 7s demonstrated that peak overall intensities were similar when examining intercepts but had clear distinguishable differences in P90 values for HSR in rugby 7s. The observed differences between rugby union and rugby 7s highlights the importance of adequately transitioning players between the two formats of the game.[19] Moreover, it supports findings from Gabbett (2015)[20], who emphasizes that sport-specific peak demands provide a better indication of training specificity requirements than average match metrics.

As only two papers have been published in the emerging metric, analysis of peak running demands is limited to elite players and generalisations across the sport is not possible. Studies on peak running demands have been examined across competition levels[21] and sports including soccer,[22] rugby union,[23] rugby league,[24] and Australian Football.[24] The findings presented in the literature underscore the applicability of utilising peak reference values to evaluate training drill intensities to target the most demanding periods of a match. Prior research in professional soccer has shown that while peak running demands can remain stable across congested and non-congested periods, training programs must carefully adjust volume to replicate match-specific physiological loads and optimize player readiness.[25] In contrast, the characteristic running and impact demands of sports such as rugby union, can complicate the ability to truly replicate the multi-faceted demands experienced in a match, and can lead to limited training specificity.[26]

Chapter Three aims to add to the limited body of knowledge of peak running demands in women's rugby 7s by examining the rolling average method in a cohort competing at international level and examining aggregation methods (maximum, 90th percentile, and mean) on reported values of peak running demand. The results identified the uniqueness of each aggregation method in their capability to represent the running intensities occurring in a match. Similarly, there is a range of reported inter-athlete variance when identifying averages across the various aggregation methods, cautioning practitioners to consider the use of peak running demands as a sole measure to accurately model match intensities in training.

The use of percentiles that indicate the distribution and relative positioning of a peak match value can aid in mitigating outliers in datasets, to provide a reference that is achieved at least 10% of the time compared to utilising the highest output from any match. There is a significant difference between reported P90 and maximum values, indicating that there is a high discrepancy within this range and should be considered in the analysis process. For the first time in women's rugby 7s, Chapter Three includes PRD analysis of acceleration load, offering novel insights into the micro-variations in movement intensity. These data reflect subtle but frequent speed changes characteristic of congested match contexts.

Distinctions in peak running demand between positional groups were not apparent and could be attributed to the high inter-variability of individual peak running demand values observed. A practical implication for this finding would be to combine values to reflect a squad average to simplify reporting computations and data burden when examining large groups longitudinally. However, applying a generic ‘squad’ value to monitor training intensities should be cautioned as it was demonstrated that there is a high inter- and intra-athlete variance in reported values for intercepts and slopes. Averaging a value that represents an individual’s PRD makes it challenging to opt for simplification, as there is the possibility of underreporting or overestimating relative intensities compared to what an individual experiences in a match.

Chapters Four details a replicable and expanded methodology that can equip future research to build upon its findings, fostering a granular understanding of match demands in rugby 7s. The analysis of peak running demands addresses limitations of whole-game averages as this method can examine fluctuations in running intensities. This may however oversimplify the demands of a match as the method is based on reporting of singular value (maximal). Transference to training prescription are limited as common prescriptive measures of volume, including distance and time are limited when applying peak running assessments in practice. This underscores the need to use peak running demands concurrently to other methods, such as those presented in Chapter Four. Furthermore, the examination of contextual factors with respect to positional groups is novel as previous studies have only examined contextual match factors as a squad. Despite there being an infinite number of match related factors, the chosen factors of tournament and opponent ranking presents as foundations to examine the effect of match factors on running demands, and in extension if there are differences between positional groups.

Chapter Five applied the methodology developed in Chapter Four and demonstrated a large contribution of low-speed activities to match demands, underscoring the interplay between high- and low-intensity periods within a match. The introduction of three positional groups reaffirms the inherent diversity of rugby 7s and the need to represent the role they play accurately. The analysis grouped participants into forwards, backs, and utility/ball players, with utility/ball players consistently exhibiting higher distance outputs (m) across absolute speed zones of 4 $m \cdot s^{-1}$, 5 $m \cdot s^{-1}$, and 6 $m \cdot s^{-1}$, highlighting their involvement in both attacking and defending situations.

Forwards typically cover significantly greater distances but spend less time at higher velocity zones due to their roles in defensive rucks and ball carries, making traditional locomotor metrics deficient in their ability to measure their match demands. By contrast, backs display a greater emphasis on sprints and high-speed running to exploit space during attacking phases, though opportunities to reach maximal velocities are limited when examined in a match context. No significant differences were observed for measures above 80% maximal velocity, reinforcing the need also examine unique metabolic and mechanical demands for playing positions.

Chapter Five involved a novel component of analysing tournaments, revealing key insights into match demands across varying contexts. Major international tournaments including the Olympic Games, exhibited consistent running outputs and underscores an athlete's need to peak due to the condensed match scheduling and importance of the major competition. Match demands can vary based on opponent rankings as higher velocity outputs were observed against lower-ranked opponents which can be attributed to factors such as increased possession, territorial dominance, and high point differentials compared to outputs seen against higher-ranked teams. Despite prior studies showing differences in running metrics against top- and bottom-ranked opponents, this study suggests that disparities between top and bottom-ranked teams are less clear and likely due to improved fatigue tolerance and high-intensity work capacity among teams.

The findings of this thesis have identified that traditional whole-game averages provide a broad reflection of overall match demands but fail to capture the variability of intensity evident within a match, which can experience intensified periods of play. Peak running demands serve as a valuable assessment tool for understanding the locomotive requirements of a match and tournament. However, the representation of 'peak' within a match can vary significantly based on the choice of aggregation (maximum, percentile, and mean). The identified gap between maximum and P90 values displays the infrequent representation of peak running demands in the context of a whole match and requires consideration to model overall training intensities based on peak running demands. Consequently, a granular approach to running demands assessments is necessary for a more precise understanding, as it reveals the pitfalls of aggregating zones commonly reported in the literature. Aggregation of zones can lead to the oversimplification of movement demands and affect interpretation based on a set threshold. The underlying physical component of speed are diminished as a result, raising the critical question: What is the most appropriate threshold to use, if any?

Compared to a full-length rugby union match, rugby 7s represents a sport with short and high-intensity efforts that are more concentrated, placing emphasis on contextualising match factors that can significantly affect running demands in a match, and consequently, interpretation and application. Beyond individual intensity measures, time and distance remain fundamental measures to prescribe volumes in a training environment. Examining positions provides additional complexity to profiling match demands. However, it improves the applicability of training interventions based on findings presented in this thesis, as there are observable differences in specific velocity bins. Furthermore, the evolving nature of the game has led to the diversification of traditional player positions of forwards and backs. The introduction of a hybrid position (utility/ball player) reflects the unique tactical and physical requirements and, associated refinements in profiling methods. Ultimately, the findings presented in the thesis underscore the complex interplay between physical, tactical, and contextual factors in international competition.

PRACTICAL APPLICATIONS

This thesis presents a series of practical applications for practitioners working within the professional rugby 7s environment. Drawing on data directly collected from elite-level competition, the findings offer a framework through which physical preparation, load monitoring, and tactical periodisation can be more precisely informed.

Practitioners employing peak running demands (PRD) to monitor match and training intensity must consider the limitations of using single aggregation methods in isolation. The analysis demonstrates that maximum, mean, and 90th percentile values each provide distinct perspectives on athlete exposure, and that relying solely on maximal outputs may lead to misrepresentation of the physical intensity typically experienced in competition. Importantly, the methodological considerations outlined in this thesis enable practitioners to critically assess the validity of current approaches and to integrate more representative methods when profiling match demands.

One of the key contributions of this research is the development of a framework that allows for greater granularity in summarising match outputs. Unlike standard software-generated reports, the approach used here permits the customisation of overlapping velocity zones and the extraction of variables more sensitive to the demands of individual players. Time spent within intensity zones, for instance, provides a valuable metric for training prescription, allowing coaches to plan drills that target specific movement intensities, and to distribute load more accurately across microcycles. This is particularly relevant when aligning on-field preparation with tournament scheduling and recovery timelines.

The positional analysis conducted also supports the need for greater differentiation beyond the traditional ‘forwards’ and ‘backs’ categorisation. The inclusion of a third group—utility or ball-playing roles—highlighted a distinct running profile that may otherwise be overlooked. From a practical standpoint, this suggests that conditioning programs should consider the nuanced demands of such hybrid positions, particularly when managing players with flexible tactical responsibilities or who transition between roles during matches.

Another key finding with practical relevance is the relative consistency of running demands across tournaments, irrespective of opponent ranking. While contextual factors undoubtedly influence tactical decisions, the data suggest that a stable physical output is generally required across the season. For performance staff, this reinforces the importance of planning for repeated peaking and ensuring adequate recovery between tournaments. Managing fatigue and maintaining physical readiness across a congested fixture calendar requires careful load management, strategic rotation, and clarity around player monitoring protocols.

Finally, the transparency of the methods used in this thesis allows for immediate application within applied environments. By providing a clear and replicable process for data handling and analysis, practitioners are equipped to conduct in-house assessments that align with their team's specific needs. This approach reduces reliance on third-party reporting tools and empowers performance staff to integrate their own athlete data into the broader context of findings presented in this thesis. As such, this research serves not only as a contribution to the academic literature but also as a practical guide for informed decision-making within high-performance rugby 7s settings.

STUDY LIMITATIONS

A limitation of the studies presented in this thesis was the use of a single rugby 7s team that is competing at an international level. This potentially limits generalisations that can be made at both the sub-elite and development level (under 18 years of age). Applying the detailed methodology to replicate the scope of analysis in sub-elite and development groups warrants further investigation. Moreover, the results depicted one international-level team, presenting as a limitation and may prevent generalisations. Presently, it is highly unlikely for other countries to share their data on match demands which presents as a common limitation in all studies that examine sports teams, particularly at elite level. Comparisons of published literature may be a viable method to compare results between studies, but can also introduce flaws such as external bias, raise concerns over data quality, and potential methodological differences that are undisclosed. Furthermore, use of a retrospective study design may limit the timeliness of actionable insights on the underlying trends displayed in the thesis. A prospective research design would better enable analysis of current datasets and aid inform evidence-based practice.

The statistical analysis conducted in Chapter Three utilises analysis techniques has not been concurrently analysed with tournament activities and opponent rankings to provide additional insight to establish the effects these main interactions have on reported peak running demands (intercepts and slopes), like those utilised in Chapter Five.

FUTURE DIRECTIONS

A single external load measure was utilised in Chapter Five. Future studies should examine additional performance metrics such as metabolic power, acceleration, deceleration, and contacts to augment this body of work and ascertain if comparable results are identified with the additional metrics. To date, with only one study published, metabolic power presents as an area that is highly promising in its application in intermittent sports but very limited in empirical evidence when applied to women's rugby 7s[1,27] and therefore presents as a future area of research.

The aggregation of data to the level of a tournament offers another area for future research utilising the methods in Chapter Six. Matches were not classified based on the stages of a tournament, that is, pool matches, quarterfinals, semi-finals, and finals such as those presented in other studies.[10,28] This may potentially mask other variability or trends that can be observed by examining match outputs under the context of a tournament. Furthermore, no previous study has examined the travel component that is unique to the sport. Investigating the effect of travel on match running outputs will be of interest. International rugby 7s tournaments are played in varying climatic conditions and often require rapid changes in time zones to prepare for tournaments scheduled every few weeks, which would play a contributing factor when understanding performance outputs in matches.

