Development and use of a Consistent Approach for Processing GNSS-derived Acceleration Data in Team Sports

by

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ABSTRACT

In team sports, player tracking systems are used to monitor training and competition. However, challenges exist for practitioners, as different tracking systems can be used for competition compared to training. Additionally, updates/changes being made to proprietary software or firmware within the tracking system can impact longitudinal analysis of the activity profile. Both scenarios can result in different athlete outputs for the same activity. Acceleration is an important metric in the team sport activity profile, which can help quantify the rate of change in athlete speed. However, acceleration as a variable can also be impacted by changes to software/firmware as well as differences between tracking systems. This thesis explored how acceleration has been quantified in the literature, examined if a common filter to Global Navigation Satellite System (GNSS) data could reduce or eliminate differences due to different systems or changes within a system, before examining two longitudinal-type studies using this common filtering method on acceleration data.

Chapter 3 identified how acceleration had previously been quantified in elite team sport research. The quantification of acceleration via counts was chosen in 72% of all studies, however only ~13% of studies included how acceleration was filtered. To determine how acceleration was filtered by providers, Chapter 4 was designed as an anonymous survey, attempting to outline current filtering practices of acceleration data. Only two responses were received from 20 invitations, indicating that system providers were unwilling to provide filtering information. Consequently, this thesis examined the use of a common filter to process GNSS data to improve the consistency in the processing of acceleration both within research and applied environments. The common filter was intended to improve the longitudinal and potentially, the between-system comparison of acceleration data. Chapter 5 examined the impact of applying a 1 Hz, fourth order Butterworth filter to two different GNSS devices during elite rugby league training sessions. Following the application of the common filter, there was no substantial difference between GNSS models for average acceleration (Diff; CI: −0.04; −0.04 to −0.04), whilst the root mean square deviation (RMSD) between devices improved (1.77 ± 0.37 to 0.27 ± 0.23 $m \cdot s^{-2}$). The

results from Chapter 5 indicated that if the use of a common filter could improve a greater similarity of results between tracking systems, then, pending validation against a criterion measure, this filter could be used on longitudinal datasets or where different systems have been used. The filter was then evaluated against three-dimensional motion capture technology (VICON) in Chapter 6 during a series of small-sided football (association) games and circuits. The RMSD for speed (0.17 ± 0.04 m·s^{-1}) was acceptable and acceleration error increased as speed increased (RMSD: 0.55 ± 0.17 m·s^{-2}). Following validation, the effects of the six-again rule change upon acceleration in National Rugby League (NRL) competition was examined. The acceleration intercepts across all positions were substantially greater following the introduction of the six-again rule in the 2020 (mean ± SD; 1.02 ± 0.10 m·s^{-2}) and 2021 seasons (1.05 ± 0.08 m·s^{-2}) compared to the previous competition format (2019; 0.91 ± 0.07 m·s^{-2}), indicating an increase in acceleration outputs. A longitudinal analysis of NRL training weeks was completed, where the distribution of training volume and intensity was examined using the common filter. Speed intensity (the magnitude of speed) was manipulated to facilitate performance when fewer training sessions were completed in shorter microcycles (5-6 days; effect size range = 0.34 – 1.26), whilst the intensity of impulse (acceleration force over time) remained stable.

This thesis identified that there's a lack of information relating to the filtering of acceleration via athlete tracking systems in research. However, this thesis identified that tracking system manufacturers do process acceleration differently which may impact upon comparisons between research and between technology. A common filter reduced the difference in acceleration metrics between GNSS devices during rugby league training sessions before being validated against VICON. With use of a common filter, this research identified that the acceleration intensity in NRL competition had increased and that speed intensity during NRL training weeks was altered with shorter turnarounds between matches, whilst impulse was maintained.

STUDENT DECLARATION

I, Robert Delves declare that the PhD thesis entitled "Development and use of a Consistent Approach for Processing GNSS-derived Acceleration Data in Team Sports" is no more than 80,000 words in length including quotes and exclusive of tables, figures, appendices, bibliography, references and footnotes. This thesis contains no material that has been submitted previously, in whole or in part, for the award of any other academic degree or diploma. Except where otherwise indicated, this thesis is my own work.

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

Signature: [redacted] Date: 31/01/2023

ETHICS DECLARATION

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

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PUBLICATIONS DURING CANDIDATURE

The following works have been published in peer reviewed journals in support of this thesis:

Chapter No.	Publication Title	Publication Status	Publication Details
3	The Quantification of Acceleration Events in Elite Team Sport: a Systematic Review	Published	Delves, R. I. M., Aughey, R. J., Ball, K., & Duthie, G. M. (2021). The Quantification of Acceleration Events in Elite Team Sport: a Systematic Review. Sports Medicine - Open, 7(1). https://doi.org/10.1186/s40798-021-00332-8
5	Applying common filtering processes to Global Navigation Satellite System-derived acceleration during team sport locomotion	Published	Delves, R. I. M., Duthie, G. M., Ball, K. A., & Aughey, R. J. (2022). Applying Common Filtering processes to Global Navigation Satellite System-derived Acceleration during Team Sport Locomotion. Journal of Sports Sciences, 40(10), 1116–1126
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Declaration: Robert Delves 02/01/2023 [redacted]

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LIST OF SYMBOLS AND ABBREVIATIONS

=	Equals
>	Greater than
≥	Greater than or equal to
<	Less than
≤	Less than or equal to
-	Minus
%	Percent
+	Plus
±	Plus, or minus
P	P-value
r^2	Coefficient of Determination
AF	Australian Football
AFLW	Australian Football League Women's
AU	Arbitrary Units
ACC	Acceleration
ADI	Acceleration Density Index
CI	Confidence Interval
CK	Creatine Kinase
CV	Coefficient of Variation
DEC	Deceleration
EPTS	Electronic Performance and Tracking Systems
XML	Extensible Markup Language
ES	Effect Size
FFT	Fast Fourier Transform
FIFA	Federation International de Football Association
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
Hz	Hertz
HDOP	Horizontal Dilution of Precision

Km	Kilometres
Kg	Kilogram
LPM	Local Positioning Measurement
LPS	Local Positioning System
$m \cdot min^{-1}$	Metres per minute
$m \cdot s^{-1}$	Metres per second
$m \cdot s^{-2}$	Metres per second squared
MED	Minimum Effort Duration
MHz	Megahertz
NRL	National Rugby League
PRISMA	Preferred items for Systematic Reviews and Meta-Analyses
RFID	Radio Frequency Identification Systems
RMSD	Root Mean Square Deviation
RMSE	Root Mean Square Error
RL	Rugby League
SD	Standard Deviation
SEE	Standard Error of the Estimate
SEM	Standard Error of Measurement
SSG	Small Sided Game
SWC	Smallest Worthwhile Change
SL	Super League
TE	Typical Error
TEE	Typical Error of the Estimate
TEM	Technical Error of Measurement
UWB	Ultra-wideband
WASP	Wireless ad hoc System for Positioning

CHAPTER 1 - INTRODUCTION

Following the initial introduction of the Global Positioning System (GPS) into team sport research in 2003, practitioners and researchers have continued to quantify the exercise volume and intensity (kinematics of athlete performance) of team sport athletes via the use of electronic performance and tracking systems (EPTS) (Aughey, 2011a; Edgecomb & Norton, 2006; Linke et al., 2018). Wearable technologies such as GPS and more recently, the Global Navigation Satellite System (GNSS) are typically worn by team sport athletes during training and in competition (Delaney et al., 2019; Jackson et al., 2018; Malone et al., 2017; Scott et al., 2016). With the application of wearable technology, practitioners and researchers can identify the distances, speeds, contacts and accelerations of athletes. The information on metrics such as acceleration allows for the formation of activity profiles which detail the volume and intensity across training and/or competition relative to position group (Aughey, 2011a; Jennings et al., 2010a; Scott et al., 2016). At the applied sport science level, exercise information gleaned from activity profiles, in conjunction with data from athlete wearable technology, allows practitioners to prescribe training programs and rehabilitation practices with greater evidence to make informed decisions surrounding athlete performance (Aughey, 2011a; Boyd et al., 2013; Bradley et al., 2009; Jennings et al., 2010a; Petersen et al., 2009; Sweeting, Cormack, et al., 2017).

Since the inception of GPS tracking in team sports, there has been continued development and advances in EPTS (Jackson et al., 2018; R. J. Johnston et al., 2014; Malone et al., 2017). With governing bodies gradually allowing EPTS in competition for many professional team sports, the use of wearable tracking technology is common in applied sport science (Malone et al., 2017). With continual demand within the elite team sport sector for wearable technologies, there is a multitude of different providers and tracking systems available to team sport practitioners. The abundance of EPTS providers has become problematic in terms of the consistency in the calculation of derivative metrics such as acceleration, as processing settings can differ between manufacturers (Thornton, Nelson, et al., 2019; Varley et al., 2017).

The calculation of acceleration via satellite-based tracking systems, is problematic as acceleration is not directly calculated by the tracking technology. Instead, acceleration is calculated as a derivative measure of athlete speed (Delaney et al., 2019; Duran & Earleywine, 2012; Malone et al., 2017; Varley et al., 2017). Typically, satellite-based tracking systems will calculate acceleration from the determination of speed via Doppler Shift (Malone et al., 2017; Varley et al., 2017). Acceleration may then be filtered via the use of mathematical algorithms. The algorithms used in the calculation of acceleration can be implemented as a form of data filtering, where the objective is to reduce the noise in the signal and to smooth points to maintain data quality (Sweeting, Cormack, et al., 2017; Winter, 2009; Winter et al., 1974). Given the many mathematical algorithms (filters) that are available to practitioners and researchers, as well as the many EPTS providers globally, there have been instances in validity and reliability research where variation in acceleration metrics between GNSS providers have existed (Malone et al., 2017; Sweeting, Cormack, et al., 2017; Thornton, Nelson, et al., 2019; Varley et al., 2017). Technology-influenced variations in acceleration within research can have the potential to hinder training program prescription and any comparison between applied sport science and research.

Therefore, this thesis investigated the quantification of acceleration in team sport research with emphasis on the filtering and processing settings in the calculation of acceleration via athlete wearable technology. Firstly, this thesis evaluated the current filtering practices for acceleration in research through a systematic review and anonymous questionnaire to EPTS providers. This evaluation outlined what filters and processing settings are used in research in the handling of athlete tracking data. Secondly, the thesis developed a common acceleration filtering process for GNSS data to attempt to reduce between-system or within-system measurement variation. This aim was envisaged to have wider use for researchers and practitioners where they can improve the consistency in reporting with the processing of acceleration data within research. The common filter was devised after analysis of the current filter methods identified from the systematic review and from those identified in the questionnaire to EPTS providers. To practically apply the common filter in applied, longitudinal scenarios, this thesis evaluated the introduction of the six-again rule upon the acceleration activity profile in National Rugby League (NRL) competition using the common filter upon GNSS match data. Additionally, this thesis quantified the weekly acceleration volume and intensity for an NRL team during training sessions across the season using the devised common filter from earlier studies within the thesis.

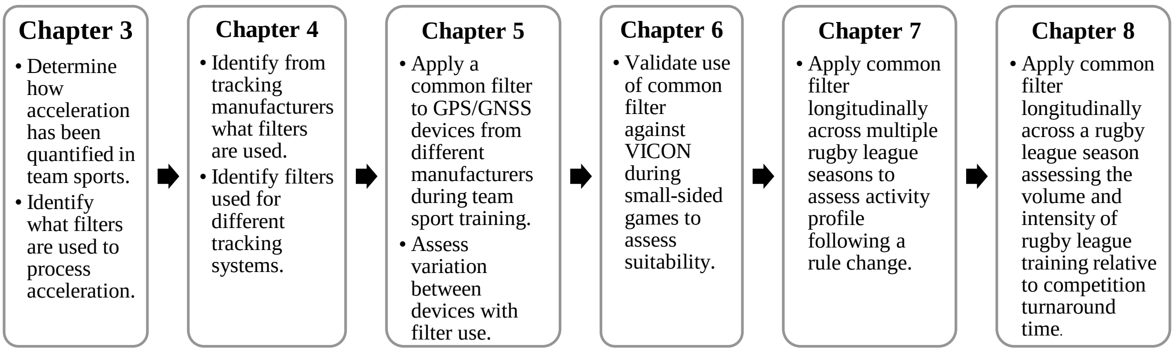

Figure 1-1 Schematic representation of Chapters within the research underpinning the relationship each study has on the direction of the thesis.

CHAPTER 2 - REVIEW OF LITERATURE

2.1 Athlete Tracking Systems

To monitor the volume and intensity of athletes during training and competition, EPTS have been introduced and adopted by researchers and practitioners (Aughey, 2011a; Malone et al., 2017). Initially, the tracking of player locomotion was facilitated through notational and video-based analysis, where analysts individually tracked each athlete during each event (Knowles & Brooke, 1974). However, modern athlete tracking systems include the Global Navigation Satellite System (GNSS), local positioning systems (LPS) and various types of camera-based, optical systems. The implementation of the GNSS or LPS systems (with the exception of optical systems) can require athletes to wear positioning receivers during training and competition. The resulting information provides researchers and practitioners with insights into distance, speed and acceleration-based metrics (Aughey, 2011a; Malone et al., 2017). The collection of athlete locomotion data from EPTS provides an understanding of the physical outputs during training and/or competition of a respective sport, which in research is labelled as an activity profile (Aughey, 2011a). Activity profiles hold great benefit for the practitioner as the outlining of physical outputs within research allows for more accurate information on the specificity of training and rehabilitation protocols relative to competition (Aughey, 2011a). However, the application and suitability of each type of tracking system varies depending on the sport being analysed and the conditions in which the sport is played. Additionally, the validity and reliability of each tracking system can influence the locomotion metrics that form the basis of activity profiles for sports. Prior to the introduction of EPTS systems, human-directed analysis of activity profiles with and without the aid of video were completed.

2.2 Notational Analysis

Notational analysis was one of the first established methods of quantifying elite team sport performance, both from a tactical and external workload perspective (Knowles & Brooke, 1974; Pollard, 2002; Reep et al., 1971). In notational analysis, athlete or team locomotion was manually tracked and movement was subjectively categorised into various thresholds and movement descriptors (Alexander & Boreskie, 1989). Movement descriptors typically involved categorising locomotion into groups such as “standing”, “walking”, “running” or “sprinting”, with estimations of athlete distances in absolute and relative metrics recorded (Knowles & Brooke, 1974). To observe athlete movement, instruments as basic as a pen and paper or custom-made analysis sheets were used for analysis (Pollard, 2002). However, despite the simplicity of the technology used in notational analysis, there was no established research on the validity of the technique in elite team sports. The lack of validity research is potentially due to the subjective interpretation of grouping athlete movement into different locomotion thresholds. Additionally, a criterion measure to evaluate the validity of the interpretations may not have existed. Given there is no established validity associated with notational analysis in team sport tracking, it should not be implemented in the development of activity profiles at the applied or research level. Athlete locomotion should be tracked using technology that has been established as valid and reliable in research.

2.3 Video-based Analysis

The introduction of video-based analysis was an improvement upon notational analysis as the filming of training and/or competition allowed for footage playback and removed the burden of live-recall on the analyst (Barris & Button, 2008; Reilly & Thomas, 1976). With replay feedback available, analysts could capture the majority of the playing squad during training or competition, depending on the number of cameras and capture points around the playing surface. Introductory techniques of video-based analysis saw capture with several cameras on opposite sides of an association football (soccer) pitch (Reilly & Thomas, 1976). With the main requirement of cameras, manual video-based analysis was a relatively inexpensive tracking solution for team sports. Initial research utilising video-based analysis was conducted in association football, where the distance of elite players were manually captured via pencil and paper during different locomotion intensities (e.g., walking through to sprinting) (Reilly & Thomas, 1976). Within research, the locomotion patterns of rugby union, Australian rules football and association football athletes have been published via the use of manual video analysis (Dawson et al., 2004; Duthie et al., 2003; Mohr et al., 2003). Typically, the different analysed locomotion metrics were measured relative to efforts, time or distance within each threshold or metric (Duthie et al., 2003). However, across the team sport literature there are no consistent definitions of the qualifying criteria for each locomotion metric and for any speed-based efforts such as the differences between jogging and sprinting. Any judgements on the differences between locomotion categories such as jogging or sprinting may have a biomechanical qualifying criterion differentiating the two, but final judgement is made by a human observer. With the largely subjective allocation of locomotion by a human observer, there is a distinct lack of validity research with respect to team sport activity profiles via manual video-based analysis. However, there is literature within team sport activity profiles presenting the intra and inter-observer reliability from human researchers. Reliability results from the same observer have been published when tracking elite rugby union athletes twice, with one month separating each analysis (Duthie et al., 2003). The technical error of measurement (%TEM) indicated that across the frequency of individual movements as well as both the mean and total durations of movement, moderate to poor reliability existed (4.3 – 13.6% TEM) (Duthie et al., 2003). The authors also contended, that despite video-based analysis being moderately reliable for experienced observers, jogging movements possessed greater levels of reliability than stationary and sprinting categories (Duthie et al., 2003). Similarly, in basketball research, high levels of observer error (5.6 – 11.2%) were identified during athlete striding and sprinting efforts (McInnes et al., 1995). The higher levels of variation were attributed to the difficulty experienced by the observer in timing these movements during fast, court-based sports such as basketball (McInnes et al., 1995).

However, despite the moderate observer reliability found in rugby union research, video-based analysis is still limited in the practical application to modern team sports. For example, given the nature of broadcast video footage, it is likely that not all athletes would be captured at every moment during competition given the tendency of broadcasters to follow the play. Athletes who may not be captured during all instances of play are still highly likely to be completing forms of locomotion that would need to be counted (Faude et al., 2012). The immediate solution to the use of broadcast footage is to supplement the vision with cameras placed at various locations around the playing surface. Whilst the use of multiple cameras may alleviate athlete occlusion concerns, this would limit practicality for the analyst as each camera may need to be setup, installed, and manned for the duration of the competition. The use of additional cameras would then also increase data collection and manipulation time, delaying the reporting or analysis of athlete locomotion. The use of manual video-analysis for tracking athlete locomotion should be avoided. Time-efficient and practical solutions that capture all athletes simultaneously should instead be preferred to examine external athlete volume and intensity during training and competition. However, it is important to outline that the introduction of video-based analysis highlighted the need for optical and eventually, wearable tracking technology. Whilst the use of video-analysis for athlete tracking is superseded, it would be remiss of this thesis to not capture the significance of the introduction of this technology. Whilst it is simple to critically analyse video-based analysis decades later, it is important to note that the advancements seen in tracking technology today could have stemmed from the research of manual video-based analysis.

2.4 Optical Tracking Systems

Optical tracking systems are comprised of a network of cameras positioned around the playing surface (French & Ronda, 2021). Initially introduced in association football and rugby union, optical tracking systems have been in operation since the latter part of the 1990s, where semi-automated camera systems were implemented to track athletes and the ball during various team sport competitions (Carling et al., 2008). Optical tracking systems are installed so that there are at least two cameras capturing the entire playing environment. However, the exact layout of cameras in both number and position generally varies between manufacturers and the stadia in which the technology is installed. To determine athlete positioning and the corresponding locomotion via optical systems, the determination of athlete "*x*" and "y" coordinates are required, which are derived from the calibration of the height, width and length of the playing surface/tracking environment (Carling et al., 2008). Once athlete position is located through the coordinates, traditional metrics including distance, speed and acceleration can be determined. However, unlike wearable tracking technologies, including GNSS and LPS, optical tracking can only measure movement in two dimensions, with no information on changes in vertical movement of the athlete (French & Ronda, 2021).

The introduction of semi-automated tracking systems was an improvement on manual video analysis as each player and the ball were simultaneously tracked over the duration of the game. Subsequently, analysis workflows were improved and the labour-intensive task of individually coding athletes throughout competition was superseded. However, semi-automated systems still require human analysis in terms of quality control for athlete identification and the verification of correct locomotion paths throughout competition (Di Salvo et al., 2006). For example, shade on the playing surface caused by the stadium infrastructure, or instances in play where athletes are tightly compacted such as a free kick in association football may require manual tracking (Carling et al., 2008). Initial validity and reliability studies on optical systems have predominately involved association football, given the early adoption of the technology into the sport (Carling et al., 2008). The validity of a ProZone ™ optical system at two outdoor stadiums was assessed when measuring average speed and changes of direction in recreational athletes (Di Salvo et al., 2006). Following the completion of various straight and curved running circuits (range: 15-60 m), average speed was found to have high correlation coefficients compared to timing gates (criterion) (r = 0.999), whilst maximal efforts over the short courses (15 – 20 m) showed similar levels of validity (r = 0.960) (Di Salvo et al., 2006). Moreover, absolute reliability across each condition saw acceptable levels of variation (CV: 0.2-1.3, r = 0.950 – 0.999). However, the applicability of the ProZone ™ findings to applied sport science is limited as the movements completed were controlled shuttles and did not represent the stochastic nature of invasion team sports. Moreover, the use of timing gates as a criterion is a limitation as timing gates provide average speeds and not measurements of instantaneous changes in speed that hold greater application to team sport movement (French & Ronda, 2021; Frencken et al., 2010; van den Tillaar et al., 2022; Waldron, Worsfold, et al., 2011). Additionally, the validity and reliability of VisionKit™ during association football-specific movement protocols has been assessed (Aughey et al., 2022; Mara et al., 2017). VisionKit™ was determined to be valid for measures of athlete distance, with the variation in distance approximately 0.25% (0.79 ± 0.56 m), but ranging as high as 4.89% during 90 degree turns (Mara et al., 2017). The agreement for VisionKit™ against a three-dimensional motion capture system was strong for position (root mean square difference: 0.18 m) and speed (0.04 $m \cdot s^{-1}$) (Aughey et al., 2022).