Despite the methodological considerations raised in Chapter Three, the use of peak running demands analysis does still present potential benefits when applied in practice. However, no longitudinal study design has been implemented to evaluate this tool in the assessment of physiological adaptation, injury, and performance readiness. In addition, the methods utilised in Chapter Five introduce an opportunity to further knowledge in the debate of appropriate speed zone prescription in women's sports. The concurrent analysis of discretised velocity bins and physiologically derived zones would provide supplementary evidence to advocate for a particular method, which has been a challenge in GPS microtechnology-based research until now.

CONCLUSION

Analysis of match demands is a common practice in understanding the demands of elite sports to optimally prepare athletes for the requirements of repeated matches and tournaments. The findings from this thesis have identified methodological considerations when utilising peak running demands in the assessment of match demands as well as provided a comprehensive analysis within a single international-level cohort. In addition, this thesis has examined the need to include contextual factors of a match such as a tournament and opposition ranking as part of match demands analysis. Due to their complexity, contextual factors, to date, have generally been overlooked as elements to be considered in analyses of match demands. This research contributes to the growing evidence on match demands in rugby 7s where there is a comparatively limited body of work focused on women, especially in contrast with the extensive research undertaken in male athletes. By addressing this imbalance, the thesis not only bridges gaps in both methodology and practical application but also supports the broader goal of advancing equity in sports science research.

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APPENDIX

Appendix 1

Electronic Supplementary Material for Chapter Two

Table 1 Data Extraction from all studies including descriptive statistics – Distance

Total Distance (m) in zones in women's rugby 7s

Primary Grouping	Group Analysed	Reference	Total Distance (m)	Low (m) (0-0.2 $m\cdot s^{-1}$)	Moderate (m) *(0.2-3.5$m\cdot s^{-1}$)*	Moderate-High (m) *(3.5-5.0$m\cdot s^{-1}$)*	High (m) *(5.0-6.5 $m\cdot s^{-1}$)*	Very High (m) *(5-5.55$m\cdot s^{-1}$)*	Sprint (m) *(>6.5 $m\cdot s^{-1}$)*	Average Sprint (m) (>5.56 $m\cdot s^{-1}$)	Average Minimal Sprint (m)	Average Maximal Sprint (m)
				<2.0 $m\cdot s^{-1}$	***2-3.5$m\cdot s^{-1}$***	***3.5-5.0$m\cdot s^{-1}$***	***> 5.0 $m\cdot s^{-1}$***					
Day	National - Day 1	[13]	3,680 (900)	1,399 (359) ‖	1,104 (345) ‖	706 (224) ‖	472 (183) ‖					
	National - Day 2	[13]	4,087 (591)	1,592 (205) ‖	1,211 (235) ‖	774 (160) ‖	492 (183) ‖					
									Unspecified			
Match Half	First Half	[11]	793 (95)						135 (67) ‖			
		[20]	776 (118)	15 (10)	518 (92)	154 (57)	69 (36)		18 (23)			
									>61% MV			
		[25]							82 (13) ‖			
				0-1.67 $m\cdot s^{-1}$	***1.67-3.33 $m\cdot s^{-1}$***	***3.33-3.89 $m\cdot s^{-1}$***	***3.89-5 $m\cdot s^{-1}$***		***>5.55$m\cdot s^{-1}$***			
		[27]		230 (52) † ‖	263 (30) † ‖	91 (39) † ‖	131 (61) † ‖	28 (17) †	42 (39) † ‖	19 (11)	8 (4)	28 (22)
									Unspecified			
	Second Half	[11]	659 (88)						80 (54)			
		[20]	640 (180)	14 (9)	429 (125)	124 (59)	54 (31)		15 (22)			
									>61% MV			
		[25]							72 (11)			
				0-1.67 $m\cdot s^{-1}$	***1.67-3.33 $m\cdot s^{-1}$***	***3.33-3.89 $m\cdot s^{-1}$***	***3.89-5 $m\cdot s^{-1}$***		***>5.55$m\cdot s^{-1}$***			
		[27]		238 (41) † ‖	258 (58) † ‖	89 (23) † ‖	122 (30) † ‖	30 (22) †	41 (29) † ‖	16 (6)	5 (0)	24 (11)
				< 2$m\cdot s^{-1}$	***2-3.5$m\cdot s^{-1}$***	***>3.5 $m\cdot s^{-1}$***						
Match	Day 1 - Match 1	[19]	1,451 (534)	631 (153) ‖	486 (249) ‖	334 (143) ‖						
	Day 1 - Match 2	[19]	1,435 (376)	651 (136) ‖	434 (149) ‖	252 (148) ‖						
	Day 1 - Match 3	[19]	1,320 (456)	562 (147) ‖	403 (144) ‖	355 (190) ‖						
	Day 2 - Match 4	[19]	1,652 (350)	859 (204) ‖	403 (135) ‖	345 (114) ‖						
	Day 2 - Match 5	[19]	1,471 (445)	582 (118) ‖	443 (191) ‖	446 (171) ‖						
	Final	[14]	1,660 (819)									
	Full Game	[20]	1,352 (306)	29 (14)	926 (214)	255 (94)	112 (51)		38 (31)			
	Game 1	[14]	1,120 (424)									
	Game 2	[14]	916 (463)									
	Game 3	[14]	1,070 (590)									
	Semi	[14]	1,080 (538)									
Match Outcome	Loss	[20]	1,455 (294)	30 (12)	964 (204)	295 (97)	133 (59)		31 (34)			
	Wins	[20]	1,312 (290)	28 (14)	913 (208)	237 (87)	104 (42)		30 (31)			
				0-2.22 $m\cdot s^{-1}$	***2.22-4.44 $m\cdot s^{-1}$***		***4.44-5.0 $m\cdot s^{-1}$***		***5.0-8.89 $m\cdot s^{-1}$***			
Playing Level	Development	[29]	1,252 (135)	541 (86) ‖	523 (153) ‖		131 (44) ‖		57 (44) ‖			
				0-3.3 $m\cdot s^{-1}$	***3.3-6$m\cdot s^{-1}$***		***6-7.5$m\cdot s^{-1}$***	**> 7.5 $m\cdot s^{-1}$**				
	Domestic	[12]	1,464 (157)	942 (107) ‖	443 (108) ‖		64 (47) ‖	14 (20) ‖				
							> 5.0 $m\cdot s^{-1}$		***Accelerating > 2$m\cdot s^{-2}$ for longer than 1 second***			
	Elite	[16]	1,078 (197)			323 (87) ‖	120 (41) ‖		149 (39) ‖			
	Senior	[16]	1,099 (228)			330 (97) ‖	102 (44) ‖		127 (43) ‖			
	Junior	[16]	1,060 (318)			289 (117)‖	89 (52) ‖		94 (47) ‖			
				0-1.67 $m\cdot s^{-1}$	***1.67-3.33 $m\cdot s^{-1}$***	***3.33-3.89 $m\cdot s^{-1}$***	***3.89-5 $m\cdot s^{-1}$***		***>5.55$m\cdot s^{-1}$***			
	National	[23]	1,363 (222)	524 (137)‖	437 (97) ‖	157 (51) ‖	199 (79) ‖	46 (33)	47 (39) ‖			
		[26]		670 (40) ‖†	730 (60) ‖†	305 (45) ‖†	445 (115) ‖†	90 (15) †	80 (90) ‖†	15 (5)		26 (16)
				0-3.3 $m\cdot s^{-1}$	***3.3-6$m\cdot s^{-1}$***		***6-7.5$m\cdot s^{-1}$***	**> 7.5 $m\cdot s^{-1}$**				
	International	[12]	1,500 (171)	959 (105) ‖	445 (115) ‖		77 (44) ‖	20 (25) ‖				
				0-1.67 $m\cdot s^{-1}$	***1.67-3.33 $m\cdot s^{-1}$***	***3.33-3.89 $m\cdot s^{-1}$***	***3.89-5 $m\cdot s^{-1}$***		***>5.55$m\cdot s^{-1}$***			
		[23]	1,642 (171)	496 (69) ‖	549 (74) ‖	165 (44) ‖	275 (88) ‖	103 (48)	119 (61) ‖			
				0-2.22 $m\cdot s^{-1}$	***2.22-4.44 $m\cdot s^{-1}$***		***4.44-5.0 $m\cdot s^{-1}$***		***5.0-8.89 $m\cdot s^{-1}$***			

		[29]	1,468 (88)	564 (40) ‖	552 (76) ‖		224 (55) ‖	128 (67) ‖
				<2.0 m·s^{-1}	***2-3.5m·s^{-1}***	***3.5-5.0m·s^{-1}***	***> 5.0 m·s^{-1}***	
Playing Level - Day	State - Day 1	[13]	2,533 (1,103)	942 (397) ‖	711 (328) ‖	524 (244) ‖	356 (181) ‖	
	State - Day 2	[13]	2,267 (1,174)	821 (374) ‖	704 (375) ‖	513 (330) ‖	228 (166) ‖	

Data are expressed as mean (SD), † Data manually calculated by author, ‖ Reported threshold different to main heading. Abbreviations: MV = Max Velocity

Table 2 Data Extraction from all studies including descriptive statistics – Distance (continued)