However, the practical application of optical tracking systems to outdoor team sport practitioners is questioned (Carling et al., 2008; Torres-Ronda, Beanland, et al., 2022; Torres-Ronda, Clubb, et al., 2022). Optical systems are predominantly used in competition as the setup of the technology requires events (e.g., halves or quarters) to adequately automate the capture process (French & Ronda, 2021). This may mean that clubs could have to swap between positioning systems and datasets for training and competition data (Thornton, Nelson, et al., 2019). Additionally, the installation of optical tracking technologies is fixed to the playing stadia and is generally expensive to implement (Torres-Ronda, Clubb, et al., 2022). For Australian football matches where ground sizes can vary, and for rugby codes, where the dimensions of the field are large, it may be impractical to install optical systems at suspended heights within stadia (Torres-Ronda, Beanland, et al., 2022). Portability of optical systems is also of concern, particularly during away fixtures where the same optical system may not be installed. Moreover, if the optical system installed in the away stadia is not compatible with the home arena, then athlete competition data may not be directly compared (French &

Ronda, 2021; Torres-Ronda, Beanland, et al., 2022). Therefore, for athlete monitoring in team sports, optical tracking technology may be impractical for those with the alternative of athlete wearable technologies (i.e., GNSS/LPS). However, some team sport leagues have not approved the use of wearable tracking technologies within competition but have approved optical systems. Practitioners that face restrictions regarding the use of wearable tracking technology should then still utilise optical tracking systems. For team sports that are allowed to wear GNSS or LPS receivers in competition, this technology should be implemented, given their enhanced practicality (Malone et al., 2017; Scott et al., 2016).

2.5 Satellite-based Tracking Technologies

2.5.1 Global Positioning System & Global Navigation Satellite System

The Global Positioning System (GPS) is a satellite network which relays time and position information to GPS receivers (Aughey, 2011a; Malone et al., 2017). Initially introduced by the United States Department of Defence for military use, the GPS comprises a network of satellites which continuously orbit the earth, emitting time and position information to earth-based GPS receivers (Aughey, 2011a; Larsson, 2003). Initial application of GPS technology was obstructed for non-military use via the deliberate degradation of the radio signal transmissions by U.S. authorities (Aughey, 2011a). Since 2000, the degradation of the signal has been removed which has paved the way for continual developments in the use of satellite tracking for human locomotion (Aughey, 2011a). In recent developments into satellite navigation systems, the Global Navigation Satellite System (GNSS) has formed which provides ground-based receivers with additional access to satellite networks. The GNSS features the GPS, the GLONASS

(Russian), Galileo (European Union) and BeiDou (Chinese) satellite systems (Delaney et al., 2019).

The GNSS network provides positional information by continually sending time information to Earth-based receivers through atomic clocks (Aughey, 2011a). The distance between the receiver and the satellite is then determined through the difference between the time encoded by the satellite's atomic clock to the receiver's internal clock (Aughey, 2011a; Larsson, 2003). If the receiver is connected to at least four satellites, the position of the receiver can then be triangulated (Aughey, 2011a; Malone et al., 2017). The identification of position can then lead to the determination of displacement over a designated epoch, which can subsequently be implemented to derive speed and acceleration measures via Doppler Shift, which is of use to team sport practitioners in the tracking of their athletes (Aughey, 2011a). Simply, Doppler Shift, for GNSS navigation, involves the motion of the satellite in connection with the earth-based receiver. As the satellite moves over a receiver (either static or dynamic), the range between the satellite and receiver continuously changes (De Agostino et al., 2010). When a satellite approaches the GNSS receiver, Doppler Shift is positive as the frequency is greater (De Agostino et al., 2010). When the satellite moves away from the receiver, doppler shift is negative as the frequency decreases (De Agostino et al., 2010).

Since the initial introduction of GNSS technology into team sport research, there has been sustained advances in the development of GNSS (Malone et al., 2017; Scott et al., 2016). The first commercially available GNSS device introduced for the intention of tracking athlete volume and intensity became available in 2003 (Aughey, 2011a). Since then, the application of GNSS technology has been adapted by team sport researchers and practitioners to quantify the exercise volume and intensity of teams (Aughey, 2011a, 2011b; Cummins et al., 2013; Jennings et al., 2010b; Jennings et al., 2012a; Scott et al., 2016). Global Navigation Satellite System units allow for the objective and time-efficient collection of athlete locomotion during training and match play with information collected on athlete distances, speeds, and accelerations (Aughey, 2011a; Jennings et al., 2010b; Malone et al., 2017). Further to the developments in GNSS, units are typically unobtrusive to athletes, positioned between the scapulae in custom-made undergarments or in specifically designed jersey pouches during training and/or competition (Aughey, 2011a; Coutts & Duffield, 2010; Jennings et al., 2010a; Jennings et al., 2010b; Malone et al., 2017).

2.5.2 Validity and Reliability of GNSS Tracking

Despite the benefits of practical and time-efficient data collection via GNSS technology, the validity and reliability of the locomotion metrics tracked by GNSS is crucial for researchers and practitioners (Aughey, 2011a; Scott et al., 2016). For practitioners, the validity and reliability of athlete locomotion data can influence the prescription of training programs and return to play protocols. In the research space, testing the validity and reliability in metrics such as acceleration or distance can help to identify the differences in quality between EPTS providers and models which can then have a subsequent impact on the applied sport science sector (Malone et al., 2017; Varley et al., 2017).

2.5.2.1 Sample Rate

A method in which to assess the quality of the GNSS hardware is to examine sample rate (Aughey, 2011a; Jackson et al., 2018; Malone et al., 2017). Sample rate is measured in hertz (Hz) and is an indication of the number of times a GNSS device is in contact with the satellite network per second (Aughey, 2011a; Scott et al., 2016). For example, a 5 Hz GNSS unit will receive positioning information five times per second. In terms of GNSS validity and reliability, it is accepted that a higher sampling rate correlates with enhanced validity and reliability across different locomotion metrics compared to an inferior sample rate (Aughey, 2011a; Jackson et al., 2018; Jennings et al., 2010a; Scott et al., 2016). Initially, the introduction of GNSS technology into team sport research saw a 1 Hz sample rate, which was largely inferior to 5 Hz and 10 Hz sample rates in later advancements (Aughey, 2011a; Duffield et al., 2010; Jennings et al., 2010a; R. J. Johnston et al., 2014; Johnston et al., 2013; Malone et al., 2017). For example, in a tennis specific repeated movements drill, 1 Hz technology significantly ($p<0.05$) underestimated distance by approximately 30%, whilst a 5 Hz sample rate showed improved validity with 7% variation from the criterion (VICON) (Aughey, 2011a; Duffield et al., 2010). However, despite research indicating enhanced validity at 5 Hz compared to 1 Hz, the intensity and duration of movement impacted validity and reliability, particularly at sample rates below 10 Hz (Jennings et al., 2010a). Moreover, the standard error of the estimate (SEE) in straight line running was seen to improve in 1 Hz and 5 Hz technology when both the distance of the shuttle increased and the intensity of the running effort decreased (Jennings et al., 2010a). For example, the SEE for both sample rates (1 Hz; 12.2 ± 2.4, 5 Hz; 11.9 ± 2.5) during a 40 m sprint were substantially improved compared to SEE results during a 10 m sprint (1 Hz; 32.4 ± 6.9, 5 Hz; 30.9 ± 5.8) (Jennings et al., 2010a). With continued improvements in chipsets, 1 Hz and 5 Hz technology has been surpassed by way of the introduction of sample rates at 10 Hz (R. J. Johnston et al., 2014; Johnston et al., 2013; Varley, Fairweather, et al., 2012). Currently, 10 Hz is recognised as being optimal for tracking athlete locomotion via GNSS technology (R. J. Johnston et al., 2014; Scott et al., 2016). In comparison to 5 Hz, 10 Hz technologies have generally shown improved validity and reliability, particularly during instances of high-intensity efforts, including acceleration and deceleration events (Varley, Fairweather, et al., 2012). For example, the validity (as measured by coefficient of variation (CV)) of deceleration efforts at a starting speed of 5–8 m·s^{-2} improved from 33.2 ± 1.64 in 5 Hz technology, to 11.3 ± 0.44 at 10 Hz (Varley, Fairweather, et al., 2012). However, given the intermittent and explosive nature of high-intensity efforts, including both speed and accelerations/decelerations events, the validity and reliability of 10 Hz to track these events has still been questioned (Akenhead et al., 2014; Buchheit, Al Haddad, et al., 2014; Jackson et al., 2018; R. J. Johnston et al., 2014).

With continued development in GNSS, sample rates in excess of 10 Hz and approaching 20 Hz, are now entering into the applied and research sectors (Beato et al., 2018; Gimenez et al., 2020; Hoppe et al., 2018). Whilst on balance, a sample rate in excess of 10 Hz would seem to possess greater validity and reliability during athlete locomotion, the limited research currently available suggests that 10 Hz technology still provides acceptable validity and reliability (Beato et al., 2018; Hoppe et al., 2018; R. J. Johnston et al., 2014; Vickery et al., 2014). Previously, 15 Hz units that had been interpolated from 10 Hz technology were introduced, but these devices were not found to be superior to 10 Hz devices (Hoppe et al., 2018; R. J. Johnston et al., 2014; Vickery et al., 2014). Up-sampling of device samples rates has been achieved through supplementing 5 and 10 Hz GNSS data with device accelerometer data (Aughey, 2011a; R. J. Johnston et al., 2014; Rawstorn et al., 2014). However, devices that sample at a “true” 18 Hz with no interpolation are commercially available (Hoppe et al., 2018). In GNSS research comparing 10 and 18 Hz sample rates, a study concluded that 18 Hz performed better for sprint mechanical properties (technical error of estimate: 4.5–14.3%; CV: 3.1–7.5%) and distances covered (1.6–8.0%; CV: 1.1–5.1%) but 10 Hz technology showed less measurement error with a loss of 10% of datasets, compared to 20% found in 18 Hz technology (Hoppe et al., 2018). It is unclear from the research as to why the 18 Hz had greater measurement error compared to the 10 Hz technology. However, given the recency of the introduction of higher sampling rates, it is anticipated that further research will continue to improve the knowledge base on the performance of GNSS technology sampling above 10 Hz. Researchers and practitioners should therefore look to incorporate GNSS technology from manufacturers with a sample rate of at least 10 Hz.

2.5.2.2 Satellite Connection Properties

The quality of athlete tracking data calculated from GNSS technology is also influenced by the strength of the connection with the satellite network (Aughey, 2011a; Malone et al., 2017; Scott et al., 2016). Firstly, the horizontal dilution of precision (HDOP) is a metric that provides an indication of the accuracy of the horizontal positional signal, which is calculated from the positioning of the satellites in relation to each other (Hsu, 1994; Malone et al., 2017). For human locomotion, a HDOP score below one is considered optimal, with possible values range from 0-50 (Hsu, 1994; Malone et al., 2017). A HDOP value closer to the value of one, indicates the geometrical positioning of satellites are spread out, whilst values greater than one indicates that satellites are positioned in a closer formation (Hsu, 1994; Malone et al., 2017). However, depending on the EPTS manufacturer, HDOP values may or may not be readily available to practitioners in the proprietary software or in exports into athlete monitoring databases. Additionally, the number of satellites in connection with GNSS devices also influences the validity and reliability of athlete tracking data (Aughey, 2011a). Research has stated that for human locomotion, a minimum of four satellites are required to be connected to the tracking technology during athlete tracking (Aughey, 2011a). Similar to the HDOP metric, the number of satellites in connection with the device during tracking may or may not be made available to practitioners/researchers depending on the manufacturer constraints on the information. However, for GNSS-based tracking it is expected that, where possible, included athlete GNSS datasets have a HDOP value less than one and at least four connected satellites (Aughey, 2011a; Malone et al., 2017).

2.5.2.3 Locomotion Metrics

The validity and reliability of locomotion metrics as tracked by GNSS is crucial to assessing the exercise intensity and volume of athletes. Despite the advancements in GNSS, with a particular emphasis on sample rates, some GNSS metrics have historically shown greater levels of validity and reliability than others. Distance (m) is historically a valid and reliable metric, including distance calculated from the earlier sample rates of 1 Hz and 5 Hz technology (Coutts & Duffield, 2010; Edgecomb & Norton, 2006; MacLeod et al., 2009; Scott et al., 2016; Vickery et al., 2014). Early validity and reliability studies analysing distance in 1 Hz units showed good to moderate results across a range of study designs which continued to improve with further development in unit sample rate towards 10 Hz (Beato et al., 2018; Coutts & Duffield, 2010; Edgecomb & Norton, 2006; Gray et al., 2010; R. J. Johnston et al., 2014; Johnston et al., 2013; MacLeod et al., 2009; Scott et al., 2016; Vickery et al., 2014). However, distance obtained at higher velocities has increased variability in terms of validity and reliability, with particular emphasis on lower (< 10 Hz) sample rates (Rampinini et al., 2015; Scott et al., 2016). For example, the validity of both 5 Hz and 10 Hz technology in sub-elite footballers during multiple 70 m bouts has been researched (Rampinini et al., 2015). 5 Hz displayed moderate validity (CV = 7.5%) across high-speed running (m) (> 4.17 $m \cdot s^{-1}$), which worsened (CV = 23.2%) with an increase to very high-speed running (m) (> 5.56 $m \cdot s^{-1}$). The 10 Hz device across the same experimental protocol, resulted in greater levels of validity, showing improved results across the high-speed (CV = 4.7%) and very high-speed (CV = 10.5%) thresholds. Moreover, 10 Hz technology has been observed during 15 m and 30 m sprint trials in trained male athletes (Castellano et al., 2011). The results indicated that as the length of the sprint interval increased from 15 m to 30 m, both the validity (standard error of measurement (%SEM); 5.1%) and reliability (CV: 0.7%) of 10 Hz technology improved, with only a slight underestimation of distance found.

However, high-intensity movements, particularly movements featuring accelerations and decelerations have consistently shown increased levels of variation and conjecture within validity and reliability research (Scott et al., 2016). The increased variation may be attributed to the dynamic rate of change in speed as a result of acceleration or deceleration efforts, with particular respect to decelerating, as the magnitude of deceleration can be more rapid (Delaney, Cummins, et al., 2018). Sample rates below 10 Hz have presented the highest levels of variation within the existing literature. During straight line running trials, high levels of variability were found within 5 Hz technology compared to 10 Hz (Varley, Fairweather, et al., 2012). Accelerations commencing at 1-3 $m\cdot s^{-1}$ saw variation as great as 14.9% (CV) in 5 Hz technology, which improved to 5.9% in the 10 Hz unit (Varley, Fairweather, et al., 2012). However, during decelerations (5-8 $m\cdot s^{-1}$), variation substantially worsened to 33.2% in the 5 Hz technology, which again improved to 11.3% in the 10 Hz unit (Varley, Fairweather, et al., 2012). Moreover, the validity of 10 Hz GNSS against VICON during team sport movements has been assessed (Delaney et al., 2019). The sole participant's acceleration as tracked by 10 Hz technology showed small to moderate bias (0.25 – 0.35; ± ~0.24) compared to VICON when the GNSS raw data was extracted (Delaney et al., 2019). However, the manufacturer's software export revealed very large bias (-3.81 to -3.77; ± ~0.24) compared to the criterion measure. It is apparent that despite improvements with the development in sample rates in excess of 10 Hz, the validity and reliability of acceleration and deceleration events are questioned. However, as alluded to in previous research, the variation in the validity of acceleration may be due to several extenuating factors (Delaney et al., 2019; Varley et al., 2017). Acceleration isn't directly calculated via the GNSS technology like distance and speed and is instead a derivative measure (Akenhead et al., 2014; Torres-Ronda, Beanland, et al., 2022; Varley, Fairweather, et al., 2012). Additionally, instances of manufacturer-applied filtering have been reported to influence the magnitude of acceleration from GNSS technology which may also influence validity and reliability compared to a criterion measure (Delaney et al., 2019; Thornton, Nelson, et al., 2019).

Maximum or peak athlete speed has consistent levels of validity and reliability when compared to acceleration events. In the initial 1 Hz technology, there has been limited research on the efficacy of GPS technology when tracking peak speed. However, In the existing research, 1 Hz technology has been found to be both valid and reliable when assessing 30 m sprint speed against timing gates (Barbero-Álvarez et al., 2010). Significant ($p<0.001$) Pearson's correlations existed between GPS peak speed and timing gate-calculated fastest sprint time (r^2 = -0.93), whilst acceptable reliability was found (CV = 1.2%) (Barbero-Álvarez et al., 2010). However, validity and reliability findings in 5 Hz technology showed greater variability in research. 5 Hz in one study showed moderate validity (CV = 6.6 – 9.8%) across 30 m sprint efforts, with improvements in speed validity seen as the length of the sprint increased (Waldron, Worsfold, et al., 2011). However, unit reliability was consistently greater across the sprinting trials (CV = 0.78 – 2.0%) (Waldron, Worsfold, et al., 2011). During field-based team sport movements, research found no significant difference in peak speed between the examined 5 Hz technology during any of the movement protocols when compared against VICON (Vickery et al., 2014). However, the differences between the two studies, could be due to the different criterion measures, as well as the respective specifications of the technology investigated.

Given the applied standard for GPS/GNSS sample rate is believed to be at 10 Hz, the modern application of findings pertaining to 1 Hz and 5 Hz technology is limited.

Like metrics of acceleration and high-speed distance, an increase in sample rate to 10 Hz and beyond shows an improvement in the validity of athlete peak speed. The validity of 10 Hz and 18 Hz technology during 20 m sprint trials against a criterion measure (radar gun) was examined (Beato et al., 2018). The results showed that both 10 Hz (26.5 ± 2.3 $km \cdot h^{-1}$) and 18 Hz (26.5 ± 2.6 $km \cdot h^{-1}$) were valid for the measurement of peak speed compared to the criterion (26.3 ± 2.4 $km \cdot h^{-1}$), with small, reported biases of 2.36 ± 1.67% (10 Hz) and 2.02 ± 1.24% (18 Hz) respectively. Similarly, research showed no significant differences between peak speed as calculated by 10 Hz technology against VICON in the field-based team sport movement protocols (Vickery et al., 2014).

Given the lowest levels of validity and reliability have been found in the now superseded 5 Hz and 1 Hz sample rates, practitioners and researchers have commonly accepted units sampling at least 10 Hz to be sufficient to measure volume and intensity metrics of athletes. However, for indoor team sport athletes, GNSS technology cannot be utilised due to an obvious lack of satellite connectivity. To quantify the exercise volume and intensity of indoor-based team sport athletes, local positioning systems are required to facilitate the athlete monitoring process.

2.5.3 Local Positioning Systems

Local positioning systems (LPS) or local position measurements (LPM) are tracking systems that provide information on athlete locomotion in either indoor or outdoor environments. Local systems differ to GNSS as instead of communicating with orbiting satellites, an LPS system operates in communication with fixed installations at various locations around stadia (Hodder et al., 2020; Serpiello et al., 2018). Currently, the majority of LPS research have been radio frequency-based (RFID), with further advances in the technology moving towards ultra-wideband (UWB) installations (Luteberget et al., 2018; Serpiello et al., 2018). Typically, RFID-based systems have operated with fixed anchor nodes that are positioned around the indoor stadium/court with radio communication occurring between anchor nodes and the mobile node worn by the athlete (Luteberget et al., 2018; Sweeting, 2017). Athlete positioning occurs via the use of a survey which outlines the distance between each anchor node and a known location on the playing surface. With positional information obtained, metrics such as distance, speed and acceleration can then be calculated (Hedley et al., 2010).

2.5.3.1 Validity and Reliability of LPS Systems

The initial research into the validity and reliability of LPS or LPM systems occurred prior to the introduction of UWB systems (Serpiello et al., 2018). However, radio-frequency systems, have been analysed in several studies across previous literature (Sweeting, Aughey, et al., 2017). For validity measures of positioning, RFID-based systems have obtained acceptable results in research. For example, the absolute error, on average, for all LPM position equations has been found at 23.4 ± 20.7 cm in one study (Ogris et al., 2012). Position results improved to errors of 12.1 cm (outdoors) and 11.9 cm (indoors) when using the Wireless Ad hoc System for Positioning (WASP) (Sathyan et al., 2012). For measures of distance, acceptable error rates were identified during a linear and non-linear running protocol, where the WASP recorded error rates of 2.2% and 2.7% respectively (Sathyan et al., 2012). During an association football-specific movement circuit, a small underestimation of distance by the LPM during the experimental protocol was identified, with mean differences ranging between 0.6 and 1.6% across walking and sprinting trials (Frencken et al., 2010). Moreover, research on athlete speed generated via RFID systems indicates acceptable levels of validity (Frencken et al., 2010). Variances as high as 3.5% for average speed and 13.2% for maximum velocities when compared to VICON (criterion) have been identified (Ogris et al., 2012). Similarly, constant speed during association football-specific movement was not significantly different ($p = 0.782$) between the LPS system and the criterion (Stevens et al., 2014). In the same research, the validity of acceleration and deceleration was also observed (Stevens et al., 2014). An average acceleration (0.01 ± 0.36 $m{\cdot}s^{-2}$) and deceleration (0.02 ± 0.38 $m{\cdot}s^{-2}$) metric (epoch: length of testing duration) reported stronger validity than peak acceleration and deceleration efforts, highlighting potential deficiencies in some RFID technology for peak changes of speed efforts (Stevens et al., 2014). However, the results of the validity studies mentioned in this section are somewhat limited in the application to elite team sport athletes. For example, the methodology in one study was based on a general team sport agility test using a mixed cohort of various team sport athletes and didn't replicate specific match movements expected in team sports (Sathyan et al., 2012). Additionally, some participants in the previously cited studies were moderately trained athletes and not elite level (Ogris et al., 2012; Stevens et al., 2014). It would be expected that elite level athletes would be able to execute higher-intensity movements in terms of speed-based and acceleration efforts.

On balance, RFID-based systems are valid and reliable for tracking human athlete locomotion within research. However, since the inception of this technology into research and the applied sector, there are reported concerns surrounding signal instability and susceptibility to transmission interference, particularly amongst stadia infrastructure (Alarifi et al., 2016; Serpiello et al., 2018). The more recent developments into UWB LPS have been stated to improve signal quality whilst reducing interference (Alarifi et al., 2016; Serpiello et al., 2018).

Ultrawideband technology is the latest development in LPS to track athlete locomotion in research and applied environments (Hodder et al., 2020; Serpiello et al., 2018). Ultrawideband technology differs from traditional RFID systems as UWB systems typically facilitate a large frequency bandwidth (≥ 500 MHz). Being able to transmit at the larger frequency bandwidths allows for signal penetration through objects such as wood and plastic, but with the exception of metal (Hodder et al., 2020; Rovnakova et al., 2008; Serpiello et al., 2018). The ability to penetrate structural objects is part of the explanation found in research surrounding the increased signal quality in UWB systems compared to RFID technologies (Hodder et al., 2020). Additionally, short pulse waveforms in UWB also contribute to reduced signal interference and greater signal quality for tracking athlete locomotion (Hodder et al., 2020). However, given the improvements in UWB systems, the cost to implement these systems remains high and may not be practically applicable for all team sport programs (Bastida-Castillo, De La Cruz Sánchez, et al., 2019). The ability of UWB systems to track athlete position and locomotion metrics has been evaluated within research. For athlete position, UWB-based systems have been reported to be valid. For example, the mean absolute error of the UWB-extracted “x” and “y” positional coordinates were 9.57 ± 2.66 cm and 7.15 ± 2.62 cm respectively, whilst the inter-unit reliability was strong in one study with the technical error of measurement (%TEM) resting between 1.12 and 1.19% (Bastida-Castillo, De La Cruz Sánchez, et al., 2019). Similarly, in other research, position variation across all estimates was 0.21 ± 0.13 m in the optimal experimental protocol and 1.79 ± 7.61 m in the sub-optimal setup (Luteberget et al., 2018). Distance has also proven to be a valid metric in UWB systems with low levels of variation (~3%) seen in several studies across varying experimental protocols (Leser et al., 2014; Luteberget et al., 2018; Rhodes et al., 2014; Serpiello et al., 2018). However, similar to RFID validity results, peak acceleration and speed-based locomotion has exhibited higher levels of variation (Hodder et al., 2020; Luteberget et al., 2018; Serpiello et al., 2018). During court-based trials, moderate variation existed during sprinting for mean acceleration (6.8 – 8.5%) and small to moderate variation during mean deceleration (-28 - - 8.1%) (Serpiello et al., 2018). Moreover, the calculation of instantaneous speed from raw LPS data was not valid with average variation in the optimal group ranging from 33-39% and as high as 91% in the sub-optimal group (Luteberget et al., 2018). The differences between instantaneous speed were claimed to increase as the speed of locomotion increased. However, as this study was examining the raw LPS data it may not have been subject to manufacturer filtering processes which is common when utilising proprietary tracking technology. It is then unclear how the examined LPS technology would perform with the use of data filtering and how that would impact the evaluation of high-intensity locomotion. For practitioners and researchers, high-intensity locomotion efforts calculated from UWB should still be treated with caution. However, given the continued development into LPS technology and the reported improvements in signal quality and interference, UWB systems are currently the preferred form of LPS in applied team sport research, with reference to literature based on athlete locomotion and activity profiles.

With the noted development into UWB systems for athlete tracking technology, there may be instances where UWB systems are preferred to GNSS technology during competition (Thornton, Nelson, et al., 2019). Some stadia may have structural occlusions which limits the effectiveness of GNSS technology, prompting the use of a local system to improve the tracking validity and reliability (Thornton, Nelson, et al., 2019). However, the interchanging of tracking systems is also subject to the validity and reliability of each system and any potential variation in locomotion metrics.

2.6 Interchanging between Athlete Tracking Technologies

The validity and reliability of athlete tracking data between different technology sources has become increasingly important at the applied level in elite team sports (Buchheit & Simpson, 2017). The sustained adoption of LPS and optical technology in outdoor team sports stadia has facilitated consideration as to the interchangeability between tracking technologies between training and competition with respect to tracking data validity and reliability (Buchheit & Simpson, 2017; Linke et al., 2018; Taberner et al., 2020). Up until the change in FIFA competition regulations in 2015, football athletes were prohibited from wearing GNSS units in matches, despite regularly wearing the technology in training (Taberner et al., 2020). To monitor the locomotion of football athletes in competition, the use of optical tracking systems was commonly implemented (Buchheit & Simpson, 2017). Additionally, in what is now becoming a common occurrence, team sport athletes have begun wearing LPS technology in outdoor stadia instead of the more traditional GNSS trackers (Thornton, Nelson, et al., 2019). In practice, the perceived benefit of LPS technology in outdoor stadia removes some of the inherent issues with GNSS technology, particularly with stadia that have overhanging structures or stand amongst high-rise developments that have the potential to interfere with the satellite line of sight (Thornton, Nelson, et al., 2019). However, depending on the training facility location of the team, the use of LPS or optical technology for athlete tracking may not be possible away from the competition arena. Instead, practitioners may be required to continue athlete monitoring via GNSS technology during training sessions.

Consequently, practitioners have been required to interchange their EPTS between competition and training settings which could have the potential to influence activity profiles (Taberner et al., 2020). Significant variation between tracking technologies would have practical implications for athlete preparation where practitioners would face conjecture over the volume and intensity of their athletes. Similarly, in research, significant variation in exercise volume and intensity between systems would create doubt as to the validity of athlete monitoring practices via the use of multiple systems.

Initial research following the introduction of GPS technology in elite team sports observed the validity and reliability of GPS technology (GPSports SPI 10) and a manual computer-based tracking system during Australian Football-related movement (TrakPerformance) (Edgecomb & Norton, 2006). When comparing distance findings, a strong correlation (*r = 0.997*) was identified between the technologies, however the distances obtained were significantly different (p = 0.02) and were overestimated (GPS: 4.8%, CBT: 5.8%) compared to the criterion (trundle wheel) (Edgecomb & Norton, 2006). However, the majority of the validity and reliability research between athlete tracking technologies has been based upon association football. The activity pattern of Spanish second and third division footballers during a test game was observed (Randers et al., 2010). The technology included in the study featured a semi-automated camera system (Amisco), a video-based time motion analysis system (VTM) and two different GPS devices (Catapult MinimaxX v2.0 & GPSports SPI Elite, sample rates: 5 Hz & 1 Hz). However, the results showed discrepancies between the tracking systems across metrics pertaining to total distance (km) as well low-intensity (km), high-intensity (km) and sprint distances (km) (Randers et al., 2010). For example, total running distance (km) was found to be over a kilometre greater in the semi-automated camera system (6.25 ± 1.04 km) compared to 5 Hz GPS (5.10 ± 1.08 km), whilst 5 Hz (10.73 ± 0.67 km) recorded a significantly higher ($p < 0.001$) total distance compared to video (9.52 ± 0.78 km) (Randers et al., 2010). The study concluded that in finding these differences between systems, practitioners should be cautious in the comparisons made in regard to the volume and intensity of athletes between systems (Randers et al., 2010).

Later research investigated the levels of agreement between a semi-automatic camera tracking system (Prozone), an LPS (Inmotio) and two GPS units (GPSports, SPI Pro XII & VX, VX340a) in association football (Buchheit, Allen, et al., 2014). However, unlike the previously discussed studies, calibration equations were presented that could be used to improve the level of agreement when interchanging between athlete tracking systems (Buchheit, Allen, et al., 2014). Calibration equations were presented for the benefit of the practitioners as practically, equations could be implemented in either training or competition to incorporate known differences between tracking systems to offset any discrepancies in athlete volume and intensity (Buchheit, Allen, et al., 2014). Whilst calibration equations for locomotion metrics between systems could be produced, small to moderate error was stated to remain in the predicted volume, which was due to the typical error of the estimate (TEE) found between technology (Buchheit, Allen, et al., 2014). Moreover, the findings from the study revealed that variation in the agreement between tracking technologies for total distance was *small*, but there was substantial variation in high-speed and acceleration metrics. For acceleration counts (> 3 $m \cdot s^{-2}$), *moderate-to-large* variation was seen between technologies, with the LPS recording substantially larger acceleration counts compared to Prozone and moderately larger counts compared to GPS on the full-pitch. Both GPS models also recorded substantially greater acceleration counts compared to Prozone™ in the full-pitch and medium pitch trials which was designated as a *large* variation. Similarly, in association football, variation in acceleration existed in a study analysing the exercise volume and intensity outputs via GPS (GPSports SPI Pro-X), LPS (Inmotio), and camera-based tracking (STATS SportVU) against VICON (criterion) (Linke et al., 2018). The root mean square error in acceleration during small-sided games showed significant differences ($p < 0.001$) and *large* effect sizes (ES) (> 0.26) in both GPS and LPS when compared to the camera-based technology.

The previously discussed research is limited by the tracking technology implemented. Research indicates that GNSS units that sample at 10 Hz or above are the most valid and reliable for tracking athlete locomotion (Malone et al., 2017). The previously referenced studies in this section sampled at a maximum of 5 Hz, regardless of any interpolation used during processing to up sample the technology. Currently there is limited research that has implemented 10 Hz GNSS technology when comparing the levels of agreement between technology. In 10 Hz research, the interchangeability between GNSS technology (STATSports Apex & Viper, 10 Hz) and a semi-automated optical system (TRACAB, 25 Hz) during under 23 and first team football matches was observed (Taberner et al., 2020). The Apex model typically performed better in comparison to the Viper model, as the SEE within calibrated functions improved from 5-22% (Viper) to 4-14%, whilst there were no significant differences found between the Apex and TRACAB in total, high-speed or sprint distance (m). The improvement in the agreement between the STATSports Apex and TRACAB was hypothesised to be due to the increased accessibility of the Apex unit to satellites given it is GNSS-enabled, whilst the Viper only has GPS accessibility (Taberner et al., 2020). The authors concluded that given the high levels of agreement between the Apex and TRACAB technologies, interchanging of tracking systems was possible and practical for the applied sector, providing practitioners are cognisant of the potential error that can exist between positions and of the availability of calibration equations (Taberner et al., 2020). Similarly, the interchangeability of athletes player movement variables from an English Premier League squad between GNSS (Catapult Sports Vector, 10 Hz) and two optical systems (TRACAB and Second Spectrum) has also been researched (Ellens, Hodges, et al., 2022). Differences between all tracking technologies for all variables (e.g., total distance [m], maximal speed [km.h^{-1}]) was evident, with total distance (m) being *largely* greater (magnitude of standardised mean difference; 1.2 – 2.0) in TRACAB and *very largely* greater (2.0 – 4.0) in Vector technologies compared to Second Spectrum (Ellens, Hodges, et al., 2022). However, standardised equations were provided by the researchers to allow for the interchangeability between tracking technologies for all examined variables with a comparable SEE compared to similar research (Taberner et al., 2020). Though, applying each individual equation (e.g., distance from GPS to TRACAB; 267 + 0.97) for each variable may not be practically efficient and given the number of variables monitored from athlete tracking systems, the provided equations and variables may not be sufficient for an applied practitioner's monitoring system.

It is difficult to make inference on the individual differences found between the tracking technologies in each respective study discussed in this chapter due to the wide range of criterions and methodologies implemented. For example, acceleration-based metrics were identified to have higher sources of error in two studies, however, this could be due to specific study factors, such as the filtering of acceleration during data processing (Buchheit, Allen, et al., 2014; Linke et al., 2018). Still, the existing literature has identified that the interchangeability between tracking technology is possible and even necessary given the previous competition constraints on wearable technologies. To interchange between systems, data translation is facilitated via the use of generic equations or algorithms that look to standardise the data based on known differences between the tracking technologies. In research and at the applied sport science level, it appears that the adoption of generic equations to process athlete volume and intensity during training or competition between tracking technologies is now a current practice. It is still recommended, (where possible) that both at the research and applied level, one tracking system is exclusively used for both training and competition.

Another consideration surrounding the interchanging of tracking technologies is the introduction of wearable devices that can have dual GPS/GNSS and LPS functionalities. There are wearable devices available that can be set for both outdoor (GNSS) and indoor (LPS) use (Catapult, 2023). The advantages of this for practitioners extends to being able to facilitate the technologies using the same software and computer system, whilst also using the same device for all training and competition events. Moreover, having a consistent device used may minimize the amount of external data handling required compared to implementing mathematical equations to help standardise data from different tracking systems and manufacturers. However, some challenges may still exist surrounding the consistency of the data handling. Despite wearing the same device, athletes would still be tracked by two different systems. The GNSS component of the device is impacted by environmental factors and strength of connection to the satellite networks, whilst the LPS component is subject to the calibration and alignment of the positioning system around the stadia or training facility (Aughey, 2011a; Hodder et al., 2020; Malone et al., 2017; Serpiello et al., 2018). Subsequently there may be differences in processing of athlete tracking data which could still result in the same issue surrounding the consistency of how the tracking data is processed which may lead to differences in athlete outputs (Buchheit, Allen, et al., 2014). There is limited research on dual-system technology which inhibits any conclusions that can be made about the suitability of these devices for use across different environments or the consistency between the tracking data and the magnitude of difference in athlete outputs in metrics such as acceleration.

After the selection and subsequent evaluation of the validity and reliability of the tracking system used for athlete locomotion, the development of an activity profile for a sport becomes possible (Aughey, 2011a, 2011b). It is the information on athlete locomotion within an activity profile that allows for further development into training analysis and subsequent training program prescription.

2.7 Activity Profiles in Team Sport Research

2.7.1 Introduction

An activity profile in team sport research generally consists of locomotion information pertaining to either the training and/or competition volume and/or intensity experienced by athletes and position groups within a respective sport (Aughey, 2011a). The notion of activity profiles within team sport research has existed before the introduction of satellite-based wearable tracking technologies. Initially, notational analysis provided early activity profiles in association football, where analysts would subjectively allocate and categorise the movement patterns of individual athletes into standing, walking, jogging, or sprinting using pen and paper (Knowles & Brooke, 1974; Sweeting, Cormack, et al., 2017). Using GNSS/LPS technology, all athletes could be tracked with their volume and intensity determined quickly and efficiently after training and/or competition.

Through the development of athlete wearable technologies, the locomotion metrics available to practitioners for analysis are greatly enhanced compared to the subjective notional and video-based analysis (Aughey, 2011a; Malone et al., 2017). Specifically, information relating to athlete velocities, accelerations, contacts, tackles, jumps or efforts are outlined in modern activity profiles which can greatly benefit practitioners at the applied sports science level (Aughey, 2011a; Scott et al., 2016). The information relating to exercise volume and intensity in both the training and competition arenas can provide the basis for training program prescription and can also inform rehab processes for athletes in return to play protocols (Cummins et al., 2013). Longitudinally, the publishing of activity profiles in research also allows for the analysis of changes in competition or training styles over established time periods (i.e., between seasons or in-season) which can also aid in training program development and athlete profiling.

2.8 Volume and Intensity Metrics in Team Sport Activity Profiles

2.8.1 Distance

The volume of athlete locomotion for a given period (e.g., a drill, match or training session) can be quantified through distance. Distance is a common volume metric in team sport activity profiles and is widely adopted as a metric of interest in the research and applied sport science environments. Team sports such as association football or Australian rules football have been identified as having high athlete distances in competition with athletes in association football averaging between (10000 m to 14000 m) compared to Australian rules athletes (11000 m to 14000 m) (Andrzejewski et al., 2019; Brewer et al., 2010; Chmura et al., 2017; Clemente et al., 2013; Coutts et al., 2015; Coutts et al., 2010; Delaney, Thornton, Burgess, et al., 2017; Janetzki et al., 2021). The open field nature of association football and Australian football, where athletes are free to roam around the full length of the pitch along with minimal substitutions in association football and a high interchange limit (~ 75 substitutions) in Australian rules promotes sustained distance. Whilst the length of an Australian rules football match is longer than a competitive association football match, the small number of interchanges in association football ensures that athletes spend maximum amounts of time on the pitch. Other invasion team sports such as rugby union (4000 m to 7500 m) and rugby league (4000 m to 9500 m) have reported lower total distances in research (Cunniffe et al., 2009; Delaney et al., 2015; Delaney, Thornton, Pryor, et al., 2017; Gabbett, 2013a; Jones et al., 2015; McLellan et al., 2011). Whilst both rugby codes are shorter in total duration (80-minutes), the nature of rugby is to limit the opponent gaining field territory. In essence, athletes are actively engaging the defensive or attacking team lines to repel or sustain movement of the ball and are therefore limited in terms of obtaining higher distances. However, whilst a total distance metric provides an indication of the external volume of athletes during training or competition, there is limited contextual information on the way in which the game was played. For example, one game of association football might see athletes achieve 12,000 m in distance, but another game of similar duration may see athletes obtain 10,000 m in distance. The difference in volume might not seem significant, but the differences in the intensity of the game could be the source of discrepancy between the volume. To rectify the difference, research and practitioners have commonly adopted a speed intensity metric which sees total athlete distance divided by competition or playing time (metres per minute, $m \cdot min^{-1}$)(Aughey, 2010; Coutts et al., 2010; Jennings et al., 2012b). Athlete volume referenced relative to time provides greater context on the speed intensity and style in which training, or competition was played. Established team sport activity profiles in research have determined the average speed intensity of competition for Australian rules football (~105 to 160 $m \cdot min^{-1}$), association football (~100 to 130 $m \cdot min^{-1}$), rugby union (~55 to 85 $m \cdot min^{-1}$) and rugby league (~85 to 110 $m \cdot min^{-1}$) (Aughey, 2010, 2011b; Austin & Kelly, 2013; Cunniffe et al., 2009; Delaney et al., 2015; Delaney, Thornton, Burgess, et al., 2017; Jones et al., 2015; Varley et al., 2014). However, the differences between the sports would still be as a result of the previously mentioned differences in game styles, duration and objectives. Research has also detailed the peak intensity in competition rather than the summary intensity over the entirety of the match (Austin & Kelly, 2013; Delaney et al., 2015; Varley, Elias, et al., 2012). Specifically, the peak intensity during instances of play has been extracted from 30 second to 10-minute moving average epochs to provide an indication to practitioners on the "worst-case" or "competition peaks" to improve training prescription and the design of small-sided conditioning games (Delaney et al., 2015; Delaney, Thornton, Burgess, et al., 2017; Delaney, Thornton, Pryor, et al., 2017; Delaney, Thornton, et al., 2018; Delves et al., 2019; Howe et al., 2020). Peak speed intensity research has been published on several team sports, including, but not limited to, Australian rules football (~200 to 220 $m \cdot min^{-1}$), association football (~180 to 205 $m \cdot min^{-1}$), rugby league (~160 to 185 $m \cdot min^{-1}$) rugby union (~150 to 185 $m \cdot min^{-1}$) and field hockey (~200 to 210 $m \cdot min^{-1}$), all detailing the expected peak intensity across position groups (Delaney et al., 2015; Delaney, Thornton, Burgess, et al., 2017; Delaney, Thornton, Pryor, et al., 2017; Delaney, Thornton, et al., 2018; Delves et al., 2019). The use of distance as a volume metric however can also be linked with athlete speed to detail the activity profile at various thresholds.