Total Distance (m) in zones in women's rugby 7s

Primary Grouping	**Group Analysed**	**Reference**	**Total Distance (m)**	**Low (m) (0-0.2 m·s^{-1})**	**Moderate (m) *(0.2-3.5m·s^{-1})***	**Moderate-High (m) *(3.5-5.0m·s^{-1})***	**High (m) *(5.0-6.5 m·s^{-1})***	**Very High (m) *(5-5.55m·s^{-1})***	**Sprint (m) *(>6.5 m·s^{-1})***	**Average Minimal Sprint (m)**	**Average Maximal Sprint (m)**
				0-1.67 m·s^{-1}	***1.67-3.33 m·s^{-1}***	***3.33-3.89 m·s^{-1}***	***3.89-5 m·s^{-1}***		***>5.55m·s^{-1}***		
Playing Level – Match Half	International – First Half	[23]	883 (122)	238 (34) ‖	306 (48) ‖	91 (29) ‖	135 (45) ‖	52 (24)	62 (38) ‖		
	International – Second Half	[23]	725 (157)	261 (46) ‖	241 (63) ‖	73 (22) ‖	114 (50) ‖	46 (19)	62 (38) ‖		
	National – First Half	[23]	719 (148)	259 (63) ‖	237 (67) ‖	86 (34) ‖	106 (45) ‖	26 (24)	15 (21) ‖		
	National - Second Half	[23]	615 (146)	251 (78) ‖	213 (52) ‖	71 (25) ‖	88 (46) ‖	19 (15)	27 (28) ‖		
				0-3.3 m·s^{-1}	***3.3-6m·s^{-1}***		***6-7.5m·s^{-1}***	**> 7.5 m·s^{-1}**			
Playing Level - Position	Domestic Forwards	[12]	1,478 (160)	946 (110) ‖	480 (109) ‖		48 (43) ‖	3 (7) ‖			
	Domestic Speed-Edge	[12]	1,468 (147)	967 (99) ‖	394 (91) ‖		79 (48) ‖	28 (29) ‖			
	Domestic Backs	[12]	1,453 (162)	921 (106) ‖	455 (104) ‖		63 (48) ‖	12 (19) ‖			
	International Backs	[12]	1,544 (168)	951 (107) ‖	502 (106) ‖		77 (46) ‖	14 (20) ‖			
	International Forwards	[12]	1,496 (171)	971 (109) ‖	446 (99) ‖		62 (38) ‖	16 (25) ‖			
	International Speed-Edge	[12]	1,431 (154)	944 (96) ‖	367 (98) ‖		91 (46) ‖	30 (31) ‖			
Position									***>5.55 m·s^{-1}***		
	Backs	[17]	1,154 (416)					69 (42)	116 (66) ‖		
		[20]	1,377 (280)	28 (13)	949 (201)	241 (80)	119 (50)		38 (34)		
							4.4-5.6 m·s^{-1}		***> 5.5m·s^{-1}***		
		[21]	1728 (486) §				223 (65)§ ‖		133 (25) § ‖	8 (5)§	29 (25)§
				< 1.9 m·s^{-1}	***1.9-3.9 m·s^{-1}***		***3.9 -5.6 m·s^{-1}***		***> 75% MV***		
		[22]	1,527 (256)	703 (118) ‖	438 (109) ‖		234 (51) ‖		113 (49) ‖		
	Backs (3/4 Line)								**> 61% MV**		
		[25]							166 (16)		
									>5.55 m·s^{-1}		
	Forwards	[17]	1,084 (415)					63 (36)	79 (54) ‖		
		[20]	1,325 (332)	30 (14)	900 (225)	269 (105)	104 (50)		31 (26)		
							4.4-5.6 m·s^{-1}		***> 5.5m·s^{-1}***		
		[21]	1,422 (378) §				174 (105) § ‖		102 (144) § ‖	5 (5) §	15 (19) §
				< 1.9 m·s^{-1}	***1.9-3.9 m·s^{-1}***		***3.9 -5.6 m·s^{-1}***		***> 75% MV***		
		[22]	1,601 (192)	757 (112) ‖	468 (64) ‖		277 (67) ‖		72 (12) ‖		
									> 61% MV		
		[25]							135 (14) ‖		
							4.4-5.6 m·s^{-1}		***> 5.5m·s^{-1}***	***> 5.5m·s^{-1}***	***> 5.5m·s^{-1}***
Position – Match Half	Backs - First Half	[21]	921 (471) §				121 (95) §‖		71 (41) §‖	4 (5) §‖	16 (12) §‖
	Backs - Second Half	[21]	807 (491) §				102 (54) §‖		62 (47) §‖	4 (3) §‖	9 (8) §‖
	Forwards - First Half	[21]	803 (315) §				91 (42) §‖		54 (67) §‖	3 (3) §‖	9 (8) §‖
	Forwards – Second Half	[21]	719 (295) §				83 (32) §‖		48 (46) §‖	2 (3) §‖	6 (8) §‖
Quarter	Quarter	[14]	1,140 (681)								
Tournament	State	[15]	4,800 (2,200)				584 (324)				
	National	[15]	7,100 (2,100)				881 (410)				
	Tournament	[12]	1,475 (164)	943 (106)	453 (111)		66 (47)	14 (23) ‖			
				0-3.3 m·s^{-1}	***3.3-6m·s^{-1}***		***6-7.5m·s^{-1}***	**> 7.5 m·s^{-1}**			
Tournament - Position	Tournament Backs	[12]	1,499 (172)	936 (107) ‖	480 (108) ‖		70 (47) ‖	13 (20) ‖			
	Tournament Forwards	[12]	1,490 (163)	957 (110) ‖	469 (107) ‖		55 (42) ‖	8 (16) ‖			
	Tournament Speed-Edge	[12]	1,456 (150)	959 (98) ‖	383 (95) ‖		85 (47) ‖	30 (30) ‖			

Data are expressed as mean (SD), § SD data manually calculated from confidence intervals, † Data manually calculated by author, ‖ Reported threshold different to main heading
MV = Max Velocity

Table 3 Data Extraction from all studies including descriptive statistics – Distance (continued)

Distance count (n) and seconds (s) in zones in women's rugby 7s

Primary Grouping	**Group Analysed**	**Reference**	**High (n) ($>5.5\ m\cdot s^{-1}$)**	**Sprint (n) ($>5.55 m\cdot s^{-1}$)**	**Repeat Sprint (n)** ***(Two consecutive sprints in 30 seconds)***	**Average Time Spent Sprinting (s)**
				>61% MV		
Match Half	First Half	[25]		3.4 (1.3) ‖	1.2 (0.3)	
		[27]		2.5 (1.6)		
	Second Half	[25]		2.4 (1.3) ‖	0.3 (0.3)	
		[27]		2.8 (1.6)		
Playing Level	National	[23]		1.9 (1.4)		
		[26]		5.3 (3)		
	International	[23]		6.1 (3.1)		
Playing Level - Match Half	International – First Half	[23]		2.9 (1.8)		
	International – Second Half	[23]		3.6 (2.0)		
	National - First Half	[23]		0.6 (0.9)		
	National - Second Half	[23]		1 (1)		
Position	Backs	[21]		4.5 (4) §		
		[22]		6.1 (1.2)		
	Backs (3/4 Line)	[25]		6.8 (1.9)	1.8 (0.8)	
	Forwards	[21]		2.5 (2) §		
		[22]		5.2 (0.5)		
		[25]		4.5 (1.4)	1.1 (0.3)	
Position - Match Half	Backs - First Half	[21]	2.25 (12) §			
	Backs - Second Half	[21]	2.25 (12) §			
	Forwards - First Half	[21]	1.25 (1) §			
	Forwards – Second Half	[21]	1.25 (1) §			
						Accelerating $> 2m\cdot s^{-2}$ for longer than 1 second
Playing Level	Elite	[16]				3.5 (1.0) ‖
	Senior	[16]				4.2 (1.78) ‖
	Junior	[16]				4.1 (0.44) ‖

Data are expressed as mean (SD), § SD data manually calculated from confidence intervals, † Data manually calculated by author, ‖ Reported threshold different to main heading

Table 4 Data Extraction from all studies including descriptive statistics – Distance (continued)

Average Speed ($m\cdot min^{-1}$) in zones in women's rugby 7s

Primary Grouping	Group Analysed	Reference	Total Distance (m)	Low (m) (0-0.2 $m\cdot s^{-1}$)	Moderate (m) *(0.2-3.5$m\cdot s^{-1}$)*	Moderate-High (m) *(3.5-5.0$m\cdot s^{-1}$)*	High (m) *(5.0-6.5 $m\cdot s^{-1}$)*	Very High (m)	Sprint (m) *(>6.5 $m\cdot s^{-1}$)*
Day	National - Day 1	[13]	100.0 (7.0)						
	National - Day 2	[13]	93.0 (4.0)						
	Day 1	[20]	86.0 (10.0) †		59.0 (5.0) †	16.1 (12.9) †	6.4 (3.5) †		2.0 (2.0) †
	Day 2	[20]	88.0 (9.0) †		60.0 (5.5) †	16.5 (11.5) †	8.0 (3.9) †		2.0 (2.0) †
Match Half	First Half	[11]	88.8 (10.6)						15.1 (7.5)
		[20]	97.5 (4.5) †		65.0 (20.0) †	19.8 (29.2) †	8.4 (4.7) †		2.0 (3.0) †
	Second Half	[11]	77.7 (10.4)						9.4 (6.3)
		[20]	88.0 (4.0) †		60.0 (6.0) †	17.0 (23.0) †	7.8 (4.1) †		2.0 (3.0) †
Match	Full Game	[20]	87.0 (11.0)	2.0 (1.0)	59.0 (7.0)	11.5 (3.0)			2.0 (2.0)
	Game 1	[14]	108.0 (7.0)						
	Game 2	[14]	116.0 (18.0)						
	Game 3	[14]	107.0 (19.0)						
	Semi	[14]	103.0 (17.0)						
	Final	[14]	109.0 (16.0)						
Match Outcome	Loss	[20]	89.0 (10.0) †		58.0 (7.0) †	18.0 (17.0) †	8.1 (3.9) †		2.0 (2.0) †
	Win	[20]	86.0 (9.5) †		60.0 (5.0) †	15.9 (9.1) †	6.8 (3.1) †		2.0 (2.0) †
Opponent	Top four Opponent	[20]	86.0 (11.0) †		56.0 (10.0) †	17.0 (12.0) †	7.9 (3.1) †		1.8 (1.8) †
	Bottom four Opponent	[20]	87.0 (12.0) †		59.0 (9.0) †	17.0 (18.0) †	7.0 (3.1) †		2.0 (2.0) †
Playing Level				***0-2.22$m\cdot s^{-1}$***	***2.22-4.44 $m\cdot s^{-1}$***		***4.44-5.0 $m\cdot s^{-1}$***		***5.0-8.89 $m\cdot s^{-1}$***
	Development	[28]	91.0 (11.0)	39.0 (6.0) ‖	38.0 (12.0) ‖		10.0 (4.0) ‖		4.0 (3.0) ‖
	Domestic	[12]	92.6 (8.1)						
	Elite	[15]	85.8 (3.9)						
	Senior	[15]	98.2 (12.4)						
	Junior	[15]	90.9 (8.1)						
		[12]	94.3 (9.0)						
	International			***0-2.22$m\cdot s^{-1}$***	***2.22-4.44 $m\cdot s^{-1}$***		***4.44-5.0 $m\cdot s^{-1}$***		***5.0-8.89 $m\cdot s^{-1}$***
		[28]	95.0 (5.0)	36.0 (2.0) ‖	36.0 (5.0) ‖		14.0 (3.0) ‖		8.0 (4.0) ‖
Playing Level - Day	State - Day 1	[13]	105.0 (7.0)						
	State - Day 2	[13]	83.0 (14.0)						
Playing Level-Position	Domestic Forwards	[12]	93.3 (8.1)						
	Domestic Speed-Edge	[12]	91.3 (7.8)						
	Domestic Backs	[12]	95.6 (8.1)						
	International Backs	[12]	91.4 (8.8)						
	International Forwards	[12]	94.4 (9.5)						
	International Speed-Edge	[12]	93.6 (8.4)						
Points Differential				***0-2 $m\cdot s^{-1}$***	***2-3.5$m\cdot s^{-1}$***	***3.5-5.0$m\cdot s^{-1}$***	***5.0-6.0 $m\cdot s^{-1}$***	***>6.0 $m\cdot s^{-1}$***	
	High Score Differentials	[24]	91.6 (9.7)	33.1 (4.0) ‖	29.8 (5.8) ‖	18.3 (4.5) ‖	6.3 (2.6) ‖	4.2 (2.4) ‖	
	Low Score Differentials	[24]	87.8 (8.9)	32.5 (4.2) ‖	28.5 (6.5) ‖	18.5 (6.0) ‖	5.5 (2.9) ‖	2.9 (3.6) ‖	
	Margin of Defeat	[20]	86.0 (8.7) †		52.0 (10.5) †		17.8 (14.2) †	8.0 (3.0) †	2.0 (2.0) †
	Margin of Victory	[20]	87.5 (9.5) †		61.0 (7.0) †		16.8 (10.2) †	6.6 (3.3) †	2.0 (2.0) †

Data are expressed as mean (SD), † Data manually calculated by author, ‖ Reported threshold different to main heading

Table 5 Data Extraction from all studies including descriptive statistics – Distance (continued)

Average Speed ($m \cdot min^{-1}$) and percentage of distance (%) in zones in women's rugby 7s

Unit of Measurement	Primary Grouping	Group Analysed	Reference	Total Distance (m)	Low (m) (0-0.2 $m \cdot s^{-1}$)	Moderate (m) *(0.2-3.5$m \cdot s^{-1}$)*	Moderate-High (m) *(3.5-5.0$m \cdot s^{-1}$)*	High (m) *(5.0-6.5 $m \cdot s^{-1}$)*	Very High (m)	Sprint (m) *(>6.5 $m \cdot s^{-1}$)*
Relative Distance ($m \cdot min^{-1}$)	Position							***5-5.56 $m \cdot s^{-1}$***	***> 5.56$m \cdot s^{-1}$***	
		Backs	[16]	91.5 (20.6)*				5.6 (2.9) ‖	9.5 (5.7) ‖	
			[20]	86.0 (9.0)*	2.0 (1.0)*	59.0 (7.0)*	11.5 (3.0)*	7.9 (2.6) †	2.0 (2.0)	
			[22]	98.0 (8.0)*						
								5-5.56 $m \cdot s^{-1}$	***> 5.56$m \cdot s^{-1}$***	
		Forwards	[16]	93.3 (17.5)*				5.3 (2.9) ‖	6.5 (4.3) ‖	
			[20]		2.0 (1.0)*	59.0 (8.0)*	12.5 (3.0)*	6.6 (3.4) †	2.0 (2.0)	
			[22]	97.0 (6.0)*						
	Quarters	Quarter	[14]	94.0 (11.0)*						
	Tournament	Tournament	[12]	93.1 (8.5)*						
	Tournament-Position	Tournament Backs	[12]	93.5 (8.7)*						
		Tournament Forwards	[12]	94.0 (8.6)*						
		Tournament Speed-Edge	[12]	92.9 (8.1)*						
Percentage (%)	Match							***> 5$m \cdot s^{-1}$***		
		Game 1	[14]				34.0 (5.0)	13.0 (6.0)		
		Game 2	[14]				35.5 (6.0)	13.0 (8.0)		
		Game 3	[14]				35.5 (7.0)	13.0 (5.0)		
		Semi	[14]				38.0 (9.0)	15.0 (5.0)		
	Playing Level	Final	[14]				38.0 (5.0)	15.0 (5.0)		
		Elite	[15]				29.7 (3.4)	11.0 (2.7)		14.2 (2.8)
		Senior	[15]				29.8 (5.2)	9.2 (2.9)		11.6 (3.3)
		Junior	[15]				27.0 (6.7)	8.3 (4.2)		8.9 (4.1)
	Position	Backs	[22]		47.0 (3.0)		29.0 (5.0)	16.0 (2.0)		7.5 (3.2)
		Forwards	[22]		48.0 (3.0)		30.0 (3.0)	18.0 (4.0)		4.6 (0.8)
	Quarters	Quarter	[14]				34.5 (6.0)	11.0 (5.0)		

Data are expressed as mean (SD, † Data manually calculated by author, ‖ Reported threshold different to main heading

Table 6 Data Extraction from all studies including descriptive statistics – Acceleration

Acceleration count (n), acceleration load (AU), maximal acceleration ($m \cdot s^{-2}$) and relative accelerations ($n \cdot min^{-1}$) in zones in women's rugby 7s

Unit of Measurement	Primary Grouping	Group Analysed	Reference	Total Accelerations (n)	Low (n) *(>1.5 $m \cdot s^{-2}$)*	Moderate (n) *(>2.0 $m \cdot s^{-2}$)*	High (n) *(>2.5 $m \cdot s^{-2}$)*	Very High (n) *(>2.75 $m \cdot s^{-2}$)*	Maximal Acceleration ($m \cdot s^{-2}$)	Acceleration Load (AU)	Acceleration Load Density (AU.min^{-1})
Count (n)	Match Half	First Half	[11]	5.3 (2.2)							
		Second Half	[11]	4.1 (2.7)							
	Position	Backs	[21]	14.0 (7.0) §	6.0 (7.0) §	5.0 (7.0) §	3.0 (1.0)				
						> 1.8 $m \cdot s^{-2}$					
						14.9 (5.4) ‖					
		Forwards	[21]	11.0 (4.0) §	7.0 (10.0) §	3.0 (3.0) §	1.0 (1.0) §				
						> 1.8 $m \cdot s^{-2}$					
						12.6 (5.3) ‖					
	Playing Level-Match Half	International – First Half	[23]		6.0 (2.7)	4.3 (1.7)	1.3 (1.2)	1.7 (1.2)			
		International – Second Half	[23]		4.9 (2.4)	3.9 (2.0)	1.2 (1.2)	1.5 (1.2)			
		National - First Half	[23]		6.0 (2.2)	3.0 (2.3)	0.4 (0.6)	0.2 (0.5)			
		National - Second Half	[23]		4.5 (2.2)	2.2 (1.6)	0.5 (0.9)	0.2 (0.4)			
	Position-Match Half	Backs - First Half	[21]	9.0 (7.0) §	3.5 (4.0) §	3.0 (3.0) §	2.5 (2.0) §				
		Backs - Second Half	[21]	5.0 (5.0) §	2.5 (3.0) §	2.0 (3.0) §	1.5 (2.0) §				
		Forwards - First Half	[21]	7.0 (7.0) §	4.3 (6.0) §	1.5 (1.0) §	0.3 (1.0) §				
		Forwards – Second Half	[21]	4.0 (4.0) §	2.7 (6.0) §	1.5 (1.0) §	0.7 (1.0) §				
Acceleration Load (AU) and Acceleration Load Density (AU.min^{-1})	Playing Level	Domestic	[12]							450.2 (48.7)	0.5 (0.0)
		International	[12]							461.2 (49.3)	0.5 (0.1)
	Playing Level-Position	Domestic Forwards	[12]							442.3 (44.5)	0.5 (0.0)
		Domestic Speed-Edge	[12]							461.4 (51.6)	0.5 (0.1)
		Domestic Backs	[12]							449.6 (50.2)	0.5 (0.0)
		International Backs	[12]							471.7 (48.5)	0.5 (0.0)
		International Forwards	[12]							453.9 (50.0)	0.5 (0.1)
		International Speed-Edge	[12]							450.7 (45.5)	0.5 (0.1)
	Tournament	Tournament	[12]							455.3 (49.1)	0.5 (0.1)
	Tournament-Position	Tournament Backs	[12]							460.8 (49.8)	0.5 (0.0)
		Tournament Forwards	[12]							448.0 (46.4)	0.5 (0.0)
		Tournament Speed-Edge	[12]							458.2 (49.1)	0.5 (0.1)
Maximal Acceleration ($m \cdot s^{-2}$)	Playing Level	Domestic	[12]						2.8 (0.3)		
		Elite	[15]						3.5 (0.4)		
		Senior	[15]						3.3 (0.4)		
		Junior	[15]						3.2 (0.4)		
		International	[12]						3.0 (0.3)		
	Playing Level-Position	Domestic Forwards	[12]						2.7 (0.3)		
		Domestic Speed-Edge	[12]						2.9 (0.4)		
		Domestic Backs	[12]						2.9 (0.3)		
		International Backs	[12]						2.8 (0.3)		
		International Forwards	[12]						3.1 (0.3)		
		International Speed-Edge	[12]						3.1 (0.4)		
	Tournament	Tournament	[12]						2.9 (0.3)		
	Tournament-Position	Tournament Backs	[12]						2.9 (0.3)		
		Tournament Forwards	[12]						2.9 (0.3)		
		Tournament Speed-Edge	[12]						3.0 (0.4)		
Relative Acceleration (count.min^{-1})	Match Half	First Half	[11]	0.59 (0.3)							
		Second Half	[11]	0.49 (0.3)							
	Position					***> 1.8 $m \cdot s^{-2}$***					
		Backs	[16]			1.20 (0.4) ‖					
		Forwards	[16]			1.10 (0.4) ‖					

Data are expressed as mean (SD), § SD data manually calculated from confidence intervals, † Data manually calculated by author ‖ Reported threshold different to main heading. Acceleration Load Density (AU.min^{-1}) = Acceleration load divided by time

Table 7 Data Extraction from all studies including descriptive statistics – Deceleration

Deceleration count (n), maximal deceleration ($m \cdot s^{-2}$) and relative ($count.min^{-1}$) deceleration in women's rugby 7s

Primary Grouping	Group Analysed	Reference	Total Decelerations (n)	Maximal Deceleration ($m \cdot s^{-2}$)	Moderate (n) *($< -1.8\ m \cdot s^{-2}$)*
Match Half	First Half	[11]	7.9 (4.0)		
	Second Half	[11]	5.9 (2.4)		
Playing Level	Domestic	[12]		-4.70 (0.90)	
	International	[12]		-5.00 (0.80)	
Playing Level-Position	Domestic Forwards	[12]		-4.20 (0.70)	
	Domestic Speed-Edge	[12]		-5.40 (1.10)	
	Domestic Backs	[12]		-4.50 (0.80)	
	International Backs	[12]		-5.10 (0.70)	
	International Forwards	[12]		-4.70 (0.80)	
	International Speed-Edge	[12]		-5.00 (0.90)	
Position	Backs	[16]			21.5 (9.1)
	Forwards	[16]			20.0 (8.5)
Tournament	Tournament	[12]		-4.70 (0.90)	
Tournament-Position	Tournament Backs	[12]		-4.75 (0.80)	
	Tournament Forwards	[12]		-4.70 (0.80)	
	Tournament Speed-Edge	[12]		-5.30 (1.00)	
Match Half	First Half	[11]	0.88 (0.45)*		
	Second Half	[11]	0.70 (0.29)*		
Position	Backs	[16]			1.2 (0.5)*
	Forwards	[16]			1.7 (0.5)*

Data are expressed as mean (SD), † Data manually calculated by author

* Values expressed as decelerations per minute ($count.min^{-1}$)

Table 8 Data Extraction from all studies including descriptive statistics – Contacts/Impacts by Count