2.8.2 Speed-based Metrics

Athlete speed during training and competition can be grouped into different locomotion categories via the use of speed thresholds (Cunniffe et al., 2009; Mohr et al., 2003; Scott et al., 2016; Sweeting, Cormack, et al., 2017). Speed "zones" are often implemented in applied team sport monitoring which outlines the accumulated volume of athletes over a spectrum of speed thresholds (Sweeting, Cormack, et al., 2017). For example, in rugby league, the locomotion category of high-speed running may be designated by a speed threshold of >5 $m \cdot s^{-1}$, whilst sprinting may be set at >7 $m \cdot s^{-1}$ (Austin & Kelly, 2013; Gabbett, 2015; Gabbett et al., 2012b). Each time this threshold is met or exceeded by the athlete, the volume in the respective threshold will update on a continuous basis throughout training and/or competition. Typically, speed-based metrics will include variables that pertain to the accumulated distance (e.g., high-speed distance (m)), efforts/counts (e.g., sprints/high-intensity efforts) or time (time spent in threshold) in a particular threshold. However, the selection of speed thresholds has been typically determined from previous research, proprietary software or arbitrarily selected by the researcher or practitioner (Cunniffe et al., 2009; Jennings et al., 2012b; Mohr et al., 2003; Sweeting, Cormack, et al., 2017). There is no current consensus within applied team sport research on how speed thresholds are determined (Sweeting, Cormack, et al., 2017). Moreover, there is evidence between respective team sport research that shows considerable variability between the speed thresholds published and the locomotion categories representing those thresholds (Hausler et al., 2016). For example, rugby league research has shown discrepancies in the selection and labelling of speed thresholds across high-intensity running bands (Hausler et al., 2016). High-intensity running has been defined as speed efforts between 18 and 20 $km \cdot h^{-1}$ (Austin & Kelly, 2013; McLellan et al., 2011) However several studies defined “high-speed running” as any and all efforts > 18 $km \cdot h^{-1}$ (Gabbett, 2013a, 2013b, 2015; Murray et al., 2014; Twist et al., 2014). Similar differences exist in the labelling of the locomotion descriptors within rugby league research (Hausler et al., 2016). Sprinting has been categorised from as low as > 21 $km \cdot h^{-1}$ to > 25 $km \cdot h^{-1}$ whilst moderate speed running has seen wide ranges from as low as 7 $km \cdot h^{-1}$ up to 18 $km \cdot h^{-1}$ (Murray et al., 2014; Twist et al., 2014; Varley et al., 2014; Waldron, Twist, et al., 2011). For both the research and applied sport science settings, the differences between speed thresholds and descriptors makes comparisons between activity profiles difficult and inhibits conclusions on changes to volume or intensity outputs or game styles. The inability to draw inferences because of differences in speed-based thresholds also extends to the acceleration volume of athletes in training and competition.

2.8.3 Acceleration

Acceleration is defined as the rate of change in speed (Little & Williams, 2005; Varley & Aughey, 2013). In many team sports, acceleration events are synonymous with key instances in competition, such as contesting the ball, point scoring, defending and creating space (Carling et al., 2008; Delaney, Thornton, et al., 2018; Varley, Fairweather, et al., 2012). Decelerations are also commonly analysed metrics in team sport activity profiles and represent negative accelerations (Dalen et al., 2016; Harper et al., 2019). In this thesis negative accelerations will be referred to as decelerations given the widespread use of the term within research and the applied setting. However, acceleration and deceleration events in training and competition need to be accounted for in the monitoring process, particularly as acceleration events are believed to carry a metabolic cost that is considered greater than continuous running (Osgnach et al., 2010; Varley & Aughey, 2013). Currently, the use of wearable tracking technologies (i.e., GNSS, LPS or optical systems) are widely used within applied sport science to track athlete acceleration.

Typically, invasion team sports played in congested space, such as rugby league or rugby union, have seen high peak acceleration intensity within competition (Delaney, Duthie, et al., 2016; Delaney, Thornton, Pryor, et al., 2017). Peak acceleration intensity in rugby league competition have been reported to be as high as 1.28 ± 0.13 m·s^{-2} (fullback) during the peak 1-minute match epoch (Delaney, Duthie, et al., 2016). The magnitude of acceleration intensity found in rugby league can be attributed to the attacking and defensive lines synonymous with rugby league match play. However, sports such as Australian rules and association football are generally played in distributed formations throughout the playing arena, allowing greater opportunities for consistent open-field running.

Acceleration in team sport activity profiles has been quantified through the use of threshold-based metrics (Akenhead et al., 2016; Dempsey et al., 2018; Furlan et al., 2015; Wellman et al., 2016). Count or effort-based variables, which detail the number of instances in which an acceleration threshold has been met or exceeded are common in team sport activity profiles (Chapter 3). However, the threshold to quantify the magnitude of accelerations efforts into different intensity categories has varied throughout the literature. Across team sport research, count-based acceleration metrics have been predominantly classified into intensity categories. Low-range thresholds in acceleration magnitude across various team sports have ranged from 0.55 $m{\cdot}s^{-2}$ to 2.77 $m{\cdot}s^{-2}$, whilst moderate-range counts have been published from as low as >0.01 $m{\cdot}s^{-2}$ to as high as > 3 $m{\cdot}s^{-2}$ (Akiyama et al., 2019; Bauer et al., 2015; Bowen et al., 2019; D. J. Cunningham et al., 2016; de Hoyo et al., 2016; Gabbett, 2012; Gabbett et al., 2012a). For high-intensity acceleration efforts, a >2.78 $m{\cdot}s^{-2}$ threshold has been widely applied in sports such as association football, rugby league and Australian rules (Aughey, 2010, 2011b; Coutts et al., 2015; Garvican et al., 2014; Johnston et al., 2015b; Varley & Aughey, 2013; Varley et al., 2014). The >2.78 $m{\cdot}s^{-2}$ threshold was initially implemented following research in untrained participants who completed standing start maximal accelerations between 2.5 $m{\cdot}s^{-2}$ and 2.7 $m{\cdot}s^{-2}$ (Varley, Fairweather, et al., 2012). Despite the use of a >2.78 $m{\cdot}s^{-2}$ threshold initially designating a high-intensity acceleration effort, there has been various descriptors of intensity associated with this threshold. For example, in rugby league research, acceleration events of a magnitude of >2.78 $m{\cdot}s^{-2}$ have been defined as “moderate”, “high”, “very high” and “maximal” across different rugby league activity profiles, which indicates inconsistency in the thresholding and reporting within the literature (Cummins et al., 2015; Gabbett, 2012; Oxendale et al., 2016; Varley et al., 2014).

The varied selection of the acceleration-based thresholds also extends to distance and time metrics. Similar to acceleration count/effort variables, acceleration distance and time spent within respective thresholds have been implemented within team sport activity profiles (Akenhead et al., 2016; Bauer et al., 2015; Delaney, Cummins, et al., 2018; Mara et al., 2015; Newans et al., 2019). For example, in elite Australian rules research, variation exists in the use of the threshold and rating of intensity. Low acceleration distance has been classified with the threshold of 0 – 2.77 $m \cdot s^{-2}$, whilst moderate acceleration distance has been classified with the threshold of 1.47 – 2.77 $m \cdot s^{-2}$ (Bauer et al., 2015; Johnston et al., 2015a). For practitioners of respective team sports, the variation between studies with respect to the use of thresholds is difficult to incorporate practically. Practitioners typically refer to research to aide their decisions in relation to athlete monitoring settings. With examples of the variation in the selection of thresholds within team sport activity profiles, it is then challenging for practitioners to identify best practices for tracking athlete locomotion. Whilst for researchers, the use of threshold-based metrics may become problematic when comparing between manufacturers and models given previous instances of variation within the technology as well as in the selection of the threshold (Thornton, Nelson, et al., 2019).

Whilst the selection of acceleration thresholds in team sport activity profiles has shown variation, acceleration metrics are also subject to data processing (Thornton, Nelson, et al., 2019; Varley et al., 2017). As acceleration is indirectly calculated by GNSS/LPS technology, the efficacy of acceleration metrics within activity profiles may vary between manufacturers (Buchheit, Al Haddad, et al., 2014; Thornton, Nelson, et al., 2019). It is understood within the literature that the validity and reliability of acceleration-based metrics can vary between manufacturers and within models, particularly those of similar sample rate, which may be as a result of data filtering (Buchheit, Al Haddad, et al., 2014; Malone et al., 2017; Thornton, Nelson, et al., 2019; Varley et al., 2017). For example, three different GNSS devices from the same manufacturer, with identical sample rates, had substantial differences in acceleration with a 43% variation in acceleration efforts (>3 $m \cdot s^{-2}$) across sled-based trials (Buchheit, Al Haddad, et al., 2014). Moreover, the influence of data filtering could be seen with updates in software. After the second software update, the number of accelerations (>1.5 $m \cdot s^{-2}$) substantially declined (251 ± 65 vs 177 ± 53) compared to the baseline software package, indicating the influence of processing upon the tracking data (Buchheit, Al Haddad, et al., 2014). Similarly, three GNSS devices were examined from different manufacturers and determined that there were substantial differences between manufacturers for threshold-based metrics of acceleration during sled-based movement simulations (Thornton, Nelson, et al., 2019). Filtering between GNSS manufacturers was suggested to be a factor behind the variation between manufacturers during the simulation protocols. However, despite the previous research, there is limited information surrounding the processing of acceleration in published team sport activity profiles and within EPTS validity and reliability research (Buchheit, Al Haddad, et al., 2014; Thornton, Nelson, et al., 2019).

Additionally, there is little research available that summarises how acceleration has been quantified in team sport activity profiles. Information pertaining to the choices of acceleration-based metrics in respective team sports may provide insight to practitioners and researchers of that sport. Similarly, given the influence of data filtering upon acceleration in wearable tracking technology, greater research upon acceleration processing is required. Particularly, given the limited information on acceleration processing, a review of previous team sport research may highlight the limitations in protocols for acceleration in activity profiles. Greater clarity on how acceleration has been quantified previously in team sports will aide practitioners with indications on choices of variables whilst also providing a summary of the different speed thresholds implemented. Moreover, at both the practical and research level, an enhanced understanding of the filtering methods used to process acceleration can aid in tracking technology validity and reliability research.

2.9 Filtering of Athlete Tracking Data

2.9.1 Common Athlete Tracking Data Filters

Regardless of the tracking system implemented to record athlete locomotion, data filtering may influence the calculation of volume and intensity metrics. For example, the filtering of athlete tracking data can directly influence acceleration, regardless of the magnitude or metric used to quantify the event (Ellens, Middleton, et al., 2022; Harper et al., 2019; Malone et al., 2017; Stevens et al., 2014; Thornton, Nelson, et al., 2019; Varley et al., 2017). However, the purpose of filtering extends to maintaining data quality, removing poor signals and to decrease the noise content of the signal (Carling et al., 2008; Rader & Gold, 1967; Sweeting, Cormack, et al., 2017; Winter, 2009; Winter et al., 1974). In human movement, there are many different types of filters which have been introduced to process athlete data from wearable technologies (Campbell et al., 2020; Malone et al., 2017; Sweeting, Cormack, et al., 2017). Many filters can be categorised into the following; low-pass, where signals above a cutoff frequency are minimised, high-pass, where signals below a frequency are reduced, band-pass, where signals outside a range of frequencies are attenuated or band-stop, where signals that occur within a range of frequencies are attenuated (Campbell et al., 2020; Sweeting, Cormack, et al., 2017). As human movement has been shown to occur between frequencies of approximately 0 and 20 Hz, low-pass filters and associated cutoff frequencies are commonly selected between these frequency ranges (Antonsson & Mann, 1985; Mathie, 2003; Wei-zhong et al., 2011). Butterworth filters are common low-pass filters selected to process human locomotion data from tracking technology, however, other low-pass filters can be selected (Campbell et al., 2020; Ellens, Middleton, et al., 2022; Malone et al., 2017; Sweeting, Cormack, et al., 2017; Winter, 2009). Median filters work by providing the result with the median value in a series, whilst moving average filters average more recent values for the filtered dataset over a specified number of inputs (Sweeting, Cormack, et al., 2017; Villar et al., 2017). Exponential filters are based on taking the weighted sum of past outputs, but modelled with an exponentially decreasing weight for previous instances (Ostertagova & Ostertag, 2011). Kalman filters estimate variables of interest over time when the variables themselves can't be directly measured (Sathyan et al., 2012; Sweeting, Cormack, et al., 2017). Band-pass filters help to convert raw data from the spatial to the time domain via the use of a Fourier Fast Transform (FFT) (Sweeting, Cormack, et al., 2017; Winter, 2009; Wundersitz et al., 2015). In LPS, common filtering methods include, but are not limited to, Kalman and Butterworth filters, whilst GPS/GNSS technology can also utilise Butterworth as well as moving average, moving median, median or exponential filters (Couderc et al., 2019; Furlan et al., 2015; Malone et al., 2017; Sathyan et al., 2012; Stevens et al., 2014; Sweeting, Aughey, et al., 2017; Sweeting, Cormack, et al., 2017; Winter, 2009).

2.9.1.1 Butterworth Filters

Low-pass Butterworth filters minimise higher frequency signals whilst allowing lower frequency signals to pass through (Campbell et al., 2020; Winter, 2009). The use of a cutoff frequency is applied as part of the low-pass Butterworth filter process, which is the designated point at which signals are allowed to pass through or at which are attenuated (Campbell et al., 2020; Winter, 2009; Yu et al., 1999). Typically, cutoff frequencies used in association with low-pass Butterworth filters have ranged between 0.02 and 15 Hz in athlete tracking data research, which is consistent with the finding that human locomotion mostly occurs between frequencies of 0 and 20 Hz (Antonsson & Mann, 1985; Bredt et al., 2020; Fischer-Sonderegger et al., 2019; Wundersitz et al., 2015). Human locomotion in this instance refers to gait, with the signal in the biomechanical measurement representing a magnitude of gait during that setting or environment. For example, artistic gymnastic movements completed upon force plates with analysis of frequency distributions along a spectrum (Campbell et al., 2020). Human gait is generally lower on the frequency spectrum, whilst noise in an analysis occurs at higher frequencies which promotes the need for a low-pass filter (Campbell et al., 2020). However, a cutoff frequency is commonly chosen through a residual analysis on the dataset which can influence the effectiveness of the filter (Campbell et al., 2020; Winter, 2009; Yu et al., 1999). A residual analysis involves filtering the dataset at a range of cut off frequencies before calculating residuals between the raw and cleaned data (Campbell et al., 2020; Winter, 2009). The data is usually plotted on a graph, (Figure 2-1) with the point at which the residuals deviate from linearity being deemed as the optimal cutoff frequency for that dataset (Campbell et al., 2020; Winter, 2009). However, it should be noted, that despite the use of a residual analysis being standard within research, the use of a residual analysis has resulted in some criticism, where the calculated cutoff frequencies were found to be lower than the calculated optimum, particularly when the sample rate was high (Yu et al., 1999). However, despite published criticism on the use of a residual analysis, low-pass Butterworth filters have been commonly used in the processing of athlete tracking data within research (Ellens, Middleton, et al., 2022). A review on the processing of acceleration and deceleration data found that 48% of studies that specified a cleaning technique selected a variation of a low-pass Butterworth filter, indicating that the selection of this filter is commonly used amongst researchers and practitioners within applied sport science (Ellens, Middleton, et al., 2022).

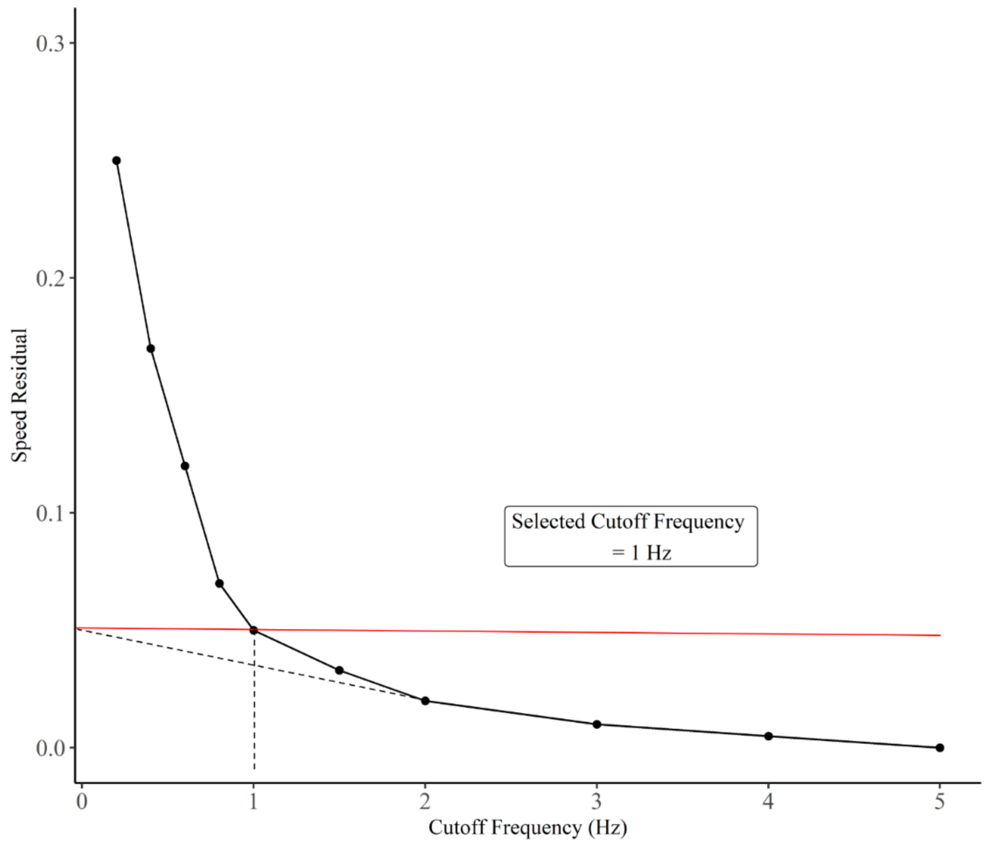

Figure 2-1 Example of a residual analysis performed on athlete GNSS data to determine appropriate cut off frequency. Duplicated from Chapter 6.

2.9.2 Limitations of Filtering on Athlete Tracking Data

The process by which manufacturers select their filtering process is unknown and can vary from manufacturer to manufacturer (Malone et al., 2017). In research and for applied sport science practitioners, this is problematic as there are many different manufacturers/providers and models commercially available (Malone et al., 2017). As such there are many different types of filters that can be modified, potentially altering the magnitude of volume and/or intensity events, particularly high-speed and acceleration efforts (Thornton, Nelson, et al., 2019). For example, a 24% difference was found in sprint distance as tracked by GPS technology during real time and post-game upon download and processing of the data, which could have been as a result of subsequent filtering upon the dataset (Aughey & Falloon, 2010). Manufacturer filtering could have been attributed to the discrepancy between the live and post-game values, however, there is no clarification on how the reported differences eventuate (Aughey & Falloon, 2010). In a practical example, manufacturers may elect to filter the speed trace using a determined filter and then calculate acceleration from the speed trace. Manufacturers may also filter the speed trace and then filter the calculation of acceleration using a predefined filter. However, this is speculation as there are numerous possibilities as to how manufacturers and even researchers or practitioners choose to filter athlete tracking data. But despite the array of filtering settings available, there is extremely limited research surrounding the application of filtering processes in player tracking data. With respect to team sport activity profiles, there are limited studies that express the filtering settings of the tracking technology used in the methodology (Chapter 3). To enable appropriate discussion between activity profiles, future research should attempt to review and outline the filtering settings used in previous research to promote the reporting of filtering settings and to identify what filtering has been implemented and how that can influence volume and intensity outputs.

2.10 Conclusions

The use of athlete tracking systems in team sports are fundamental to the determination of activity profiles which detail the athlete volume and intensity of competition. The information obtained via the use of tracking technology allows researchers and practitioners to formulate athlete training programs and rehabilitation protocols that are designed to prepare athletes for the rigors of competition.

Previous athlete tracking methods of notational analysis and video-based analysis have been superseded by optical tracking systems, as well as wearable technologies, including GNSS and LPS units. The use of wearable technologies has seen widespread adoption in both the applied team sport environment and research following the approval to wear the technologies in most major team sport competitions. The highest levels of EPTS validity and reliability have been seen in GNSS technology that sample at 10 Hz or above and in LPS units that are facilitated through UWB technology. However, despite the continued development into wearable technology, dynamic events such as high-intensity accelerations and decelerations are still questioned in the literature.

It is now not uncommon for applied sport scientists to operate multiple athlete tracking systems in training and competition, with particular reference to association football. Global Navigation Satellite System devices are commonly worn in training, whilst optical systems may be implemented on matchday. Similarly, outdoor stadia are increasingly opting to utilise LPS technology within the stadium fittings to increase accuracy and reduce the impact of stadium infrastructure on GNSS signal quality. Limited research has explored the use of interchanging EPTS. Whilst the existing research suggests that exclusively operating one tracking technology is preferred, the publishing of corrective algorithms and mathematical equations suggests that interchanging systems is possible.

The volume and intensity metrics tracked by wearable technologies underpin the formation of team sport activity profiles. Speed-based metrics have seen substantial variation within team sport which is potentially due to a lack of standardised thresholds and descriptors of locomotion within research. Similarly, acceleration metrics have seen similar issues with variation in the thresholds determining the intensity of acceleration or deceleration events. However, the presence of data filtering upon EPTS via manufacturers may influence the validity and reliability of athlete acceleration as acceleration is a derivative measure. However, the current knowledgebase is limited as to the data filtering settings used by EPTS manufacturers and additionally any potential influence of data filtering upon athlete acceleration. Given the importance of acceleration as an underpinning metric in many team sport activity profiles, research should attempt to investigate the influence of data filtering upon athlete acceleration.

CHAPTER 3 - A SYSTEMATIC REVIEW OF THE QUANTIFICATION OF ACCELERATION EVENTS IN ELITE TEAM SPORT.

3.1 Declaration of co-authorship and co-contribution

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

This declaration is to be completed for each conjointly authored publication and placed at the beginning of the thesis chapter in which the publication appears.

1. PUBLICATION DETAILS (to be completed by the candidate)

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2. CANDIDATE DECLARATION

I declare that the publication above meets the requirements to be included in the thesis as outlined in the HDR Policy and related Procedures – policy.vu.edu.au.