Contacts/Impacts count (n) in zones in women’s rugby 7s

Primary Grouping	Group Analysed	Reference	Number of Physical Contact with Others (n)	Number of Total Impacts (n)		
			Notational Analysis	8 - 10g (n)	> 10 g (n)	Total (n)
Match	Day 1 – Match 1	[19]	7.5 (4.8)			
	Day 1 – Match 2	[19]	5.8 (4.2)			
	Day 1 – Match 3	[19]	6.4 (5.1)			
	Day 2 – Match 4	[19]	6.8 (6.6)			
	Day 2 – Match 5	[19]	5.5 (4.0)			
Playing Level	Elite	[15]			12.6 (4.7)	
	Senior	[15]			10.2 (7.1)	
	Junior	[15]			4.9 (2.6)	
Playing Level - Day	National – Day 1	[13]		32.0 (14.0)	15.0 (6.0)	3,855.0 (974.0)
	National – Day 2	[13]		34.0 (24.0)	17.0 (9.0)	4,126.0 (989.0)
	State – Day 1	[13]		26.0 (18.0)	12.0 (7.0)	2,642.0 (1,187.0)
	State – Day 2	[13]		23.0 (17.0)	10.0 (5.0)	2,519.0 (1,353.0)
Playing Level - Tournament	State – Tournament	[15]			22 (11)	5,200 (2,400)
	National – Tournament	[15]			29 (11)	7,300 (2,200)

Data are expressed as mean (SD), † Data manually calculated by author

Table 9 Data Extraction from all studies including descriptive statistics – Metabolic Load & PlayerLoad

Energy cost ($kj.kg^{-1}$), mean power ($W.kg^{-1}$), metabolic load distance (m) and PlayerLoad (AU) in zones in women's rugby 7s

Primary Grouping	**Playing Level**	**Reference**	**Low (m)** *(<10 $W.kg^{-1}$)*	**Intermediate (m)** *(10-20 $W.kg^{-1}$)*	**High (m)** *(20-35 $W.kg^{-1}$)*	**Elevated (m)** *(35-55 $W.kg^{-1}$)*	**Maximal (m)** *(> 55 $W.kg^{-1}$)*	**Energy Cost** ($kJ.kg^{-1}$)	**Mean Power** ($W.kg^{-1}$)	**PlayerLoad (AU)**
Playing Level	Development	[28]						6.9 (0.8)		
	International	[28]						7.8 (1.0)		
	Development	[28]							8.5 (1.1)	
	International	[28]							8.8 (0.7)	
	Development	[28]	602.0 (77.0)	314.0 (91.0)	210.0 (54.0)	76.0 (20.0)	30.0 (15.0)			
	International	[28]	641.0 (34.0)	353.0 (36.0)	264.0 (36.0)	118.0 (17.0)	69.0 (17.0)			
Match Half	First Match Half	[20]								84.00 (18.0)
	Second Match Half	[20]								69.00 (20.0)
Match	Full Match	[20]								144.00 (34.0)
Match Outcome	Match loss	[20]								144.00 (34.0)
	Match win	[20]								140.00 (34.0)
Position	Backs	[20]								147.00 (36.0)
	Forwards	[20]								141.00 (34.0)

Data are expressed as mean (SD), † Data manually calculated by author. AU = Arbitrary Unit

Table 10 Data Extraction from all studies including descriptive statistics – Velocity

Velocity (m·s^{-1}) and percentage maximal velocity (%) in women's rugby 7s

Primary Grouping	Group Analysed	Reference	Average Speed (m·s^{-1})	Maximal Velocity (m·s^{-1})	Percentage Maximal Velocity (%)
Position	Backs	[22]			95.00 (7.70)
	Forwards	[22]			89.10 (4.50)
Match Half	First Half	[20]		6.60 (0.90)	
		[25]		6.56 (0.86)	
		[27]		6.44 (0.61)	
	Second Half	[20]		6.50 (0.80)	
		[25]		6.61 (0.95)	
		[27]		6.36 (0.42)	
Match	Full Game	[20]		6.90 (0.80)	
Match Outcome	Loss	[20]		7.00 (0.70)	
Outcome	Wins	[20]		6.90 (0.80)	
Playing Level	Domestic	[12]	1.54 (0.10)	7.30 (0.80)	
		[29]		6.83 (0.75)	
	Elite	[15]		8.05 (0.55)	
	Senior	[15]		7.40 (0.52)	
	Junior	[15]		7.08 (0.83)	
	National	[23]	5.20 (0.60)		
		[26]		6.28 (0.28)	
	International	[12]	1.57 (0.10)	7.70 (0.20)	
		[23]	6.00 (0.30)		
		[29]		7.36 (0.53)	
Playing Level - Match Half	International – First Half	[23]	6.10 (0.30)		
		[23]	7.36 (0.53)		
	International – Second Half	[23]	5.90 (0.40)		
		[23]	6.78 (0.56)		
	National - First Half	[23]	5.50 (0.90)		
		[23]	6.92 (0.44)		
	National - Second Half	[23]	5.10 (0.40)		
		[23]	5.78 (0.72)		
Playing Level-Position	Domestic Forwards	[12]	1.60 (0.10)	6.90 (0.70)	
	Domestic Speed-Edge	[12]	1.60 (0.10)	7.90 (0.60)	
	Domestic Backs	[12]	1.50 (0.10)	7.30 (0.70)	
	International Backs	[12]	1.60 (0.20)	7.60 (0.60)	
	International Forwards	[12]	1.60 (0.20)	7.60 (0.70)	
	International Speed-Edge	[12]	1.50 (0.10)	7.90 (0.60)	
Playing Level-Quarters	International – First Quarter	[23]	6.20 (0.40)		
	International – Second Quarter	[23]	6.10 (0.40)		
	International – Third Quarter	[23]	6.10 (0.60)		
	International – Fourth Quarter	[23]	5.80 (0.60)		
	National - First Quarter	[23]	5.40 (1.20)		
	National – Second Quarter	[23]	5.50 (0.90)		
	National – Third Quarter	[23]	5.50 (0.70)		
	National – Fourth Quarter	[23]	4.70 (0.40)		
Tournament	Tournament	[12]	1.60 (0.10)	7.40 (0.80)	
Tournament-Position	Tournament Backs	[12]	1.54 (0.10)	7.48 (0.70)	
	Tournament Forwards	[12]	1.57 (0.10	7.16 (0.80)	
	Tournament Speed-Edge	[12]	1.50 (0.10)	7.90 (0.60)	
Position	Backs	[20]		7.10 (0.70)	
		[21]		7.69 (1.00) §	
		[22]		7.50 (0.70)	
		[25]		7.19 (0.65)	
	Forwards	[20]		6.70 (0.70)	

		[21]		7.51 (1.00) §
		[22]		6.70 (0.50)
		[25]		6.08 (0.72)
Position-Match Half	Backs - First Half	[21]		7.71 (2.00) §
	Backs - Second Half	[21]		7.52 (2.00) §
	Forwards - First Half	[21]		7.50 (0.00) §
	Forwards – Second Half	[21]		7.39 (0.00) §
Tournament	Tournament	[12]	1.60 (0.10)	7.40 (0.80)
Tournament-Position	Tournament Backs	[12]	1.54 (0.10)	7.48 (0.70)
	Tournament Forwards	[12]	1.57 (0.10)	7.16 (0.80)
	Tournament Speed-Edge	[12]	1.50 (0.10)	7.90 (0.60)

Data are expressed as mean (SD), § SD data manually calculated from confidence intervals, † Data manually calculated by author. AU = Arbitrary Unit

Table 11 Data Extraction from all studies including descriptive statistics – Velocity (continued)

Speed exertion (AU) in women's rugby 7s

Primary Grouping	Group Analysed	Reference	Speed Exertion (AU)
Playing Level	Domestic	[12]	9.80 (4.20)
	International	[12]	11.70 (7.00)
Playing Level-Position	Domestic Forwards	[12]	8.90 (4.20)
	Domestic Speed-Edge	[12]	10.60 (4.60)
	Domestic Backs	[12]	9.70 (3.90)
	International Backs	[12]	10.50 (6.70)
	International Forwards	[12]	10.70 (5.80)
	International Speed-Edge	[12]	14.70 (8.50)
Tournament	Tournament	[12]	10.40 (5.60)
Tournament-Position	Tournament Backs	[12]	10.09 (5.50)
	Tournament Forwards	[12]	9.85 (4.80)
	Tournament Speed-Edge	[12]	12.40 (6.70)

Data are expressed as mean (SD), † Data manually calculated by author
AU = Arbitrary Unit

Appendix 2

Electronic Supplementary Material for Chapter Three

Figure 1 Tightly fitted GPS device pockets imbedded in player's match jerseys.

Table 1. Average Speed over various rolling average windows (m·min^{-1}).

Percentile	1-minute	2-minutes	3-minutes	4-minutes	5-minutes	6-minutes	7-minutes
100th	164.4 ± 32.8	128.8 ± 24.5	114.7 ± 23.4	106.1 ± 23.3	99.2 ± 23.5	93.8 ± 24	89 ± 24.5
90th	106.7 ± 34.1	96.1 ± 30.2	90.4 ± 29.5	85.8 ± 29.3	81.9 ± 29.2	78.7 ± 29	76.1 ± 28.4
80th	81.9 ± 38.1	77.4 ± 34.5	74.3 ± 33.3	71.9 ± 32.8	69.9 ± 32.1	68.3 ± 31.2	66.5 ± 30
70th	63.5 ± 41	62.2 ± 38.5	60.7 ± 37.1	59.6 ± 35.9	58.7 ± 34.7	58.1 ± 33.1	57.3 ± 32
50th	51.3 ± 39.4	52 ± 38.5	51.3 ± 37.9	50.5 ± 37	50 ± 36	49.4 ± 35.1	49.1 ± 34.4
Mean	41.3 ± 36.4	44.2 ± 36.5	44.5 ± 35.9	44.4 ± 35.4	44.1 ± 35	44 ± 34.5	44.2 ± 34.2

Data expressed as mean ± SD

Table 2. Relative High-Speed Running (> 5 $m \cdot s^{-1}$) over various rolling average windows ($m \cdot min^{-1}$).

Percentile	1-minute	2-minutes	3-minutes	4-minutes	5-minutes	6-minutes	7-minutes
100th	53.4 ± 28.6	32.2 ± 16.8	24.7 ± 12.9	20.9 ± 11.3	18.2 ± 9.9	16.5 ± 9.1	15.1 ± 8.4
90th	21.8 ± 16.6	20 ± 13.5	16.8 ± 11	14.8 ± 9.6	13.6 ± 8.9	12.6 ± 8.1	11.8 ± 7.7
80th	11.2 ± 11.9	11.7 ± 10.2	11.3 ± 9.1	11.3 ± 8.7	10.6 ± 8	10.1 ± 7.5	9.6 ± 7
70th	5.8 ± 8	7.9 ± 8.3	8 ± 7.9	8 ± 7.4	8.1 ± 7.2	8 ± 6.8	7.8 ± 6.5
50th	2.9 ± 5.4	5.4 ± 6.5	6.1 ± 6.5	6.3 ± 6.6	6.3 ± 6.5	6.4 ± 6.4	6.4 ± 6.2
Mean	1.1 ± 3	3.4 ± 5.1	4.4 ± 5.4	5 ± 5.7	5.1 ± 5.7	5.2 ± 5.7	5.4 ± 5.8

Data expressed as mean ± SD

Table 3. Relative Acceleration count (> 2.5 $m \cdot s^{-2}$) over various rolling average windows ($count.min^{-1}$).