Signature	Date
[redacted] Digitally signed by Robert Delves Date: 2022.07.05 14:19:09 +10'00'	5/07/2022

3. CO-AUTHOR(S) DECLARATION

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

The undersigned certify that:

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

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

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

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

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

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Name(s) of Co-Author(s)	Contribution (%)	Nature of Contribution	Signature	Date
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3.2 Introduction

Through the continued development of athlete wearable technology, team sport practitioners have increasingly elected to monitor their athlete's exercise volume and intensity during training and competition with EPTS (Linke et al., 2018; Malone et al., 2017). Technologies, such as the Global Positioning System (GPS) and optical-based systems are established player tracking methods, whilst progressions have been made in the development of local positioning systems (LPS) and access to the Global Navigation Satellite System (GNSS). Regardless of the technology implemented, LPS and GNSS-based tracking systems allow for the relatively unobtrusive and objective collection of a player's locomotion during training and match-play, with information obtained on athlete distances and speeds (Aughey, 2011a; Malone et al., 2017). Tracking information allows for the creation of activity profiles for respective sports, which details the different volume and intensity placed upon athletes and positions played within that sport (Malone et al., 2017; Scott et al., 2016). For performance staff, an activity profile enables specific prescription of athlete training programs and rehabilitation processes that are centred towards preparing the athlete for the rigours of competition (Malone et al., 2017).

The ability to change speed and direction through acceleration and deceleration are important attributes for successful performance in many team sports (Delaney, Cummins, et al., 2018; Delaney, Thornton, et al., 2018; Osgnach et al., 2010; Reilly et al., 2000). Subsequently, team sport research has produced a wide variety of metrics to assess acceleration in training and competition (Delaney, Cummins, et al., 2018; Harper et al., 2019). Given the stochastic nature of team sport movement, the assessment of acceleration is imperative in depicting the activity profile of competition (Delaney, Cummins, et al., 2018). For example, team sport athletes across the football codes of rugby league, rugby union, association football and Australian football represent average match speeds that would be considered low speed intensity at approximately 80 to 140 $m \cdot min^{-1}$ (1.3 - 2.3 $m \cdot s^{-1}$) (Delaney, Cummins, et al., 2018). However, the football codes mentioned can see peak intensity up to 170 to 210 $m \cdot min^{-1}$ during a 1-minute moving average epoch and have been shown to further increase to an intensity up to 380 $m \cdot min^{-1}$ with smaller moving average window lengths (e.g., 5 seconds) (Delaney, Duthie, et al., 2016; Delaney, Thornton, Burgess, et al., 2017; Delaney, Thornton, Pryor, et al., 2017; Delaney, Thornton, et al., 2018; Howe et al., 2020). The wide range in intensity from match averages to competition peaks indicates that the ability to change speed (acceleration) is important to performance. In invasion/combat sports such as rugby league, where general play is contested in tight confines, acceleration volume is highest compared to other football codes, indicating the ability to rapidly change speed is important to successful performance in this code (Delaney, Duthie, et al., 2016; Delaney, Thornton, Burgess, et al., 2017; Delaney, Thornton, Pryor, et al., 2017; Delaney, Thornton, et al., 2018). Similarly, in American football, where players are also actively trying to gain or negate yardage, skill players such as wide receivers, defensive backs and line-backers accumulate substantial counts of high-accelerations (>3.5 $m \cdot s^{-2}$) per game (range: 26-38 counts per game) (Wellman et al., 2016).

Whilst being able to perform accelerations is important to successful athletic performance, quantifying accelerations is also important to practitioners for athlete management (Harper et al., 2019). Accelerations incorporate a significant portion of the total overall exercise volume during team sport training and competition (de Hoyo et al., 2016; Gastin et al., 2019; Harper et al., 2019; Russell, Sparkes, Northeast, Cook, Bracken, et al., 2016; Young et al., 2012). However, the magnitude of acceleration efforts can provide different sources of stimuli experienced by the athlete. For example, accelerations will place a greater metabolic cost on the body compared to deceleration events, as accelerations require greater energy to fuel the change in speed (Gastin et al., 2019; Howatson & Milak, 2009; Osgnach et al., 2010; Young et al., 2012). Deceleration events however differ from accelerations with respect to the mechanically demanding, eccentric stimulus placed upon the body when braking (particularly at high intensity). Athlete breaking (decelerating) is dampened by soft-tissue structures which attempt to attenuate the force of each deceleration effort (de Hoyo et al., 2016; Gastin et al., 2019; Harper et al., 2019; Russell, Sparkes, Northeast, Cook, Bracken, et al., 2016; Thompson et al., 1999; Young et al., 2012). In team sport athletes, an increased count of high-intensity accelerations is associated with neuromuscular fatigue and muscle damage (marked by increased creatine kinase [CK]) post competition (Gastin et al., 2019; Nedelec et al., 2014). Therefore, it is important that acceleration and deceleration can be appropriately quantified and monitored during training and competition to ensure athletes are adequately prepared for this volume (Delaney, Cummins, et al., 2018; Delaney, Duthie, et al., 2016).

For team sport practitioners and researchers however, the existing research on acceleration and how acceleration volume in competition and training is quantified, has varied greatly between studies (Delaney, Cummins, et al., 2018; Harper et al., 2019). Currently there are a multitude of different methods in which to quantify accelerations in team sport research (Cummins et al., 2013). Specifically, acceleration in applied team sports has been quantified via threshold based counts, time or distance spent in certain thresholds (e.g., >3.5 $m \cdot s^{-2}$ Threshold for “high-intensity accelerations”) or more recently, by combining all absolute acceleration data (regardless of intensity) and averaging over a defined time period (Cummins et al., 2013; Delaney, Cummins, et al., 2018; Malone et al., 2017; Nedelec et al., 2014; Sweeting, Cormack, et al., 2017; Varley, Fairweather, et al., 2012).

Regardless of the metric chosen to quantify acceleration, the measurement of acceleration is subject to the quality and filtering settings of the tracking system. In GNSS technology, there has been continual improvements in unit capabilities, with 10 Hz sample rates being deemed most valid and reliable for measuring acceleration (Akenhead et al., 2014; Delaney, Cummins, et al., 2018; Scott et al., 2016; Varley, Fairweather, et al., 2012). 10 Hz devices have been stated to, at worst, detect an acceleration had occurred, but otherwise have possessed acceptable validity for accelerations at various starting velocities in straight running (CV: 3.6-5.9%) (Varley, Fairweather, et al., 2012). However, deceleration at a starting speed between 5 – 8 $m \cdot s^{-1}$ had greater variability (CV: 11.3%) which was attributed to the rapid change in speed during deceleration compared to acceleration (Akenhead et al., 2014; Delaney, Cummins, et al., 2018; Varley, Fairweather, et al., 2012).

To analyse the quality of positional data in GPS/GNSS technology, the horizontal dilution of precision (HDOP) and the average number of connected satellites is extracted (Malone et al., 2017; Witte & Wilson, 2004). For GPS/GNSS technology, HDOP and the number of satellites provide an indication of the quality of connection and signal strength (Aughey, 2011a; Witte & Wilson, 2004). However, despite the importance of HDOP and the number of satellite information, the reporting of these metrics has been inconsistent in team sport research (Malone et al., 2017). With the development of online GNSS planning tools providing evidence of the number of available satellites for a given period, researchers and practitioners should endeavour to compare the satellite tracking information from their devices compared to website-based tools outlining satellite availability. Extracting satellite quality information can then aid in assessing the overall data quality of metrics surrounding acceleration events. Given the importance of signal quality on athlete positioning data, the HDOP and the number of connected satellites are significant variables that need to be reported upon in athlete tracking research. In practice, the publishing of HDOP and satellite data then aids practitioners to determine what data they should include and exclude in their athlete monitoring systems, including acceleration metrics. For example, HDOP values substantially greater than one or satellite numbers less than four to six, may be grounds for data exclusion in daily monitoring processes (Aughey, 2011a; Malone et al., 2017). Higher HDOP outputs indicate satellites closer together in proximity which is not optimal for athlete tracking. At least four satellites need to be connected to the receiver during human locomotion, but a greater number of satellites are believed to enhance athlete tracking data quality (Aughey, 2011a; Malone et al., 2017).

The processing or calculation of an acceleration event may also influence the measurement of athlete acceleration (Malone et al., 2017). It is believed that despite the similarities in hardware between manufacturers, the filtering and minimum effort durations in the calculation of acceleration/deceleration largely differ between units, potentially creating technology-driven differences in acceleration/deceleration-based research (Malone et al., 2017; Thornton, Nelson, et al., 2019; Varley et al., 2017). Despite the previously stated need for greater consistency in the reporting of wearable technology specifications and processes, there are still large inconsistencies in reporting of acceleration in team sport research.

With the ongoing development of athlete tracking systems as a measure of external athlete output and the approval to implement technology during competition, there is an increasing prevalence of the technology in team sport research (Harper et al., 2019; Malone et al., 2017). Additionally, with the extensive number of studies that have outlined activity profiles of respective sports during training and competition, numerous systematic reviews have been published (Harper et al., 2019; Hausler et al., 2016; Taylor et al., 2017; Whitehead et al., 2018). However, there is currently no systematic review that has outlined the different metrics and the calculation of the metrics used to quantify accelerations in team sport research. A previous systematic review outlined and compared high and very high-intensity accelerations in competitive team sports but this study was dependent upon intensity thresholds, which limited the overall scope of the study (Harper et al., 2019). The introduction of metrics such as absolute acceleration prompted this review to include all acceleration events/metrics regardless of the magnitude, as ultimately all acceleration and deceleration events carry a physiological cost (Delaney, Cummins, et al., 2018). With the inevitable further developments in player tracking technologies (e.g., optical systems) and the importance of accelerations in team sport activity profiles, it is pertinent to review and appraise the metrics that have been used to quantify acceleration/deceleration. Therefore, the primary aim of this systematic review was to outline and compare the different methods that have been adopted to quantify acceleration and deceleration events in team sport research. A secondary aim was to identify the processing methods used by researchers in calculating acceleration/deceleration by way of data filtering methods and minimum effort durations.

3.3 Methods

3.3.1 Study Design

The systematic review was undertaken in accordance with the Preferred items for Systematic Reviews and Meta-Analyses (PRISMA) statement on the transparent reporting of systematic reviews (Moher et al., 2009).

3.3.2 Search Strategy

Three electronic databases (CINAHL, Medline and SPORTDiscus) were systematically reviewed in May 2020 by the researcher to identify articles that investigated the quantification of acceleration and/or deceleration as a metric in the monitoring of team sport athletes in either training or competitive environments. Peer-reviewed research articles published in the English language between January 1, 2010, and April 2020 were reviewed for selection into the study. The search terms devised for this review were constructed using the PICo framework, where population (team sport/team sport athletes), interest (Quantification of Acceleration/Deceleration metrics) and context (in competition or training) were accounted for. Search terms and exclusion criteria (Table 3-1) relating to team sport athletes and the quantification of acceleration and deceleration in competition or training were then identified (Table 3-2). Boolean operators "OR" and "AND" were used in the final search to combine all search terms together (Table 3-2).

3.3.3 Screening Strategy and Study Selection

Upon execution of the search, all returned studies were collated and exported into a reference manager (EndNote X9, Thomson Reuters, Philadelphia, PA, USA) for further review. The initial review process incorporated three stages to identify qualifying articles. Firstly, all duplicate articles were identified and removed from the reference manager. Secondly, studies were scanned via their abstracts and keywords to establish relevance. If studies were deemed to be irrelevant at this juncture they were excluded. If doubt remained after inspection of the abstract as to the relevance of the study, it would advance to the next stage for further scrutiny. The final stage consisted of reviewing the full-text documents of each study and excluding articles that were subject to the exclusion criteria (Table 3-1). If doubt remained as to the eligibility of respective studies following this process, the researcher resolved the process through deliberation. If an article was identified through this process or identified in any other way other than the initial search it would be subject to the same review process to determine qualification.

Table 3-1. Search inclusion and exclusion criteria

Study inclusion/exclusion criteria	
Inclusion	**Exclusion criteria**
Original research articles	Systematic reviews, reviews, letters to the editors, non-peer reviewed articles, editorial, books, periodicals, surveys, opinion pieces, conference abstracts
Team-based sports	Outdoor court games (tennis, volleyball) Water-based, ice-based and sand-based sports.
Participants with a mean age ≥ 18 years	Research with the mean age of athletes below the age of ≤ 18 years.
Elite-level, able bodied, participants playing at the elite domestic competition for their respective team sport or international representation above U18 competition	Sub-elite level, amateur and novice athletes or athletes not playing within the top tier of their respective domestic league/competitions. Athletes with a physical or mental disability. Referees & Officials
Official team activities: Including competition/game/match observations and training sessions (e.g., small-sided games, match simulations, individual training drills)	Validation or reliability studies on wearable technologies using athletes in an experimental setting
GPS/GNSS-based trackers (Sampling ≥ 5 Hz) Optical/LPS-based Camera Systems	Accelerometers
Acceleration or deceleration events measured during designated team activities of any magnitude and measured in any available metric (e.g., counts, metres, time spent, average acceleration, acceleration load) that is not combined with any separate metric (e.g., metabolic power)	Combined metrics (metabolic power, repeat high-intensity efforts, PlayerLoad)
Research available in English (full text)	Research articles that are not published in English or cannot be accessed in English.

Table 3-2. Search terms and key words used in each database. Searches 1, 2, 3 and 4 were combined with 'AND'.

Key Search Terms	Related Search Terms
1. Acceleration/Deceleration	accelerat* OR decelerat* OR metabolic power OR metabolic load OR energetic cost
2. Athlete Tracking System	global positioning system* OR GPS OR global navigation satellite system* OR GNSS OR local positioning system* OR LPS OR microtechnology OR microsensor* OR tracking system* OR athlete tracking system OR notational analysis OR camera-based tracking OR optical tracking system
3. Team sport	team sport* OR team-sport* OR intermittent sport OR professional team sport OR elite sport OR elite team sport OR australian rules football OR australian rules OR australian football OR australian football league OR AFL OR australian football team OR australian rules football team OR australian football club OR australian rules football club OR soccer OR soccer player OR soccer team OR football OR footballer OR football player OR football team OR field hockey OR field hockey athlete OR field hockey player OR rugby league OR rugby OR rugby league player OR rugby league team OR rugby football OR rugby league competition OR rugby union OR rugby union player OR rugby union competition OR rugby union club OR rugby sevens OR rugby sevens competition OR lacrosse OR lacrosse competition OR american football OR american football player OR national collegiate athletic association OR NCAA OR gaelic football OR gaelic football player OR hurling OR hurling player OR cricket OR netball OR basketball
4.Training/Competition	movement demands OR movement pattern OR external load OR external demands OR physical workload OR physical demand* OR activity demand* OR activity profile OR activit* profile* OR match profile OR match demand* OR match play OR match-play OR match intensit* OR game load* OR game intensit* OR competit* demand* OR training OR training demands OR practice OR small sided games OR match simulation OR game simulation

3.3.4 Data Extraction

All relevant search data was extracted into a custom-made Microsoft Excel spreadsheet by the researcher. The extracted data from each eligible study included: athlete population (sport, competition, age, height, weight), athlete tracking system used (e.g., GNSS, LPS or camera-based) and the associated properties (e.g., unit sample rate, HDOP, number of satellites), acceleration metrics measured (e.g., counts, distance, or average acceleration), the filtering/processing method used to quantify the acceleration and any relevant acceleration findings. All acceleration events, regardless of the magnitude were included into the analysis. There were no exclusion criteria based on the speed threshold of the acceleration event. Similarly, all organised team activities, (training and competition) were eligible for inclusion into the study. Studies that only presented information on tracking reliability or validity in an experimental setting were excluded from analysis. Additionally, given the recent guidance on the reporting of GPS/GNSS device properties in research and similar systematic review publications, all available GPS/GNSS information was extracted from each relevant study (Harper et al., 2019; Malone et al., 2017). Specifically, the characteristics observed included: HDOP, number of satellites connected during activity, device sample rate, model and manufacturer.

3.4 Results

3.4.1 Search Results

The combined search of three databases returned 706 studies (SPORTSDiscus = 263, Medline = 272, CINAHL = 171) for analysis. All 706 studies were exported into a reference manager where 357 articles were removed as being duplicates. This resulted in the screening of 349 titles and abstracts. Of these titles and abstracts, 167 articles were deemed well outside the scope of the review and were subsequently removed. 182 full-text articles were reviewed and assessed relative to the parameters of the inclusive criteria. Upon review of all full text articles, 62 were excluded based on athlete skill level (n = 27), athlete age (n = 14), GPS sample rate (n = 12), inappropriate study type (n = 3) and other exclusions (including accelerometer derived acceleration and the use of combined metrics such as metabolic power) (n = 6). 120 studies remained at the completion of this process. Additionally, four studies were identified and included outside of the database search via the review process for this research. Therefore, 124 studies were included. Figure 3-1 identifies the classification of studies and pathway of eligibility into the study.

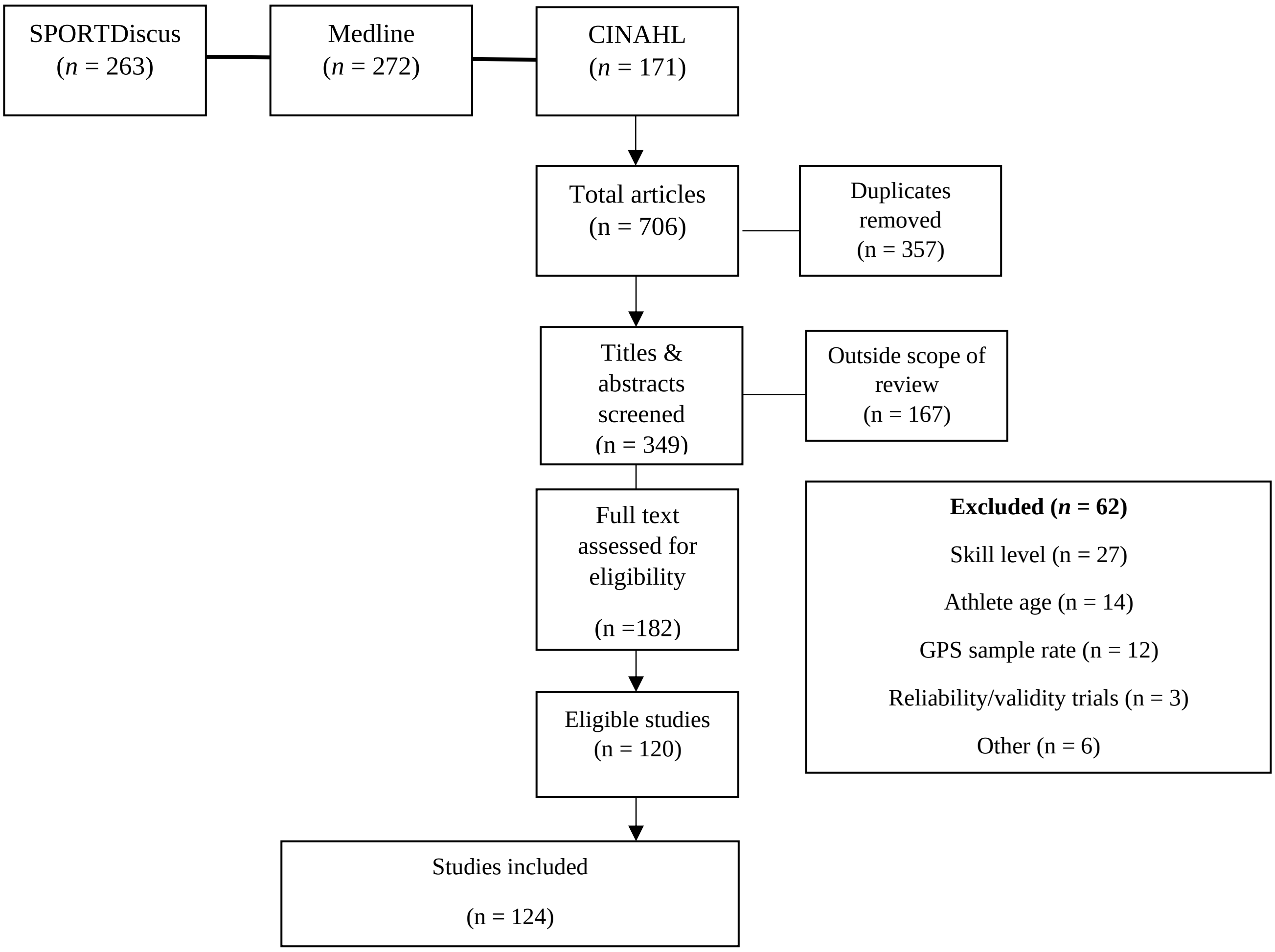

Figure 3-1. Systematic review inclusion process for qualification into the review

3.4.2 Study Characteristics

The accepted studies in this review outlined acceleration volume and/or intensity during an organised, elite team sport activity. This was measured through various player tracking technologies, including GPS/GNSS, local positioning systems or optical-based tracking systems. The results of this review are focused on how acceleration was quantified in these studies and the metrics used to present the acceleration activity profile. The characteristics of each of the included studies are summarised in Table 3-3.