Percentile	1-minute	2-minutes	3-minutes	4-minutes	5-minutes	6-minutes	7-minutes
100th	2.3 ± 1.1	1.5 ± 0.8	1.1 ± 0.6	1 ± 0.5	0.9 ± 0.5	0.8 ± 0.4	0.7 ± 0.4
90th	1 ± 0.7	0.8 ± 0.5	0.7 ± 0.5	0.7 ± 0.4	0.6 ± 0.4	0.6 ± 0.4	0.5 ± 0.4
80th	0.5 ± 0.6	0.5 ± 0.5	0.5 ± 0.4	0.5 ± 0.4	0.5 ± 0.4	0.5 ± 0.3	0.4 ± 0.3
70th	0.3 ± 0.5	0.4 ± 0.4	0.4 ± 0.4	0.4 ± 0.3	0.4 ± 0.3	0.4 ± 0.3	0.4 ± 0.3
50th	0.2 ± 0.4	0.3 ± 0.3	0.3 ± 0.3	0.3 ± 0.3	0.3 ± 0.3	0.3 ± 0.3	0.3 ± 0.3
Mean	0.1 ± 0.2	0.2 ± 0.3	0.2 ± 0.3	0.2 ± 0.3	0.2 ± 0.3	0.2 ± 0.3	0.2 ± 0.3

Data expressed as mean ± SD

Table 4. Acceleration Load Density (AU.min^{-1}).

Percentile	1-minute	2-minutes	3-minutes	4-minutes	5-minutes	6-minutes	7-minutes
100th	50.2 ± 23	38.6 ± 16.8	34.3 ± 15.9	31.7 ± 15	29.5 ± 14.1	28 ± 14.4	26.6 ± 14.1
90th	31.8 ± 12.7	28.5 ± 12.4	26.8 ± 12.5	25.4 ± 12.8	24.3 ± 12.3	23.4 ± 12.1	22.6 ± 11.5
80th	24.1 ± 10.7	22.7 ± 9.4	22 ± 9.1	21.3 ± 8.9	20.7 ± 8.7	20.2 ± 8.5	19.7 ± 8.2
70th	19.2 ± 10.9	18.6 ± 10.2	18.3 ± 9.9	17.9 ± 9.7	17.7 ± 9.4	17.4 ± 9	17.2 ± 8.6
50th	15.4 ± 10.4	15.7 ± 10.2	15.5 ± 10.1	15.3 ± 10	15.1 ± 9.7	15 ± 9.5	14.9 ± 9.3
Mean	12.2 ± 9.5	13.3 ± 9.8	13.3 ± 9.7	13.3 ± 9.6	13.3 ± 9.5	13.3 ± 9.4	13.3 ± 9.2

Data expressed as mean ± SD

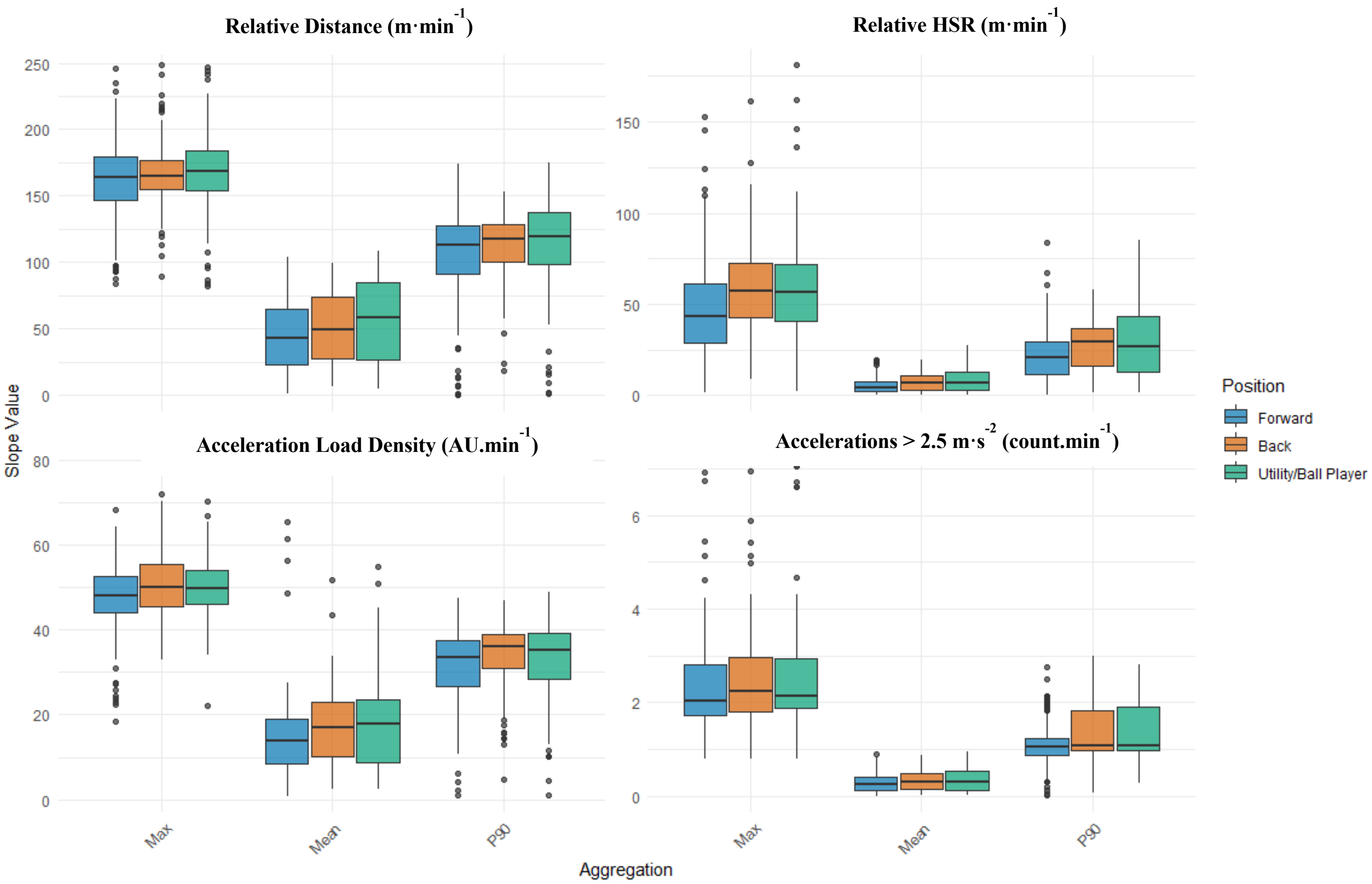

Figure 2 Distribution of Intercepts by aggregation method, position, and metric. Values expressed as mean (SD). Abbreviations: P90, 90th Percentile.

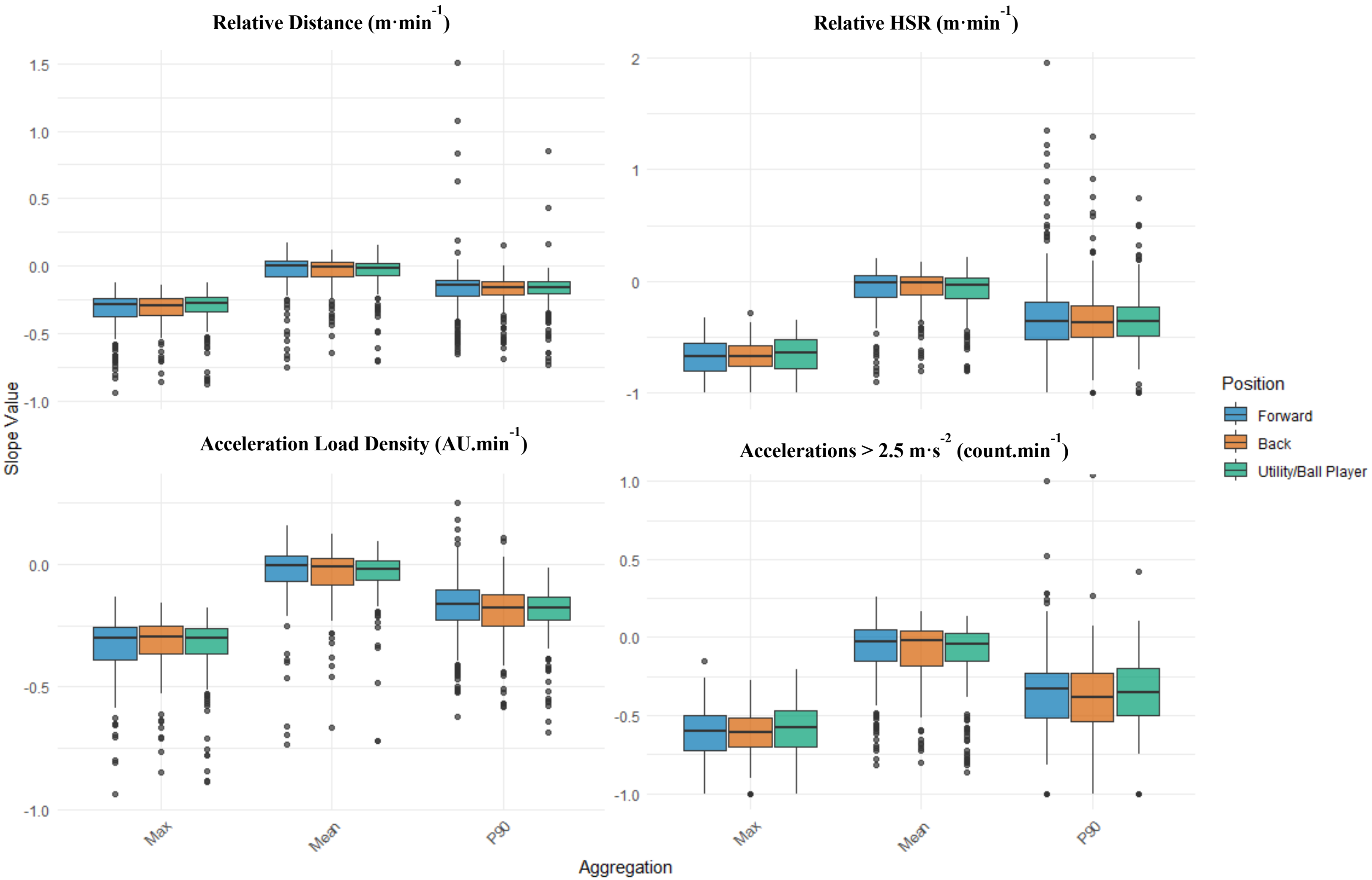

Figure 3 Distribution of Slopes by aggregation method, position, and metric. Values expressed as mean (SD). Abbreviations: P90, 90th Percentile.

Appendix 3

Electronic Supplementary Material for Chapter Four

Analysing Seconds spent in Absolute Speed Zones in RStudio

```
rm(list = ls())


library(dplyr)
library(readr)
library(ggplot2)
library(gridExtra)
library(png)
library(grid)

# Set the working directory to the folder with the CSV files
path1 <- "C:/Users/…"

# Set the second directory to save the csv and pdf file with all collated graphs in a
specific folder
path2 <- "C:/Users/…"

setwd(path1)


# Function to apply Doppler shift correction to velocity data
correct_velocity_doppler <- function(velocity) {
  doppler_factor <- 0.98
  return(velocity * doppler_factor)
}


# Initialize a list to store the graphs
graphs_list <- list()


# Read multiple CSV files and store their names
csv_files <- list.files(pattern = "*.csv")
file_names <- tools::file_path_sans_ext(csv_files)


# Initialize a data frame to store the collated summary data
collated_summary <- data.frame()
```

```
# Loop through each CSV file, skip first 8 rows, and process the data
for (i in seq_along(csv_files)) {
  csv_data <- read_csv(csv_files[i], col_types = cols(Seconds = col_double(), Velocity =
col_double()), skip = 8)


  # Add a new column "Lookup Name" and populate it with the file name
  csv_data$`Lookup Name` <- file_names[i]
    # Keep only rows corresponding to first-half or second-half periods
  if ("Period" %in% names(csv_data)) {
    csv_data <- csv_data %>% filter(Period %in% c("First Half", "Second Half"))
  }

# Apply Doppler shift correction
 csv_data$Velocity_Corrected <- correct_velocity_doppler(csv_data$Velocity)


  # Create bins for velocity in 1 m/s increments
  bins <- seq(0, 10, 1)
  csv_data$Bin <- cut(csv_data$Velocity, breaks = bins, labels = FALSE, right = FALSE)


  # Exclude rows where "Velocity" is 0
  csv_data <-  csv_data %>%
    filter(`Velocity` != 0)


  # Summarize the time spent in each bin
  summary_data <- csv_data %>%
    group_by(Bin) %>%
    summarise(TimeSpent = sum(0.1 * n()))


  # Add parent folder and sub-folder columns to the summary data
  summary_data$ParentFolder <- basename(dirname(path1))
  summary_data$SubFolder <- basename(path1)
  summary_data$FileName <- file_names[i]
```

```
  # Append the summary data to the collated summary data frame
  collated_summary <- rbind(collated_summary, summary_data)

  # Extract the sub-folder name from the path
  sub_folder <- basename(path1)

  # Extract the parent folder name from the path
  parent_folder <- basename(dirname(path1))

  # Save the combined summary data to a CSV file in the designated folder
  csv_output_file <- paste0(parent_folder, " - ", sub_folder, " Absolute Velocity Total Time Summary.csv")
  csv_output_full_path <- file.path(path2, csv_output_file)
  write_csv(collated_summary, csv_output_full_path)

  # Create the graph
  graph <- ggplot(summary_data, aes(x = Bin, y = TimeSpent)) +
    geom_bar(stat = "identity", fill = "steelblue") +
    geom_text(aes(label = sprintf("%.1f", TimeSpent)), vjust = -0.5, size = 4) +
    labs(x = "Velocity (m/s)", y = "Total Time Spent (seconds)", title = file_names[i]) +
    scale_x_continuous(breaks = seq(0, 10, 1)) +
    theme_minimal() +
    theme(axis.title.y = element_text(size = 6),  # Reduce y-axis title size
          axis.text.x = element_text(angle = 0, hjust = 0.5, vjust = 1),
          strip.text.x = element_text(size = 6),
          panel.grid.major.x = element_blank(),
          panel.grid.minor.x = element_blank(),
          plot.title = element_text(size = 8))

  # Store the graph in the list
  graphs_list[[i]] <- graph
```

```r
}
# Determine the number of rows and columns for each page of the grid
num_plots <- length(graphs_list)
num_rows_per_page <- 4
num_cols_per_page <- 3

# Create the PDF file with the parent folder and sub-folder names in the file name
pdf_file <- file.path(path2, paste0(parent_folder, " - ", sub_folder, " Absolute Velocity Total Time Summary.pdf"))
# Create the PDF with multiple pages and save the plots
pdf(file = pdf_file, width = 12, height = 18)
for (page_start in seq(1, num_plots, by = num_rows_per_page * num_cols_per_page)) {
  page_end <- min(page_start + num_rows_per_page * num_cols_per_page - 1, num_plots)
  num_rows <- ceiling((page_end - page_start + 1) / num_cols_per_page)
  grid.arrange(grobs = graphs_list[page_start:page_end], nrow = num_rows, ncol = num_cols_per_page)
}
dev.off()

# Define png_files
png_files <- list.files(pattern = "\\.png$")

# Delete the individual PNG files
for (i in seq_along(png_files)) {
  file.remove(png_files[i])
}
# Display a message indicating that the PDF file has been saved
cat("All PNGs have been collated and saved to '", pdf_file, "'.")

# Display a message indicating that the PDF file has been saved
cat("All plots and collated summary data have been saved.")
```

Analysing Absolute Distance spent in Zones in RStudio

```
rm(list = ls())
library(dplyr)
library(readr)
library(ggplot2)
library(gridExtra)
library(png)
library(grid)

# Set the working directory to the folder with the CSV files
path1 <- "C:/Users/…"
# Set the second directory to save the csv and pdf file with all collated graphs in a
specific folder
path2 <- "C:/Users/…"
setwd(path1)

# Function to apply Doppler shift correction to velocity data
correct_velocity_doppler <- function(velocity) {
  doppler_factor <- 0.98
  return(velocity * doppler_factor)
}


# Initialize a list to store the graphs
graphs_list <- list()

# Read multiple CSV files and store their names
csv_files <- list.files(pattern = "*.csv")
file_names <- tools::file_path_sans_ext(csv_files)

# Initialize a data frame to store the collated summary data
collated_summary <- data.frame()

# Loop through each CSV file, skip first 8 rows, and process the data
for (i in seq_along(csv_files)) {
  csv_data <- read_csv(csv_files[i], col_types = cols(Seconds = col_double(), Velocity =
col_double()), skip = 8)


  # Add a new column "Lookup Name" and populate it with the file name
  csv_data$`Lookup Name` <- file_names[i]

  # Keep only rows corresponding to first-half or second-half periods

  if ("Period" %in% names(csv_data)) {
```

```
    csv_data <- csv_data %>% filter(Period %in% c("First Half", "Second Half"))
  }

# Apply Doppler shift correction
 csv_data$Velocity_Corrected <- correct_velocity_doppler(csv_data$Velocity)


  # Calculate distance travelled by integrating velocity over time
  csv_data <- csv_data %>%
    mutate(Distance = Velocity / 10)

  # Create bins for velocity in 1 m/s increments
  bins <- seq(0, 10, 1)
  csv_data$Bin <- cut(csv_data$Velocity, breaks = bins, labels = FALSE, right = FALSE)
  # Exclude rows where "Percentage of Max Velocity" is 0
  csv_data <-  csv_data %>%
    filter(`Velocity` != 0)

  # Summarize the distance travelled in each bin
  summary_data <- csv_data %>%
    group_by(Bin) %>%
    summarise(DistanceTraveled = sum(Distance))

  # Add parent folder and sub-folder columns to the summary data
  summary_data$ParentFolder <- basename(dirname(path1))
  summary_data$SubFolder <- basename(path1)
  summary_data$FileName <- file_names[i]

  # Append the summary data to the collated summary data frame
  collated_summary <- rbind(collated_summary, summary_data)

  # Extract the sub-folder name from the path
  sub_folder <- basename(path1)

  # Extract the parent folder name from the path
  parent_folder <- basename(dirname(path1))

  # Save the combined summary data to a CSV file in the designated folder
  csv_output_file <- paste0(parent_folder, " - ", sub_folder, " Absolute Velocity Total
Distance Summary.csv")
  csv_output_full_path <- file.path(path2, csv_output_file)
  write_csv(collated_summary, csv_output_full_path)

  # Create the graph
  graph <- ggplot(summary_data, aes(x = Bin, y = DistanceTraveled)) +
    geom_bar(stat = "identity", fill = "steelblue") +
    geom_text(aes(label = sprintf("%.1f", DistanceTraveled)), vjust = -0.5, size = 4) +
    labs(x = "Velocity (m/s)", y = "Total Distance Traveled", title = file_names[i]) +
```

```
    scale_x_continuous(breaks = seq(0, 10, 1)) +
    theme_minimal() +
    theme(axis.title.y = element_text(size = 6),  # Reduce y-axis title size
          axis.text.x = element_text(angle = 0, hjust = 0.5, vjust = 1),
          strip.text.x = element_text(size = 6),
          panel.grid.major.x = element_blank(),
          panel.grid.minor.x = element_blank(),
          plot.title = element_text(size = 8))

  # Store the graph in the list
  graphs_list[[i]] <- graph
}


# Determine the number of rows and columns for each page of the grid
num_plots <- length(graphs_list)
num_rows_per_page <- 4
num_cols_per_page <- 3


# Create the PDF file with the parent folder and sub-folder names in the file name
pdf_file <- file.path(path2, paste0(parent_folder, " - ", sub_folder, " Absolute Velocity
Total Distance Summary.pdf"))

# Create the PDF with multiple pages and save the plots
pdf(file = pdf_file, width = 12, height = 18)
for (page_start in seq(1, num_plots, by = num_rows_per_page * num_cols_per_page)) {
  page_end <- min(page_start + num_rows_per_page * num_cols_per_page - 1,
num_plots)
  num_rows <- ceiling((page_end - page_start + 1) / num_cols_per_page)
  grid.arrange(grobs = graphs_list[page_start:page_end], nrow = num_rows, ncol =
num_cols_per_page)
}
dev.off()

# Define png_files
png_files <- list.files(pattern = "\\.png$")

# Delete the individual PNG files
for (i in seq_along(png_files)) {
  file.remove(png_files[i])
}

# Display a message indicating that the PDF file has been saved
cat("All PNGs have been collated and saved to '", pdf_file, "'.")

# Display a message indicating that the PDF file has been saved
cat("All plots and collated summary data have been saved.")
```