Table 3-3. Tracking technology and acceleration/deceleration characteristics of each included study

Study	Team Sport	Device	Manufacturer	Model	Sample Rate (Hz)	HDOP	No. Satellites	Acc /Dec	Filter	Calculation Interval/ MED	Threshold ($m \cdot s^{-2}$)	Acc/Dec Metric	Calculation of Metric
(Akenhead et al., 2016)	Association Football	GPS	Catapult Sports	MinimaxX S4	10 Hz	0.9 ± 0.1	12 ± 1	Acc Dec	Smoothing Filter of 0.5s	0.5s	Low: 1 – 2 Moderate: 2 – 3 High: >3 Total: >1	Distance (m)	Distance attained in respective threshold band Acc/dec also pooled at 1 and 3 $m \cdot s^{-2}$
(Akenhead et al., 2013)	Association Football	GPS	Catapult Sports	MinimaxX	10 Hz	0.8 ± 0.1	13 ± 1	Acc Dec	N/S	N/S	Low: 1 – 2 Moderate: 2 – 3 High: >3 Total: >1	Acc & Dec Distance (m)	Threshold-based sum of acc/dec distances
(Akiyama et al., 2019)	Lacrosse	GPS	Polar Electro	Polar Team Pro	10 Hz	N/S	N/S	Acc Dec	N/S	N/S	Low: 0 – 1.99 Moderate: 2.0 – 3.99 High: > 4	Counts (n)	Efforts in respective threshold band
(Altavilla et al., 2017)	Association Football	GPS	K-Sport	N/S	10 Hz	N/S	N/S	Acc Dec	N/S	N/S	High: >2	Distance (m)	Distance attained in respective threshold band

Table 3-3. Continued

Study	Team Sport	Device	Manufacturer	Model	Sample Rate (Hz)	HDOP	No. Satellites	Acc /Dec	Filter	Calculation Interval/ MED	Threshold ($m \cdot s^{-2}$)	Acc/Dec Metric	Calculation of Metric
(Aughey, 2010)	Australian Football	GPS	Catapult Sports	MinimaxX Team Sport 2.0	5 Hz	N/S	N/S	Acc	N/S	0.4 s	Maximal: >2.78	Counts (n) Counts per minute (n/min^{-2})	At least two consecutive efforts at same rate of change in speed (0.4s) respective threshold band
(Aughey, 2011b)	Australian Football	GPS	Catapult Sports	MinimaxX Team Sport 2.0	5 Hz	N/S	N/S	Acc	N/S	0.4 s	Maximal: >2.78	Counts (n) Counts per minute (n/min^{-2})	At least two consecutive efforts at same rate of change in speed (0.4s) respective threshold Efforts with respect to activity time
(Aughey, 2013)	Australian Football	GPS	Catapult Sports	MinimaxX Team Sport 2.0	5 Hz	1.5 ± 0.9	7.5 ± 1.2	Acc	N/S	N/S	Maximal: >2.78	Counts (n) Counts per minute (n/min^{-2})	Efforts with respect to activity time
(Aughey et al., 2014)	Australian Football	GPS	Catapult Sports	MinimaxX Team Sport 2.0	5 Hz	N/S	N/S	Acc	N/S	0.4 s	Maximal: >2.78	Counts (n) Counts per minute (n/min^{-2})	At least two consecutive efforts at same rate of change in speed (0.4s) respective threshold band Efforts with respect to activity time

Table 3-3. Continued

Study	Team Sport	Device	Manufacturer	Model	Sample Rate (Hz)	HDOP	No. Satellites	Acc /Dec	Filter	Calculation Interval/ MED	Threshold ($m\cdot s^{-2}$)	Acc/Dec Metric	Calculation of Metric
(Bauer et al., 2015)	Australian Football	GPS	Catapult Sports	MinimaxX v4.0	10 Hz	1.8 ± 0.4	N/S	Acc	N/S	N/S	Low: 0 – 2.77 Hard: ≥2.78	Counts (n) Distance (m)	Efforts in respective threshold band Distance attained in respective threshold band
(Bayliff et al., 2019)	American Football	GPS	Catapult Sports	Optimeye S5	10 Hz	N/S	N/S	Acc Dec	N/S	N/S	Band 1: 0 – 1 Band 2: 1 – 2 Band 3: 2 – 3 Band 4: 3 – 10	Distance (m)	Metres attained in respective threshold band
(Blair et al., 2017)	Rugby Sevens	GPS	GPSports	SPI Pro 10	10 Hz	N/S	N/S	Acc Dec	N/S	N/S	Low: 1.5-2.5 High: >2.5-3.6	Counts (n)	Efforts in respective threshold band
(Bowen et al., 2019)	Association Football	GPS Optical	STATSports ChyronHego	Viper 2 TRACAB	10 Hz	N/S	N/S	Acc Dec	N/S	0.5 s	All: >0.5	Counts (n)	Efforts in respective threshold band lasting at least 0.5 s and > 0.5 $m\cdot s^{-2}$

Table 3-3. Continued

Study	Team Sport	Device	Manufacturer	Model	Sample Rate (Hz)	HDOP	No. Satellites	Acc /Dec	Filter	Calculation Interval/ MED	Threshold ($m{\cdot}s^{-2}$)	Acc/Dec Metric	Calculation of Metric
(Bradley et al., 2010)	Association Football	Optical	ProZone Sports	ProZone Version 3.0	N/A	N/A	N/A	Acc	N/S	N/S	Medium: >2.5-4 High: > 4	Counts (n)	Efforts in respective threshold band
(Brooks et al., 2020)	Netball	LPS	Catapult Sports	Catapult T6 ClearSky	10 Hz	N/A	N/A	Acc Dec	N/S	0.2 s	Z1: 0–2 Z2: 2–3.5 Z3: 3.5–6 Z4: 6–10	Acceleration Density: (Average Acc/Dec) ($m{\cdot}s^{-2}$) Acceleration Density Index: (avg Acc/Dec per 10 m; $m{\cdot}s^{-2}$) Total Acceleration Load: (total Acc/Dec; $m{\cdot}s^{-2}$) Distance (m)	Average acc values across the specified period Average acc performed per 10 m of distance (Acc Load/Distance) Sum of acc values across the analysed period (acc values were calculated at 0.2 s intervals) Distance attained in respective threshold

Table 3-3. Continued

Study	Team Sport	Device	Manufacturer	Model	Sample Rate (Hz)	HDOP	No. Satellites	Acc /Dec	Filter	Calculation Interval/ MED	Threshold ($m \cdot s^{-2}$)	Acc/Dec Metric	Calculation of Metric
(Campos-Vázquez et al., 2019)	Association Football	GPS	Catapult Sports	MinimaxX S4	10 Hz	N/S	N/S	Acc Dec	N/S	N/S	Moderate: 2 – 3 High: > 3	Distance per hour ($m \cdot hr^{-1}$)	Distance attained in respective threshold
(Chesher et al., 2019)	Field Hockey	GPS	Catapult Sports	MinimaxX S4	10 Hz	0.88 ± 0.03	11 ± 0.59	Dec	N/S	N/S	Low: -3 – -5.99 Medium: -6 – -8.99 High: -9 – -11.99 Very High: <-12	Counts (n) Average Deceleration ($m \cdot s^{-2}$)	Efforts in respective threshold band Mean Dec in each competitive match
(Clemente et al., 2019)	Association Football	GPS	JOHAN Sports	N/S	10 Hz	N/S	N/S	Acc Dec	N/S	N/S	High: >3	Counts (n)	Efforts in respective threshold band
(Couderc et al., 2019)	Rugby Sevens	GPS	Digital Simulation	Sensor Everywhere	8 Hz	N/S	N/S	Acc	Butterworth low-pass 2nd order Cutoff frequency: 1 Hz	0.5 s	High: >2.5	Counts (n)	Efforts in respective threshold band

Table 3-3. Continued

Study	Team Sport	Device	Manufacturer	Model	Sample Rate (Hz)	HDOP	No. Satellites	Acc /Dec	Filter	Calculation Interval/ MED	Threshold ($m \cdot s^{-2}$)	Acc/Dec Metric	Calculation of Metric
(Coutts et al., 2015)	Australian Football	GPS	Catapult Sports	MinimaxX Team Sport 2.5	10 Hz	N/S	N/S	Acc Dec	N/S	0.2 s	> 2.78	Counts (n)	Two consecutive samples exceeding 2.78 $m \cdot s^{-2}$
(Cummins et al., 2016)	Rugby League	GPS	GPSports	SPI Pro X	15 Hz[a]	N/S	N/S	Acc Dec	Butterworth 4th order Cutoff frequency: 1 Hz	N/S	Moderate: <1.12 High: 1.13 – 2.78 Very High: > 2.78	Counts per minute (n/min^{-2})	Efforts in respective threshold band with respect to activity time
(Cummins et al., 2019)	Rugby League	GPS	Catapult Sports	Optimeye S5	10 Hz	N/S	N/S	Acc Dec	N/S	N/S	All: >1.5	Counts (n)	Efforts in respective threshold band
(Cummins et al., 2018)	Rugby League	GPS	GPSports	SPI Pro X	15 Hz[a]	N/S	N/S	Acc Dec	Butterworth 4th Order Cutoff frequency: 1 Hz	N/S	Moderate: < 1.12 High: 1.13– 2.78 Very High: > 2.78	Counts (n)	Efforts in respective threshold band

[a]15 Hz device interpolated from 5 Hz

Table 3-3. Continued

Study	Team Sport	Device	Manufacturer	Model	Sample Rate (Hz)	HDOP	No. Satellites	Acc /Dec	Filter	Calculation Interval/ MED	Threshold ($m \cdot s^{-2}$)	Acc/Dec Metric	Calculation of Metric
(D. Cunningham et al., 2016)	Rugby Union	GPS	STATSports	Viper	10 Hz	N/S	N/S	Acc Dec	N/S	N/S	Moderate: 2 – 3 High: 3 – 4 Severe: >4	Counts (n)	Efforts in respective threshold band
(D. J. Cunningham et al., 2016)	Rugby Union	GPS	STATSports	Viper	10 Hz	N/S	4 Best Satellites	Acc Dec	N/S	N/S	Moderate: 2 – 3 High-Intensity: 3 – 4 Severe: > 4	Counts (n)	Efforts in respective threshold band
(Dalen et al., 2021)	Association Football	Radio Freq. Tracking	ZXY Sport Tracking	RadioEye Sensors	20 Hz	N/A	N/A	Acc	N/S	0.5 s	All: >2	Counts per minute (n/min^{-2})	Efforts lasting for at 0.5s in respective threshold band Efforts in respective threshold band with respect to activity time
(Dalen et al., 2016)	Association Football	Radio Freq. Tracking	ZXY Sport Tracking	RadioEye Sensors	20 Hz	N/A	N/A	Acc Dec	N/S	0.5 s	All: >2	Counts (n) Distance (m)	Efforts lasting for at 0.5s in respective threshold band

Table 3-3. Continued

Study	Team Sport	Device	Manufacturer	Model	Sample Rate (Hz)	HDOP	No. Satellites	Acc /Dec	Filter	Calculation Interval/ MED	Threshold ($m{\cdot}s^{-2}$)	Acc/Dec Metric	Calculation of Metric
(de Hoyo et al., 2016)	Association Football	GPS	GPSports	SPI Elite	10 Hz	N/S	N/S	Acc Dec	N/S	N/S	Moderate: 2 – 3 High: >3	Counts (n)	Efforts in respective threshold band
(Delaney, Cummins, et al., 2018)	Rugby League	GPS	GPSports	SPI HPU	5 Hz	N/S	N/S	Acc Dec	N/S	N/S	Low: 1 Moderate: 2 High: >3	Counts (n) Time (s) Distance (m) Average Acc ($m{\cdot}s^{-2}$) Average Dec ($m{\cdot}s^{-2}$) Average Acc/Dec ($m{\cdot}s^{-2}$)	Efforts, time and/or distance in respective threshold band Absolute values of acc averaged over given analysis period. Absolute values of dec averaged over given analysis period. Absolute values of acc/dec averaged over given analysis period
(Delaney, Duthie, et al., 2016)	Rugby League	GPS	GPSports	SPI HPU	15 Hz[a]	1.1 ± 0.1	8.3 ± 1.4	Acc Dec	Butterworth 4th Order Cutoff frequency: 1 Hz	N/S	N/A	Average Acc ($m{\cdot}s^{-2}$) / min	Absolute values of acc/dec averaged over given analysis period

[a]15 Hz device interpolated from 5 Hz

Table 3-3. Continued

Study	Team Sport	Device	Manufacturer	Model	Sample Rate (Hz)	HDOP	No. Satellites	Acc /Dec	Filter	Calculation Interval/ MED	Threshold ($m \cdot s^{-2}$)	Acc/Dec Metric	Calculation of Metric
(Delaney, Thornton, Burgess, et al., 2017)	Australian Football	GPS	Catapult Sports	Optimeye S5	10 Hz	N/S	N/S	Acc Dec	N/S	N/S	N/A	Average Acc ($m \cdot s^{-2}$) / min	Absolute values of acc/dec averaged over given analysis period
(Delaney, Thornton, Pryor, et al., 2017)	Rugby Union	GPS	GPSports	SPI HPU	15 Hz[a]	N/S	N/S	Acc Dec	N/S	N/S	N/A	Average Acc ($m \cdot s^{-2}$) / min	Absolute values of acc/dec averaged over given analysis period
(Delaney, Thornton, et al., 2018)	Association Football	GPS	Catapult Sports	Optimeye S5	10 Hz	0.86 ± 0.28	10.6 ± 1.7	Acc Dec	N/S	N/S	N/A	Average Acc ($m \cdot s^{-2}$) / min	Absolute values of acc/dec averaged over given analysis period
(Delves et al., 2019)	Field Hockey	GPS	Catapult Sports	Optimeye X4 MinimaxX S4	10 Hz	N/S	N/S	Acc Dec	N/S	N/S	N/A	Average Acc ($m \cdot s^{-2}$) / min Average Acc ($m \cdot s^{-2}$)	Absolute values of acc/dec averaged over given analysis period

[a]15 Hz device interpolated from 5 Hz

Table 3-3. Continued

Study	Team Sport	Device	Manufacturer	Model	Sample Rate (Hz)	HDOP	No. Satellites	Acc /Dec	Filter	Calculation Interval/ MED	Threshold ($m \cdot s^{-2}$)	Acc/Dec Metric	Calculation of Metric
(Dempsey et al., 2018)	Rugby League	GPS	GPSports	SPI Pro X	10 Hz	N/S	N/S	Acc Dec	N/S	N/S	High: >3.0	Counts (n) Counts per minute (n/min^{-2})	Efforts in respective threshold band Efforts calculated in absolute terms with respect to activity time and threshold
(Dubois et al., 2017)	Rugby Union	GPS	GPSports	SPI HPU	15 Hz[a]	N/S	N/S	Acc Dec	N/S	N/S	All: >2.5	Counts (n)	Efforts in respective threshold band
(Duthie et al., 2022)	Field Hockey	GPS	Catapult Sports	Optimeye X4	10 Hz	N/S	N/S	Acc Dec	N/S	N/S	N/A	Average Acc ($m \cdot s^{-2}$) / min	Absolute values of acc/dec averaged over given analysis period
(Figueiredo et al., 2019)	Association Football	GPS	STATSports	Viper Pod	10 Hz	N/S	N/S	Acc Dec	N/S	N/S	N/S	Counts (n)	Efforts in respective threshold band

[a]15 Hz device interpolated from 5 Hz

Table 3-3. Continued

Study	Team Sport	Device	Manufacturer	Model	Sample Rate (Hz)	HDOP	No. Satellites	Acc /Dec	Filter	Calculation Interval/ MED	Threshold ($m \cdot s^{-2}$)	Acc/Dec Metric	Calculation of Metric
(Furlan et al., 2015)	Rugby Sevens	GPS	GPSports	SPI HPU	5 Hz	N/S	N/S	Acc Dec	Butterworth 4^{th} Order cut off frequency: 1 Hz	N/S	Moderate: 2 – 3 High: 3.1 – 4 Very High: > 4	Counts per minute (n/min^{-2})	Acc/Dec counts calculated from filtered 15 Hz data Efforts in respective threshold band with respect to activity time
(Gabbett, 2012)	Rugby League	GPS	Catapult Sports	MinimaxX	5 Hz	N/S	N/S	Acc	N/S	N/S	Mild: 0.55 - 1.11 Moderate: 1.12 - 2.78 Maximal: >2.79	Counts (n)	Efforts in respective threshold band
(Gabbett, 2010)	Field Hockey	GPS	Catapult Sports	MinimaxX	5 Hz	N/S	N/S	Acc	N/S	2 s	High: >0.5	Counts (n)	Efforts in respective threshold band lasting at least 2 seconds
(Gabbett, 2013b)	Rugby League	GPS	Catapult Sports	MinimaxX Team Sport 2.5	5 Hz	N/S	N/S	Acc	N/S	N/S	Maximal: >2.79	Counts (n) Counts per minute (n/min^{-2})	Efforts in respective threshold band Efforts in respective threshold band with respect to activity time

Table 3-3. Continued

Study	Team Sport	Device	Manufacturer	Model	Sample Rate (Hz)	HDOP	No. Satellites	Acc /Dec	Filter	Calculation Interval/ MED	Threshold ($m \cdot s^{-2}$)	Acc/Dec Metric	Calculation of Metric
(Gabbett et al., 2012a)	Rugby League	GPS	Catapult Sports	MinimaxX	5 Hz	N/S	N/S	Acc	N/S	N/S	Mild: 0.55 - 1.11 Moderate: 1.12 - 2.78 Maximal: >2.79	Distance (m)	Distance in respective threshold band
(Gabbett & Ullah, 2012)	Rugby League	GPS	Catapult Sports	MinimaxX	5 Hz	N/S	N/S	Acc	N/S	N/S	Mild: 0.55 - 1.11 Moderate: 1.12 - 2.78 Maximal: >2.79	Distance (m)	Distance in respective threshold band
(Garvican et al., 2014)	Association Football	GPS	Catapult Sports	MinimaxX Team Sport 4.0	10 Hz	N/S	N/S	Acc	N/S	N/S	Maximal: >2.78	Counts (n) Counts per minute (n/min^{-2})	Efforts in respective threshold band Efforts in respective threshold band with respect to activity time
(Gaudino et al., 2014)	Association Football	GPS	GPSports	SPI Pro X	15 Hz[a]	N/S	Range: 8-11 Satellites	Acc Dec	N/S	1 s	Moderate: 2 – 3 High: >3	Counts (n) Maximum Acc/Dec ($m \cdot s^{-2}$)	Efforts in respective threshold band lasting for at least 1 s Maximum acc & dec effort in analysed period.

[a]15 Hz device interpolated from 5 Hz

Table 3-3. Continued

Study	Team Sport	Device	Manufacturer	Model	Sample Rate (Hz)	HDOP	No. Satellites	Acc /Dec	Filter	Calculation Interval/ MED	Threshold ($m \cdot s^{-2}$)	Acc/Dec Metric	Calculation of Metric
(Gaudino et al., 2015)	Association Football	GPS	STATSports	Viper	10 Hz	N/S	N/S	Acc Dec	N/S	0.5 s	Total: >3	Counts (n) Counts per minute (n/min^{-2})	Efforts in respective threshold band lasting for at least 0.5 s and of magnitude >0.5 $m \cdot s^{-2}$
(Hauer et al., 2021)	Lacrosse	GPS	Polar Electro	Polar Team Pro	10 Hz	N/S	N/S	Acc Dec	N/S	N/S	Z1: 0–1.0 Z2: 1.0–2.0 Z3: 2.0–3.0 Z4: >3.0	Counts (n)	Efforts in respective threshold band
(Higham et al., 2012)	Rugby Sevens	GPS	Catapult Sports	MinimaxX Team Sport 2.5	5 Hz	N/S	N/S	Acc Dec	N/S	0.4 s	Moderate: 2 – 4 High: >4	Counts per minute (n/min^{-2})	Efforts in respective threshold band with respect to activity time
(Higham et al., 2016)	Rugby Sevens	GPS	GPSports	SPI Pro X	15 Hz[a]	N/S	N/S	Acc Dec	N/S	1s	Total: >1	Counts per minute (n/min^{-2})	Efforts in respective threshold band with respect to activity time lasting at least 1 second.

[a]15 Hz device interpolated from 5 Hz

Table 3-3. Continued

Study	Team Sport	Device	Manufacturer	Model	Sample Rate (Hz)	HDOP	No. Satellites	Acc /Dec	Filter	Calculation Interval/ MED	Threshold ($m \cdot s^{-2}$)	Acc/Dec Metric	Calculation of Metric
(Hoppe et al., 2017)	Association Football	GPS	Catapult Sports	Minimax X S4	10 Hz	1.1 ± 0.1	11.8 ± 0.5	Acc Dec	Butterworth 2 Passes Cutoff: 1 Hz	N/S	High: >3	Time (s)	Time spent in respective threshold band
(Ihsan et al., 2021)	Field Hockey	GPS	Catapult Sports	Minimax X Team Sport 2.5	5 Hz	N/S	N/S	Acc Dec	N/S	N/S	High: >2	Counts (n)	Efforts in respective threshold band
(Ingebrigtsen et al., 2015)	Association Football	Radio Tracking	ZXY SportTracking	ZXY Sport Chip	40 Hz	N/A	N/A	Acc	N/S	0.5 s	Total: >2	Counts (n)	1) The start of Acc is marked by the Acc reaching the minimum limit (1 m·s) 2) Acc has to reach 2 m·s 3) Acc must remain above the 2 m·s for at least 0.5 s. 4) The duration of the Acc lasts until it passes the minimum Acc limit (1 m·s)

Table 3-3. Continued

Study	Team Sport	Device	Manufacturer	Model	Sample Rate (Hz)	HDOP	No. Satellite	Acc /Dec	Filter	Calculation Interval/ MED	Threshold ($m \cdot s^{-2}$)	Acc/Dec Metric	Calculation of Metric
(Jackson et al., 2018)	Field Hockey	GPS	Catapult Sports	MinimaxX S4 Optimeye S5	10 Hz	MinimaxX (0.89 [0.04]) Optimeye S5: (0.67 [0.05])	N/S	Acc Dec	Smoothing Filter	0.2 s - Calc 0.6 s – Minimum Effort Duration	Total: >1.46 Maximum Count per athlete	Counts (n) Maximum Acc/Dec ($m \cdot s^{-2}$)	Efforts in respective threshold band Max Acc/Dec recorded
(Jaspers, De Beéck, et al., 2018)	Association Football	GPS	Catapult Sports	Optimeye S5	10 Hz	N/S	N/S	Acc Dec	N/S	N/S	Z1: 0 – 1 Z2: 1 – 2 Z3: 2 – 3.5 Z4: >3.5	Counts (n) Distance (m)	Efforts in respective threshold band Distance attained in respective threshold band
(Jaspers, Kuyvenhoven, et al., 2018)	Association Football	GPS	Catapult Sports	Optimeye S5 MinimaxX S4	10 Hz	<1.5	≥8 satellites	Acc Dec	Smoothing Filter 0.2 s	0.4 s	Total: >1	Counts (n)	Efforts in respective threshold band

Table 3-3. Continued

Study	Team Sport	Device	Manufacturer	Model	Sample Rate (Hz)	HDOP	No. Satellites	Acc /Dec	Filter	Calculation Interval/ MED	Threshold ($m \cdot s^{-2}$)	Acc/Dec Metric	Calculation of Metric
(Johnston, Devlin, et al., 2019)	Rugby League	GPS	STATSports	Apex	10 Hz	0.76 ± 0.25	17.7 ± 1.9	Acc Dec	N/S	N/S	N/A	Average Acc ($m \cdot s^{-2}$) / min	Absolute values of acc/dec averaged over given analysis period
(Johnston et al., 2022)	Australian Football Rugby League	GPS	AF: Catapult Sports RL: STATSports	AF: Optimeye S5 RL: Apex	10 Hz	AFL: 0.69 ± 0.09 NRL: 0.76 ± 0.25	AFL: 10.5 ± 0.65 NRL: 17.7 ± 1.90	Acc Dec	N/S	N/S	N/A	Average Acc ($m \cdot s^{-2}$) / min	Absolute values of acc/dec averaged over given analysis period
(Johnston, Weaving, et al., 2019)	Rugby League	GPS	Catapult Sports	Optimeye S5	10 Hz	N/S	N/S	Acc Dec	N/S	N/S	N/A	Average Acc ($m \cdot s^{-2}$) / min	Absolute values of acc/dec averaged over given analysis period

Table 3-3. Continued

Study	Team Sport	Device	Manufacturer	Model	Sample Rate (Hz)	HDOP	No. Satellites	Acc /Dec	Filter	Calculation Interval/ MED	Threshold ($m\cdot s^{-2}$)	Acc/Dec Metric	Calculation of Metric
(Johnston et al., 2015a)	Australian Football	GPS	Catapult Sports	MinimaxX S3 MinimaxX S4	S3: 5 Hz S4: 10 Hz	1.0 ± 0.3	12.2 ± 0.7	Acc Dec	N/S	N/S	Low: 0.65–1.46 Moderate: 1.47–2.77 High: >2.78	Counts per minute (n/min^{-2}) Distance per minute (m/min) Time (%)	Efforts calculated in absolute terms with respect to activity time and threshold Distance in respective threshold band with respect to activity time and threshold Time spent as a percentage in respective threshold band
(Johnston et al., 2015b)	Australian Football	GPS	Catapult Sports	MinimaxX S3 MinimaxX S4	5 Hz 10 Hz	1.0 ± 0.2	12.1 ± 0.7	Acc Dec	N/S	N/S	Low: 0.65 - 1.46 Moderate: 1.47 - 2.77 High: >2.78	Counts per minute (n/min^{-2}) Distance per minute (m/min^{-2}) Time ($\%.\ min^{-2}$)	Efforts in respective threshold band with respect to activity time and threshold Distance attained in respective threshold band with respect to activity time and threshold Percentage time spent in respective threshold band with respect to activity time

Table 3-3. Continued

Study	Team Sport	Device	Manufacturer	Model	Sample Rate (Hz)	HDOP	No. Satellites	Acc /Dec	Filter	Calculation Interval/ MED	Threshold ($m\cdot s^{-2}$)	Acc/Dec Metric	Calculation of Metric
(Johnston et al., 2016)	Australian Football	GPS	Catapult Sports	MinimaxX S3 Minimax X S4	5 Hz 10 Hz	1.0 ± 0.1	12.2 ± 0.6	Acc Dec	N/S	N/S	Low: 0.65 - 1.46 Moderate: 1.47 - 2.77 High: >2.78	Counts per minute (n/min^{-2}) Distance per minute (m/min^{-2}) Time (%. min^{-2})	Efforts in respective threshold band with respect to activity time Distance attained in respective threshold band with respect to activity time Percentage time spent in respective threshold band with respect to activity time
(Jones et al., 2015)	Rugby Union	GPS	Catapult Sports	MinimaxX V4	10 Hz	N/S	N/S	Acc Dec	N/S	N/S	Low: 1 – 2 Moderate: 2 – 3 High: > 3	Distance (m)	Metres attained in respective threshold band
(Kempton & Coutts, 2015)	Rugby League Nines	GPS	GPSports	SPI Pro X	15 Hz[a]	N/S	N/S	Acc Dec	N/S	N/S	Total: >2.78	Counts (n) Counts per minute (n/min^{-2})	Efforts in respective threshold band Efforts calculated in absolute terms with respect to activity time and threshold

[a]15 Hz device interpolated from 5 Hz

Table 3-3. Continued

Study	Team Sport	Device	Manufacturer	Model	Sample Rate (Hz)	HDOP	No. Satellites	Acc /Dec	Filter	Calculation Interval/ MED	Threshold ($m \cdot s^{-2}$)	Acc/Dec Metric	Calculation of Metric
(Kempton et al., 2017)	Rugby League	GPS	GPSports	SPI Pro X	15 Hz[a]	N/S	N/S	Acc Dec	N/S	N/S	Total: > 2.78	Counts (n) Counts per minute (n/min^{-2})	Efforts in respective threshold band Efforts calculated in absolute terms with respect to activity time and threshold
(Kempton, Sirotic, Rampinini, et al., 2015)	Rugby League	GPS	GPSports	SPI Pro	5 Hz	N/S	9.1 ± 1.4	Acc Dec	N/S	0.4 s	Total: >2.78	Counts (n)	Two consecutive samples exceeding 2.78 $m \cdot s^{-2}$
(Lacome et al., 2014)	Rugby Union	PC-based tracking	Sport Universal Process	Amisco Pro	10 Hz Speed	N/A	N/A	Acc	Butterworth low-pass 2nd order Cutoff frequency: 1 Hz Double phase-lag filter	0.5 s	Z1: 1 – 2 Z2: 2 – 3 Z3: >3	Mean Acceleration ($m \cdot s^{-2}$)	Values of acc averaged over given analysis period. Distribution of acc values over given analysis period with respect to thresholds

[a]15 Hz device interpolated from 5 Hz

Table 3-3. Continued

Study	Team Sport	Device	Manufacturer	Model	Sample Rate (Hz)	HDOP	No. Satellites	Acc /Dec	Filter	Calculation Interval/ MED	Threshold ($m \cdot s^{-2}$)	Acc/Dec Metric	Calculation of Metric
(Lacome et al., 2014)	Rugby Union	PC-based tracking	Sport Universal Process	Amisco Pro	10 Hz Speed	N/A	N/A	Acc	Butterworth low-pass 2nd order Cutoff frequency: 1 Hz Double phase-lag filter	0.5 s	Z1: 1 – 2 Z2: 2 – 3 Z3: >3	Mean Acceleration ($m \cdot s^{-2}$)	Values of acc averaged over given analysis period. Distribution of acc values over given analysis period with respect to thresholds
(Malone et al., 2018)	Association Football	GPS	Catapult Sports	Optimeye G5	10 Hz	N/S	N/S	Acc Dec	N/S	N/S	High: >3	Counts (n)	Efforts in respective threshold band

Table 3-3. Continued

Study	Team Sport	Device	Manufacturer	Model	Sample Rate (Hz)	HDOP	No. Satellites	Acc /Dec	Filter	Calculation Interval/ MED	Threshold ($m\cdot s^{-2}$)	Acc/Dec Metric	Calculation of Metric
(Mara et al., 2016)	Association Football	GPS	GPSports	N/S	15 Hz[a]	N/S	5-8 Satellites	Acc	N/S	N/S	Efforts: >2	Time (s) Distance (m) Max Distance (m) Max Acceleration ($m\cdot s^{-2}$) Repeat Acceleration	Average time spent in acc in analysed period Average distance accumulated in analysed period Average max distance accumulated in analysed period Max acc effort in analysed period Acc efforts performed with <21 seconds separation
(Mara et al., 2015)	Association Football	GPS	GPSports	SPI HPU	15 Hz[a]	N/S	N/S	Acc Dec	N/S	N/S	High: >2	Counts (n)	Efforts in respective threshold band
(Marrier et al., 2019)	Rugby Sevens	GPS	Digital Simulation	Sensor Everywhere V2	16 Hz	< 2	7 [1]	Acc	N/S	0.5 s	All: >2.5	Counts (n)	Efforts in respective threshold band lasting for at least 0.5 s

[a]15 Hz device interpolated from 5 Hz

Table 3-3. Continued

Study	Team Sport	Device	Manufacturer	Model	Sample Rate (Hz)	HDOP	No. Satellites	Acc /Dec	Filter	Calculation Interval/ MED	Threshold ($m \cdot s^{-2}$)	Acc/Dec Metric	Calculation of Metric
(Martin-Garcia et al., 2019)	Association Football	GPS	STATSports	Viper	10 Hz	N/S	N/S	Acc Dec	N/S	N/S	High: >3	Counts (n)	Efforts in respective threshold band
(Martín-García et al., 2020)	Association Football	GPS	STATSports	Viper	10 Hz	N/S	N/S	Acc Dec	N/S	0.5 s	High: >3	Counts (n)	Efforts in threshold band lasting for at least 0.5 s and of magnitude > 0.5 $m \cdot s^{-2}$
(Martin-Garcia et al., 2018)	Association Football	GPS	STATSports	Viper	10 Hz	N/S	N/S	Acc Dec	N/S	N/S	High: >3	Counts (n)	Efforts in respective threshold band
(Modric et al., 2019)	Association Football	GPS	Catapult Sports	Optimeye S5 Optimeye X4	10 Hz	N/S	N/S	Acc Dec	N/S	N/S	Total Events: > 0.5 High: >3	Counts (n)	Efforts in respective threshold band

Table 3-3. Continued

Study	Team Sport	Device	Manufacturer	Model	Sample Rate (Hz)	HDOP	No. Satellites	Acc /Dec	Filter	Calculation Interval/ MED	Threshold ($m \cdot s^{-2}$)	Acc/Dec Metric	Calculation of Metric
(Montgomery & Maloney, 2018)	3x3 Basketball	GPS	Catapult Sports	Optimeye S5	10 Hz	N/S	N/S	Acc Dec	N/S	N/S	Low: <2.5 Medium: 2.5–3.5 High: >3.5	Intensity ($m \cdot s^{-2}$)	Average intensity in respective threshold band.
(Morencos et al., 2019)	Field Hockey	GPS	GPSports	SPI Elite	10 Hz	N/S	10.6 ± 1.2	Acc Dec	N/S	N/S	Low: 1 – 1.99 Moderate: 2.0 – 2.99 High: > 3	Counts (n) Counts per minute (n/min^{-2})	Efforts in respective threshold band Efforts calculated in absolute terms with respect to activity time and threshold
(Morencos et al., 2018)	Field Hockey	GPS	GPSports	SPI Elite	10 Hz	N/S	N/S	Acc Dec	N/S	N/S	Low: 1.0–1.9 Moderate: 2.0–2.9 High: > 3.0	Counts (n) Counts per minute (n/min^{-2})	Efforts in respective threshold band Efforts in respective threshold band with respect to activity time
(Murray & Varley, 2015)	Rugby Sevens	GPS	Catapult Sports	MinimaxX S4	10 Hz	N/S	11.3 ± 1.4	Acc	N/S	0.4 s	Maximal: > 2.78	Counts (n) Counts per minute (n/min^{-2})	Efforts in respective threshold band lasting at least 0.4 s Efforts calculated in absolute terms with respect to activity time and threshold lasting at least 0.4 s

Table 3-3. Continued

Study	Team Sport	Device	Manufacturer	Model	Sample Rate (Hz)	HDOP	No. Satellites	Acc /Dec	Filter	Calculation Interval/ MED	Threshold ($m \cdot s^{-2}$)	Acc/Dec Metric	Calculation of Metric
(Newans et al., 2019)	Association Football	GPS	Catapult Sports	Optimeye S5 Optimeye X4	10 Hz	N/S	N/S	Acc Dec	N/S	0.5 s	Moderate: 1 – 2 High: >2	Time (s) Ratio of Dec: Acc	Time spent in each respective threshold lasting at least 0.5 s Duration of Dec (High) and Dec (Mod) divided by total Acc time (High + Mod) in each period. Determined a moderate and high Dec:Acc ratio
(Owen et al., 2020)	Association Football	GPS	STATSports	Viper Pod	10 Hz	N/S	N/S	Acc Dec	N/S	N/S	Total: >3.3	Counts (n)	Efforts in respective threshold band
(Owen et al., 2015)	Rugby Union	GPS	GPSports	SPI HPU	15 Hz[a]	N/S	N/S	Acc Dec	N/S	N/S	Light: 1 – 1.99 Moderate: 2.0 – 2.99 Heavy: 3 – 5.99	Counts (n)	Efforts in respective threshold band

[a]15 Hz device interpolated from 5 Hz

Table 3-3. Continued

Study	Team Sport	Device	Manufacturer	Model	Sample Rate (Hz)	HDOP	No. Satellites	Acc /Dec	Filter	Calculation Interval/ MED	Threshold ($m \cdot s^{-2}$)	Acc/Dec Metric	Calculation of Metric
(Oxendale et al., 2016)	Rugby League	GPS	Catapult Sports	MinimaxX Team Sport 2.5	10 Hz	N/S	N/S	Acc Dec	N/S	N/S	Maximal: >2.79	Counts (n)	Efforts in respective threshold band
(Palmer et al., 2022)	Ultimate Frisbee	GPS	Catapult Sports	Optimeye X4	10 Hz	0.90 ± 0.10	13.7 ± 0.5	Acc	Proprietary Filter	0.6 s	Total: >1.5	Counts (n) Counts per minute (n/min^{-2})	Efforts in respective threshold band lasting for at least 0.6 s and with respect to time
(Guilherme Passos Ramos et al., 2019)	Association Football	GPS	Catapult Sports	MinimaxX Team S5	10 Hz	N/S	N/S	Acc Dec	N/S	N/S	1: -1 – 1 2: 1 – 2.5 3: > 2.5	Counts (n) Counts per minute (n/min^{-2})	Efforts in respective threshold band and with respect to time
(Guilherme . Passos Ramos et al., 2019)	Association Football	GPS	Catapult Sports	MinimaxX Team S5	10 Hz	0.75 ± 0.3	12.4 ± 0.5	Acc Dec	Exponential Filter (from GPS Software)	0.5 s	Total: >1	Counts (n)	Efforts in respective threshold band

Table 3-3. Continued

Study	Team Sport	Device	Manufacturer	Model	Sample Rate (Hz)	HDOP	No. Satellites	Acc /Dec	Filter	Calculation Interval/ MED	Threshold ($m \cdot s^{-2}$)	Acc/Dec Metric	Calculation of Metric
(Passos Ramos et al., 2017)	Association Football	GPS	Catapult Sports	MinimaxX Team S5	10 Hz	0.75 ± 0.3	15.5 ± 0.5	Acc Dec	N/S	N/S	Total: >2	Counts (n)	Efforts in respective threshold band
(Peeters et al., 2019)	Rugby Sevens	GPS	Digital Simulation	Sensor Everywhere	16 Hz	1.35 ± 0.34	8 ± 1	Acc	N/S	N/S	Total: >2.5	Counts (n) Counts per minute (n/min^{-2})	Efforts in respective threshold band Efforts calculated in absolute terms with respect to activity time
(Polglaze et al., 2018)	Field Hockey	GPS	Catapult Sports	MinimaxX S4	10 Hz	1.00 ± 0.07	11.6 ± 0.5	Acc	Proprietary Filter	0.6 s	Low: <2.0 High: >2.0	Counts (n) Counts per minute (n/min^{-2}) Time (s) Distance (m)	Eligible Acc was determined once a participant changed speed by 2 m.s for a minimum within 0.6 s. Efforts in respective threshold band Efforts calculated in absolute terms with respect to activity time and threshold Time spent in respective threshold band Distance attained in respective threshold band

Table 3-3. Continued

Study	Team Sport	Device	Manufacturer	Model	Sample Rate (Hz)	HDOP	No. Satellites	Acc /Dec	Filter	Calculation Interval/ MED	Threshold ($m \cdot s^{-2}$)	Acc/Dec Metric	Calculation of Metric
(Pollard et al., 2018)	Rugby Union	GPS	STATSports	Viper	10 Hz	N/S	N/S	Acc	N/S	N/S	Total: >3	Counts per minute (n/min^{-2})	Efforts in respective threshold band Efforts in respective threshold band with respect to activity time
(Portillo et al., 2014)	Rugby Sevens	GPS	GPSports	SPI Pro X	15 Hz[a]	N/S	N/S	Acc	N/S	N/S	Z1: >1.5 Z2: >2.0 Z3: >2.5 Z4: >2.75	Counts (n)	Efforts in respective threshold band
(M. J. Rennie et al., 2020)	Australian Football	GPS	Catapult Sports	Optimeye S5	10 Hz	1.1 ± 0.1	18.2 ± 1.1	Acc Dec	N/S	0.2 s Two Samples	Efforts: >2.78	Counts (n)	Two consecutive samples in respective threshold band
(Romero-Moraleda et al., 2020)	Field Hockey	GPS	GPSports	SPI Elite	10 Hz	N/S	N/S	Acc Dec	N/S	N/S	Low: 1 – 1.9 Moderate: 2 – 2.9 High: >3	Counts per minute (n/min^{-2})	Efforts in respective threshold band with respect to activity time

[a]15 Hz device interpolated from 5 Hz

Table 3-3. Continued

Study	Team Sport	Device	Manufacturer	Model	Sample Rate (Hz)	HDOP	No. Satellites	Acc /Dec	Filter	Calculation Interval/ MED	Threshold ($m \cdot s^{-2}$)	Acc/Dec Metric	Calculation of Metric
(Russell et al., 2015)	Association Football	GPS	STATSports	Viper	10 Hz	N/S	N/S	Acc Dec	N/S	N/S	Total: >0.5 High: >3	Counts (n)	Efforts in respective threshold band
(Russell, Sparkes, Northeast, Cook, Love, et al., 2016)	Association Football	GPS	STATSports	Viper	10 Hz	N/S	N/S	Acc Dec	N/S	0.5 s	Total: >0.5 High: >3	Counts (n)	Efforts in respective threshold band
(Sangnier et al., 2019)	Association Football	GPS	K-Sport	K-GPS	10 Hz	N/S	N/S	Acc Dec	N/S	0.4 s (over 3s threshold)	Distance: >2 Counts: >3	Counts per minute (n/min^{-2}) Distance per min (m/min)	Efforts >0.4 s (over 3 $m \cdot s^{-2}$ threshold) Distance in threshold band with respect to activity time
(Silva et al., 2018)	Association Football	GPS	STATSports	Viper	10 Hz	N/S	N/S	Acc Dec	N/S	0.5 s	Z1: >2 Z2: >2.5 Z3: >3	Counts (n) Counts per minute (n/min^{-2})	Efforts in respective threshold band lasting at least 0.5 s of magnitude > 0.5 $m \cdot s^{-2}$

Table 3-3. Continued

Study	Team Sport	Device	Manufacturer	Model	Sample Rate (Hz)	HDOP	No. Satellites	Acc /Dec	Filter	Calculation Interval/ MED	Threshold ($m \cdot s^{-2}$)	Acc/Dec Metric	Calculation of Metric
(Smpokos et al., 2018a)	Association Football	GPS	STATSports	Viper Pod 2	10 Hz	N/S	N/S	Acc Dec	N/S	0.5 s	Total: >2	Counts (n) & Counts per minute (n/min^{-2})	Efforts in respective threshold band lasting at least 0.5 s of magnitude > 0.5 $m \cdot s^{-2}$
. **(Smpokos et al., 2018b)**	Association Football	GPS	STATSports	Viper Pod 2	10 Hz	N/S	N/S	Acc Dec	N/S	0.5 s	Total: >2	Counts (n) & Counts per minute (n/min^{-2})	Efforts in respective threshold band lasting at least 0.5 s of magnitude > 0.5 $m \cdot s^{-2}$
(Stevens et al., 2016)	Association Football	LPS	Inmotio	Inmotio LPS	24 Hz	N/A	N/A	Acc	Weighted Gaussian Average	N/S	>2	Distance (m)	Distance in respective threshold band
(Stevens et al., 2017)	Association Football	LPS	Inmotio LPS	Inmotio LPS	31 Hz	N/A	N/A	Acc Dec	Weighted Gaussian Average	0.5 s	Medium: >1.5 High: >3	Counts (n)	Efforts in respective threshold band