Analysing Relative Distance spent in Zones in RStudio

```
rm(list = ls())


library(dplyr)
library(readr)
library(ggplot2)
library(gridExtra)
library(png)
library(grid)


# Set the working directory to the folder with the CSV files
path1 <- "C:/Users/…"

# Set the second directory to save the csv and pdf file with all collated graphs in a
specific folder
path2 <- "C:/Users/…"


setwd(path1)


# Function to apply Doppler shift correction to velocity data
correct_velocity_doppler <- function(velocity) {
  doppler_factor <- 0.98
  return(velocity * doppler_factor)
}


# Initialize a list to store the graphs
graphs_list <- list()


# Read multiple CSV files and store their names
csv_files <- list.files(pattern = "*.csv")


###ADDITIONAL LINE TO ALLOW FOR ANALYSIS OF ALL SUBFOLDERS
# csv_files <- list.files("C:/Users/…"
```

```
file_names <- tools::file_path_sans_ext(csv_files)


# Initialize a data frame to store the collated summary data
collated_summary <- data.frame()


# Read the reference spreadsheet
reference_file <- "C:/Users/…"
reference_data <- read_csv(reference_file, show_col_types = FALSE)


# Check if the required columns "Name" and "Max Velocity" exist in the reference data
if (!("Name" %in% names(reference_data)) || !("Max Velocity" %in%
names(reference_data))) {
  stop("The required columns 'Name' and 'Max Velocity' are missing in the reference
data.")
}
# Loop through each CSV file, skip first 8 rows, and merge with reference data
for (i in seq_along(csv_files)) {
  csv_data <- read_csv(csv_files[i], col_types = cols(Seconds = col_double(), Velocity =
col_double()), skip = 8)


  # Add a new column "Lookup Name" and populate it with the file name
  csv_data$`Lookup Name` <- file_names[i]


  # Keep only rows corresponding to first-half or second-half periods
  if ("Period" %in% names(csv_data)) {
    csv_data <- csv_data %>% filter(Period %in% c("First Half", "Second Half"))
  }

# Apply Doppler shift correction
 csv_data$Velocity_Corrected <- correct_velocity_doppler(csv_data$Velocity)


   # Merge based on the "Lookup Name" column to get "Max Velocity" values
  merged_data <- merge(csv_data, reference_data, by.x = "Lookup Name", by.y =
"Name", all.x = TRUE)
```

```
  # Calculate "Percentage of Max Velocity" and add it as a new column
  merged_data <- merged_data %>%
    mutate(`Percentage of Max Velocity` = ifelse(!is.na(Velocity) & !is.na(`Max Velocity`) & Velocity != 0 & `Max Velocity` != 0,
                                               (Velocity / `Max Velocity`) * 100,
                                               0))



  # Convert velocity to distance and add it as a new column
  merged_data <- merged_data %>%
    mutate(Distance = ifelse(!is.na(Velocity) & !is.na(Seconds) & Velocity != 0,
                             Velocity /10,
                             0))

  # Remove rows where "Percentage of Max Velocity" is greater than 120%
  merged_data <- merged_data %>%
    filter(`Percentage of Max Velocity` <= 120)

  # Create bins for "Percentage of Max Velocity" in 10% increments
  bins <- seq(0, 120, 10)
  merged_data$Bin <- cut(merged_data$`Percentage of Max Velocity`, breaks = bins, labels = FALSE, right = FALSE)

  # Exclude rows where "Percentage of Max Velocity" is 0
  merged_data <- merged_data %>%
    filter(`Percentage of Max Velocity` != 0)

  # Summarize the distance travelled in each bin
  summary_data <- merged_data %>%
    group_by(Bin) %>%
    summarise(Distance = sum(Distance))
```

```
# Add parent folder and sub-folder columns to the summary data
summary_data$ParentFolder <- basename(dirname(path1))
summary_data$SubFolder <- basename(path1)
summary_data$FileName <- file_names[i]

# Append the summary data to the collated summary data frame
collated_summary <- rbind(collated_summary, summary_data)

# Extract the sub-folder name from the path
sub_folder <- basename(path1)

# Extract the parent folder name from the path
parent_folder <- basename(dirname(path1))

# Save the combined summary data to a CSV file in the designated folder
csv_output_file <- paste0(parent_folder, " - ", sub_folder, " Distance Summary.csv")
csv_output_full_path <- file.path(path2, csv_output_file)
write_csv(collated_summary, csv_output_full_path)

# Create the graph
graph <- ggplot(summary_data, aes(x = as.numeric(as.character(Bin)), y = Distance)) +
  geom_bar(stat = "identity", fill = "steelblue") +
  geom_text(aes(label = sprintf("%.1f", Distance)), vjust = -0.5, size = 4) +
  labs(x = "Percentage of Max Velocity", y = "Total Distance (m) ", title = file_names[i])
+
  scale_x_continuous(breaks = seq(0, 12, 1), labels = seq(0, 120, 10)) +
  theme_minimal() +
  theme(axis.title.y = element_text(size = 6),
        axis.text.x = element_text(angle = 0, hjust = 0.5, vjust = 1),
        strip.text.x = element_text(size = 6),
        panel.grid.major.x = element_blank(),
```

```
    panel.grid.minor.x = element_blank(),
    plot.title = element_text(size = 8))

  # Store the graph in the list
  graphs_list[[i]] <- graph
}

# Determine the number of rows and columns for each page of the grid
num_plots <- length(graphs_list)
num_rows_per_page <- 4
num_cols_per_page <- 3

# Create the PDF file with the parent folder and sub-folder names in the file name
pdf_file <- file.path(path2, paste0(parent_folder, " - ", sub_folder, " Distance Summary.pdf"))

# Create the PDF with multiple pages and save the plots
pdf(file = pdf_file, width = 12, height = 18)
for (page_start in seq(1, num_plots, by = num_rows_per_page * num_cols_per_page)) {
  page_end <- min(page_start + num_rows_per_page * num_cols_per_page - 1, num_plots)
  num_rows <- ceiling((page_end - page_start + 1) / num_cols_per_page)
  grid.arrange(grobs = graphs_list[page_start:page_end], nrow = num_rows, ncol = num_cols_per_page)
}
dev.off()

# Define png_files
png_files <- list.files(pattern = "\\.png$")
# Delete the individual PNG files
for (i in seq_along(png_files)) {
  file.remove(png_files[i])
```

```
}

# Display a message indicating that the PDF file has been saved
cat("All PNGs have been collated and saved to '", pdf_file, "'.")

# Display a message indicating that the PDF file has been saved
cat("All plots and collated summary data have been saved.")
```

Analysing Seconds spent in Relative Speed Zones in RStudio

```
rm(list = ls())
library(dplyr)
library(readr)
library(ggplot2)
library(gridExtra)
library(png)
library(grid)
# Set the working directory to the folder with the CSV files
path1 <- "C:/Users/…"

# Set the second directory to save the csv and pdf file with all collated graphs in a
specific folder
path2 <- "C:/Users/…"

setwd(path1)

# Function to apply Doppler shift correction to velocity data
correct_velocity_doppler <- function(velocity) {
  doppler_factor <- 0.98
  return(velocity * doppler_factor)
}

# Create a list to store graphs
graphs_list <- list()

# Read multiple CSV files and store their names
csv_files <- list.files(pattern = "*.csv")
file_names <- tools::file_path_sans_ext(csv_files)

# Initialize a data frame to store the collated summary data
collated_summary <- data.frame()
```

```
# Read the reference spreadsheet in csv format

reference_file <-  "C:/Users/…"

reference_data <- read_csv(reference_file, show_col_types = FALSE)


# Check if the required columns "Name" and "Max Velocity" exist in the reference data

if (!("Name" %in% names(reference_data)) || !("Max Velocity" %in%
names(reference_data))) {

  stop("The required columns 'Name' and 'Max Velocity' are missing in the reference
data.")

}


# Loop through each CSV file, skip first 8 rows, and merge with reference data

for (i in seq_along(csv_files)) {

  csv_data <- read_csv(csv_files[i], col_types = cols(Seconds = col_double(), Velocity =
col_double()), skip = 8)


  # Add a new column "Lookup Name" and populate it with the file name

  csv_data$`Lookup Name` <- file_names[i]


  # Keep only rows corresponding to first-half or second-half periods
  if ("Period" %in% names(csv_data)) {
    csv_data <- csv_data %>% filter(Period %in% c("First Half", "Second Half"))
  }

# Apply Doppler shift correction

 csv_data$Velocity_Corrected <- correct_velocity_doppler(csv_data$Velocity)


  # Merge based on the "Lookup Name" column to get "Max Velocity" values

  merged_data <- merge(csv_data, reference_data, by.x = "Lookup Name", by.y =
"Name", all.x = TRUE)


  # Calculate "Percentage of Max Velocity" and add it as a new column

  merged_data <- merged_data %>%
```

```
    mutate(`Percentage of Max Velocity` = ifelse(!is.na(Velocity) & !is.na(`Max Velocity`) & Velocity != 0 & `Max Velocity` != 0,
                                              (Velocity / `Max Velocity`) * 100,
                                              0))

  # Remove rows where "Percentage of Max Velocity" is greater than 120%
  merged_data <- merged_data %>%
    filter(`Percentage of Max Velocity` <= 120)

  # Create bins for "Percentage of Max Velocity" in 10% increments
  bins <- seq(0, 120, 10)
  merged_data$Bin <- cut(merged_data$`Percentage of Max Velocity`, breaks = bins, labels = FALSE, right = FALSE)

  # Exclude rows where "Percentage of Max Velocity" is 0
  merged_data <- merged_data %>%
    filter(`Percentage of Max Velocity` != 0)

  # Summarize the time spent in each bin
  summary_data <- merged_data %>%
    group_by(Bin) %>%
    summarise(TimeSpent = sum(0.1 * n()))  # Each row represents 0.1 seconds

  # Add parent folder and sub-folder columns to the summary data
  summary_data$ParentFolder <- basename(dirname(path1))
  summary_data$SubFolder <- basename(path1)
  summary_data$FileName <- file_names[i]
   # Append the summary data to the collated summary data frame
  collated_summary <- rbind(collated_summary, summary_data)

  # Extract the sub-folder name from the path
  sub_folder <- basename(path1)
```

```
  # Extract the parent folder name from the path
  parent_folder <- basename(dirname(path1))

  # Save the combined summary data to a CSV file in the designated folder
  csv_output_file <- paste0(parent_folder, " - ", sub_folder, " Seconds Summary.csv")
  csv_output_full_path <- file.path(path2, csv_output_file)
  write_csv(collated_summary, csv_output_full_path)

  # Create the graph
  graph <- ggplot(summary_data, aes(x = as.numeric(as.character(Bin)), y = TimeSpent))
+
    geom_bar(stat = "identity", fill = "steelblue") +
    geom_text(aes(label = sprintf("%.1f", TimeSpent)), vjust = -0.5, size = 4) +
    labs(x = "Percentage of Max Velocity", y = "Total Time Spent (seconds)", title =
file_names[i]) +
    scale_x_continuous(breaks = seq(0, 12, 1), labels = seq(0, 120, 10)) +
    theme_minimal() +
    theme(axis.title.y = element_text(size = 6),  # Reduce y-axis title size
          axis.text.x = element_text(angle = 0, hjust = 0.5, vjust = 1),  # Horizontal x-axis labels
          strip.text.x = element_text(size = 6),
          panel.grid.major.x = element_blank(),
          panel.grid.minor.x = element_blank(),
          plot.title = element_text(size = 8))

  # Store the graph in the list
  graphs_list[[i]] <- graph
}
# Determine the number of rows and columns for each page of the grid
num_plots <- length(graphs_list)
num_rows_per_page <- 4
num_cols_per_page <- 3
```

```
# Create the PDF file with the parent folder and sub-folder names in the file name
pdf_file <- file.path(path2, paste0(parent_folder, " - ", sub_folder, ".pdf"))

# Create the PDF with multiple pages and save the plots
pdf(file = pdf_file, width = 12, height = 18)
for (page_start in seq(1, num_plots, by = num_rows_per_page * num_cols_per_page)) {
  page_end <- min(page_start + num_rows_per_page * num_cols_per_page - 1, num_plots)
  num_rows <- ceiling((page_end - page_start + 1) / num_cols_per_page)
  grid.arrange(grobs = graphs_list[page_start:page_end], nrow = num_rows, ncol =
num_cols_per_page)
}
dev.off()
# Define png_files
png_files <- list.files(pattern = "\\.png$")
# Delete the individual PNG files
for (i in seq_along(png_files)) {
  file.remove(png_files[i])
}

# Display a message indicating that the PDF file has been saved
cat("All PNGs have been collated and saved to '", pdf_file, "'.")

# Display a message indicating that the PDF file has been saved
cat("All plots and collated summary data have been saved.")
```