Table 3-3. Continued

Study	Team Sport	Device	Manufacturer	Model	Sample Rate (Hz)	HDOP	No. Satellites	Acc /Dec	Filter	Calculation Interval/ MED	Threshold ($m \cdot s^{-2}$)	Acc/Dec Metric	Calculation of Metric
(Suarez-Arrones et al., 2016)	Rugby Sevens	GPS	GPSports	SPI Pro X	15 Hz[a]	N/S	N/S	Acc Dec	N/S	1 s	Maximal: 2.78 – 4 Extremely High: > 4	Counts (n)	1-second at >2.78 $m \cdot s^{-2}$ or above
(Suarez-Arrones et al., 2014)	Rugby Union	GPS	GPSports	SPI Pro X	15 Hz[a]	N/S	N/S	Acc	N/S	N/S	Maximal: >2.78	Counts (n)	Efforts in respective threshold band
(Sullivan et al., 2014a)	Australian Football	GPS	Catapult Sports	MinimaxX Team Sport 2.5	10 Hz	1.25 ± 0.19	N/S	Acc	N/S	N/S	One Threshold: 0 - 4	Counts per minute (n/min^{-2})	Efforts with respect to activity time
(Sullivan et al., 2014b)	Australian Football	GPS	Catapult Sports	MinimaxX Team Sport 2.5	10 Hz	1.25 ± 0.19	N/S	Acc	N/S	N/S	One Threshold: 0 - 4	Counts per minute (n/min^{-2})	Efforts with respect to activity time

[a]15 Hz device interpolated from 5 Hz

Table 3-3. Continued

Study	Team Sport	Device	Manufacturer	Model	Sample Rate (Hz)	HDOP	No. Satellites	Acc /Dec	Filter	Calculation Interval/ MED	Threshold ($m \cdot s^{-2}$)	Acc/Dec Metric	Calculation of Metric
(Sweeting, Aughey, et al., 2017)	Netball	Radio Tracking System	WASP	WASP Node	10 Hz	N/A	N/A	Acc	Kalman Filter	N/S	N/A	Intensity-based clusters ($m \cdot s^{-2}$)	Acceleration calculated from speed data.
(Tee et al., 2019)	Rugby Union	GPS	GPSports	SPI Pro	10 Hz	N/S	N/S	Acc	N/S	N/S	Efforts: >2.75	Minutes per Accel (n/min)	Efforts with respect to activity time
(Tee et al., 2016)	Rugby Union	GPS	GPSports	SPI Pro	5 Hz	N/S	N/S	Acc	N/S	1 s	Maximal: >2.75	Minutes per Accel (n/min)	Efforts in respective threshold band with respect to activity time
(Tee et al., 2017)	Rugby Union	GPS	GPSports	SPI Pro	5 Hz	N/S	N/S	Acc	N/S	N/S	Total: >2.75	Minutes per Accel (n/min)	Efforts in respective threshold band with respect to activity time

Table 3-3. Continued

Study	Team Sport	Device	Manufacturer	Model	Sample Rate (Hz)	HDOP	No. Satellites	Acc /Dec	Filter	Calculation Interval/ MED	Threshold ($m \cdot s^{-2}$)	Acc/Dec Metric	Calculation of Metric
(Thornton et al., 2018)	Rugby League	GPS	GPSports	SPI HPU	15 Hz[a]	N/S	N/S	Acc Dec	N/S	N/S	N/A	Acc/Dec Load (AU)	Average absolute value of all acc/dec data relative to a defined period. Absolute value multiplied by defined duration to convert to load metric
(Varley & Aughey, 2013)	Association Football	GPS	GPSports	SPI Pro	5 Hz	N/S	8 ± 1	Acc	N/S	N/S	Maximal: >2.78	Counts (n)	Efforts in respective threshold band
(Varley et al., 2014)	Association Football Rugby League Australian Football	GPS	AF & RL: Catapult Sports Association Football GPSports	AF & RL: MinimaxX Team Sport 2.5 Association Football: SPI Pro	5 Hz	N/S	N/S	Acc	N/S	N/S	Maximal: >2.78	Counts (n) Counts per minute (n/min^{-2})	Efforts in respective threshold band Efforts in respective threshold band with respect to activity time

[a]15 Hz device interpolated from 5 Hz

Table 3-3. Continued

Study	Team Sport	Device	Manufacturer	Model	Sample Rate (Hz)	HDOP	No. Satellites	Acc /Dec	Filter	Calculation Interval/ MED	Threshold ($m \cdot s^{-2}$)	Acc/Dec Metric	Calculation of Metric
(Vazquez-Guerrero et al., 2018)	Basketball	LPS	Realtrack Systems	WIMU Pro	20 Hz	N/A	N/A	Acc Dec	N/S	N/S	Total Acc: All counts High-Intensity: >2	Peak Acceleration ($m \cdot s^{-2}$) Counts (n) Counts per minute (n/min^{-2})	Highest acc value obtained during analysed period Efforts in respective threshold band Efforts in respective threshold band with respect to activity time
(Vescovi & Frayne, 2015)	Field Hockey	GPS	GPSports	SPI Pro	5 Hz	Values <4	8–12 Satellites connected during collection	Acc Dec	N/S	N/S	All Events:	Counts (n)	Efforts in respective threshold band
(Vigh-Larsen et al., 2018)	Association Football	Radio Tracking System	Chryon-Hego	ZXY Tracking System	20 Hz	N/A	N/A	Acc Dec	N/S	0.5 s	Total: >2	Counts (n) Counts per minute (n/min^{-2})	Efforts lasting at least 0.5 s and reaching at least $1 m \cdot s^{-2}$ Efforts lasting for at least 0.5 s and reaching at least $1 m \cdot s^{-2}$.

Table 3-3. Continued

Study	Team Sport	Device	Manufacturer	Model	Sample Rate (Hz)	HDOP	No. Satellites	Acc /Dec	Filter	Calculation Interval/ MED	Threshold ($m \cdot s^{-2}$)	Acc/Dec Metric	Calculation of Metric
(Wehbe et al., 2014)	Association Football	GPS	GPSports	SPI Pro	5 Hz	N/S	N/S	Acc Dec	N/S	0.5 s	Medium: 2.5 – 4 High: >4	Counts (n)	Efforts in respective threshold band lasting at least 0.5 s
(Wellman et al., 2017)	American Football	GPS	Catapult Sports	MinimaxX S5	10 Hz	N/S	N/S	Acc Dec	N/S	N/S	Low: 0 – 1.0 Medium: 1.1 – 2.0 High: 2.1 – 3.0 Maximal: >3.0	Distance (m)	Distance attained in respective threshold band
(Wellman et al., 2019)	American Football	GPS	Catapult Sports	Optimeye S5	10 Hz	N/S	N/S	Acc Dec	N/S	N/S	Low: 0 – 1.0 Medium: 1.1 – 2.0 High: 2.1 – 3 Maximal: >-3	Distance (m)	Distance attained in respective threshold band

Table 3-3. Continued

Study	Team Sport	Device	Manufacturer	Model	Sample Rate (Hz)	HDOP	No. Satellites	Acc /Dec	Filter	Calculation Interval/ MED	Threshold ($m \cdot s^{-2}$)	Acc/Dec Metric	Calculation of Metric
(Wellman et al., 2016)	American Football	GPS	GPSports	SPI HPU	15 Hz[a]	N/S	N/S	Acc Dec	N/S	N/S	Moderate: 1.5–2.5 High: 2.6–3.5 Maximal: > 3.5	Counts (n)	Efforts in respective threshold band
(White & MacFarlane, 2013)	Field Hockey	GPS	Catapult Sports	MinimaxX	5 Hz	Scotland Analysis: 1.3 ± 0.4 Ukraine Analysis: 1.0 ± 0.4	Scotland Analysis: 12.3 ± 1.0 Ukraine Analysis: 10.3 ± 1.2	Acc	N/S	N/S	High: >2	Counts (n)	Efforts in respective threshold band
(White & MacFarlane, 2015a)	Field Hockey	GPS	Catapult Sports	MinimaxX	5 Hz	Scotland Analysis: 1.3 ± 0.4 Ukraine Analysis: 1.0 ± 0.4	Scotland Analysis: 12.3 ± 1.0 Ukraine Analysis: 10.3 ± 1.2	Acc Dec	N/S	1 s	High: >2	Counts (n)	Efforts in respective threshold band lasting for at least 1 s

[a]15 Hz device interpolated from 5 Hz

Table 3-3. Continued

Study	Team Sport	Device	Manufacturer	Model	Sample Rate (Hz)	HDOP	No. Satellites	Acc /Dec	Filter	Calculation Interval/ MED	Threshold ($m \cdot s^{-2}$)	Acc/Dec Metric	Calculation of Metric
(White & MacFarlane, 2015b)	Field Hockey	GPS	Catapult Sports	MinimaxX	5 Hz	0.99 ± 0.2	11.2 ± 1.3	Acc	N/S	>1 s	High-Intensity: >3	Counts (n)	Efforts in respective threshold band lasting at least 0.5 s
(Yamamoto et al., 2020)	Rugby Union	GPS	GPSports	SPI Pro X	5 Hz	N/S	N/S	Acc	N/S	N/S	AZ1: 1.5–2.0 AZ2: 2–2.5 AZ3: >2.5	Counts (n)	Efforts in respective threshold band
(Young et al., 2019)	Hurling	GPS	STATSports	Viper Pod	10 Hz	N/S	N/S	Acc Dec	N/S	N/S	Total: >2	Counts (n)	Efforts in respective threshold band

3.4.3 Team Sport Characteristics

The team sport characteristics of each of the 124 studies is featured in Table 3-4. Of the 124 articles, research from association football provided the greatest contribution of studies to the review (33.9%), followed by rugby league (14.2%), Australian Football (11.8%) and field hockey (11.0%). Athlete sex was mixed in each sport contribution, except for Australian and American football, basketball, hurling, rugby league, rugby league nines and ultimate frisbee.

Table 3-4 Characteristics of Studies

Sport	Study Count	% Sport Contribution to Review	Study Athlete Sex		Athlete Level
			% Male	% Female	
3x3 Basketball	1	0.8	50	50	Elite, Junior International
American Football	4	3.1	100	0	Elite Collegiate
Australian Football	15	11.8	100	0	Elite
Basketball	1	0.8	100	0	Elite
Field Hockey	14	11.0	66	33	Elite, Elite Collegiate
Hurling	1	0.8	100	0	Elite
Lacrosse	3	2.4	66	33	Elite
Netball	2	1.6	0	100	Elite

Table 3.4 Continued

Sport	Study Count	% Sport Contribution to Review	Study Athlete Sex		Athlete Level
			% Male	% Female	
Rugby League	18	14.2	100	0	Elite
Rugby League Nines	1	0.8	100	0	Elite
Rugby Sevens	10	7.9	90	10	Elite
Rugby Union	13	10.2	92	8	Elite, Junior International
Association Football	43	33.9	88	12	Elite, Junior International
Ultimate Frisbee	1	0.8	0	100	Junior International
Total	**127**	**100**	**75**	**25**	

3.4.4 Tracking Device Characteristics

The wearable technology type, as well as respective manufacturers and devices is outlined in Table 3-5. Global Positioning System/GNSS-based studies were assessed on two data quality metrics. HDOP (mean ± SD) and the number of satellites (mean ± SD) in connection with the GPS device during athlete tracking were observed in this review. Of the 113 eligible GPS/GNSS studies, 23.9% (27/113 studies) of the included articles specified the mean HDOP for their research. For the number of satellite connections during the tracking period, 27.4% (31/113) of studies specified the mean ± SD value. This information is presented in Table 3-6.

Table 3-5 Tracking System Characteristics

Tracking Technology	Manufacturer	Device	Sample Rate
GPS	Catapult Sports	Optimeye S5	10 Hz
		Optimeye G5	10 Hz
		Optimeye X4	10 Hz
		MinimaxX S5	10 Hz
		MinimaxX S4	10 Hz
		MinimaxX S3	5 Hz
		MinimaxX Team Sport 2.0	5 Hz
		MinimaxX Team Sport 2.5	5 Hz 10 Hz
		MinimaxX Team Sport 4.0	10 Hz
		MinimaxX	5 Hz 10 Hz
	STATSports	APEX	10 Hz
		Viper	10 Hz
		Viper 2	10 Hz

Table 3.5 Continued

Tracking Technology	Manufacturer	Device	Sample Rate
GPS	GPSports	SPI Elite	10 Hz
		SPI HPU	15 Hz[a]
			5 Hz
		SPI Pro	10 Hz
			15 Hz[a]
		SPI Pro X	10 Hz
	Polar	Polar Team Pro	10 Hz
	Digital Simulation	SensorEverywhere	8 Hz 16 Hz
	JOHAN Sports	Johan GPS	10 Hz
	K-Sport	K-GPS	10 Hz
LPS	Catapult Sports	ClearSky T6	10 Hz
	Realtrack Systems	WIMU Pro	20 Hz
	Inmotio	Inmotio LPM	24 Hz
		Inmotio LPM	31 Hz
Radio Frequency	Chyron Hego	ZXY Tracking System	40 Hz
		ZXY Tracking System	20 Hz
	WASP	WASP Node	10 Hz
Optical-based tracking	ProZone Sports	ProZone 3.0	N/S
	Sport Universal Process	Amisco Pro	25 Hz

Table 3-6 GPS/GNSS data quality metrics of included studies

GPS/GNSS Data Quality Metric	Unit of Measure	Studies that outlined variable	% of Studies in Review that outlined information
Horizontal Dilution of Precision (HDOP)	Mean ± SD	27/113	23.9%
Number of Satellites Connected	Mean ± SD	31/113	27.4%

3.4.5 Acceleration Processing Characteristics

The processing methods in which studies implemented to calculate acceleration events is outlined in Table 3-7. The speed/acceleration filters that were implemented to process athlete movement data was specified by 12.9% (16/124 studies) of the studies included in this review. The minimum effort duration for the calculation of acceleration metrics were specified in 32.3% (40/124 studies) of the included studies. The specified minimum effort duration of 0.5 s was most frequent in the included studies, followed by 0.4 s, 1 s and 0.2 s.

Table 3-7 Acceleration Characteristics of Included Studies

Acceleration/Deceleration Calculation Metric	Unit of Measure	Minimum Effort Duration	Outlined in Studies	% of Studies in review
Speed or Acceleration Filter	N/A	N/A	16/124	12.9%
Minimum Effort Duration/Calculation Interval	Seconds (s)	Total	40/124	32.3%

3.4.6 Acceleration Metrics

Acceleration events in this review were quantified via numerous different metrics. These metrics encompassed counts, distance, time, load, intensity and ratio markers. Of these metrics, count-based variables were predominant. Acceleration counts were selected in 72% of the studies in this review. 63% of studies included absolute acceleration counts (regardless of magnitude), whilst 32% of studies implemented acceleration counts relative to the athlete or team's time during the activity (counts per minute). Distance, (m) was next highest in terms of prevalence with 13.7% of the research in this review opting to quantify acceleration events with respect to the distance attained in threshold bands. Metrics of acceleration intensity followed, with a combined 10.9% of studies (acceleration ($m \cdot s^{-2}$): 6.7%, deceleration ($m \cdot s^{-2}$): 4.2%) opting to quantify acceleration with respect to the acceleration distance relative to the time period. Similarly, absolute acceleration was selected in 9.2% of the included studies for this review. Statistics for the acceleration metrics included are presented in Table 3-8.

Table 3-8 Acceleration Metrics of Included Studies

Acceleration/Deceleration Metric	Unit of Measure	Metric Definition	% of Studies featuring metric
Counts	Counts (number)	Efforts in respective threshold band	62.9%
	Counts (number) per minute	Efforts in respective threshold band with respect to activity time	31.7%
	Counts (absolute and relative)	Overall absolute and relative count contribution to review	71.8%
Distance	Metres	Acc/Dec Distance attained in respective threshold band	13.7%
	Per minute	Distance in respective threshold band with respect to activity time and threshold	3.3%
	Per Hour	Distance attained in respective threshold band	0.8%

Table 3.8 Continued

Acceleration/Deceleration Metric	Unit of Measure	Metric Definition	% of Studies featuring metric
Acceleration	$m \cdot s^{-2}$	Intensity metric of any magnitude of acc over given analysis period.	6.7%
Deceleration	$m \cdot s^{-2}$	Intensity metric of any magnitude of dec over given analysis period.	4.2%
Acceleration Density Index	Avg Acc/Dec per 10 m; $m \cdot s^{-}$	Average acceleration performed per 10 m of distance covered (Acceleration Load/Distance)	0.8%
Acceleration Load	Total Acc/Dec; $m \cdot s^{-2}$	Sum of acceleration values across the analysed period	0.8%
		Average absolute value of all acc/dec data relative to a defined period.	
	AU	Absolute value multiplied by defined duration to convert to load metric	0.8%
Average Accel/Decel	($m \cdot s^{-2}$)	Absolute acceleration/deceleration values averaged across the specified period	9.2%

Table 3.8 Continued

Acceleration/Deceleration Metric	Unit of Measure	Metric Definition	% of Studies featuring metric
Time	Seconds	Time in respective threshold band	4.2%
	% time	Time spent as a percentage in respective threshold band	0.8%
	% time per minute	Percentage time spent in respective threshold band with respect to activity time and threshold	1.7%
	Minutes per count	Efforts in respective threshold band with respect to activity time	2.5%
Ratio of Dec:Acc	Ratio Dec:Acc	Duration of Dec (High) and Dec (Mod) divided by total Acc time (High + Mod) in each period.	0.8%

3.5 Discussion

The aim of this systematic review was to outline and compare the different methods that have been adopted to quantify acceleration events in previous team sport research. The main finding in this review was that the vast majority of included studies elected to quantify acceleration events using GPS/GNSS technology (113/124 studies) and via the use of count-based metrics (72% of all studies featured counts). Whilst the aim to ascertain how accelerations were quantified by way of metrics was achieved, this review could not achieve the secondary aim which was to determine how acceleration events were commonly processed in team sport research. Specifically, there was a lack of information provided by the studies in this review that outlined the filtering processes of acceleration events and the minimum effort duration in which these events were designated. In this review only ~13% of studies specified the filtering settings of their acceleration data whilst 32% outlined the minimum effort duration. Moreover, for GPS/GNSS research, the reporting of HDOP and the number of satellites was only specified in approximately a quarter of all eligible studies. Given the known influence of data quality metrics, filtering techniques and calculation intervals on acceleration/deceleration as it's calculated, future team sport research should endeavour to outline how acceleration and deceleration events are processed.

3.5.1 Variables chosen to Quantify Acceleration

The results of this review overwhelmingly highlight the use of counts to outline acceleration of team sport athletes. Counts and to a lesser extent, counts relative to time, accounted for the vast majority (counts: ~72% of all metrics) of acceleration variables selected by team sport researchers. The use of counts is not surprising given the practicality of implementing count-based metrics into the athlete monitoring process. Counts are advantageous to the practitioner for several reasons. Firstly, due to the ability to detail the number of actions occurring, usually with respect to thresholds. The volume of counts provides an indication of the total acceleration activity profile and when coupled with activity time of the athlete, can also provide an indication of the acceleration intensity. Secondly, it is relatively simple for a practitioner to apply thresholds to count metrics via the manufacturer proprietary software. This simplicity allows for efficient processing and analysis of the acceleration activity profile of the athlete or team.

In isolation, outlining the acceleration activity profile via counts is an acceptable choice for most researchers and practitioners. However, counts are regularly implemented in conjunction with speed-based thresholds that may separate efforts into corresponding bands (Harper et al., 2019). Despite the use of threshold bands being a common practice in applied sport science, this method is limited by the validity and reliability of the athlete tracking system recording the event (Delaney, Cummins, et al., 2018). Specifically, threshold-based counts for accelerations have been set at discrete intervals which may separate counts from being moderate or high with small differences separating the bands. For example, acceleration counts have been quantified using thresholds of 0 – 2.77 $m \cdot s^{-2}$ (low) and >2.78 $m \cdot s^{-2}$ (high) (Bauer et al., 2015). Moreover, similar research specified low acceleration counts at 1.5 – 2.5 $m \cdot s^{-2}$ and high counts at > 2.5 $m \cdot s^{-2}$ (Blair et al., 2017). Whilst it is logical to define a lower and upper threshold for each band, counts are also influenced by the level of error in the wearable technology (Delaney, Cummins, et al., 2018; Thornton, Nelson, et al., 2019). For example, large inter-unit variations were found between GPS units in acceleration and deceleration counts (Coefficient of Variation (CV): 10 – 56%) during a team sport movement simulation (Buchheit, Al Haddad, et al., 2014; Delaney, Cummins, et al., 2018). Following on from the team sport movement simulation research, the issue was raised that the variation seen in the study could have been a result of the use of threshold-based counts (Delaney, Cummins, et al., 2018). Specifically, the use of discrete bands for count-based acceleration events were suggested to be subject to the unit reliability and that the intensity threshold could then be subject to between-device variation (Delaney, Cummins, et al., 2018). Using the example previously provided, a 3 m·s^{-2} threshold could be measured differently by two different tracking devices (Delaney, Cummins, et al., 2018). One device may measure the event at 2.98 m·s^{-2}, which would not qualify for the threshold, whilst the other may measure the effort at 3.01 m·s^{-2}, which would constitute an event. It is then problematic if one device records the effort as an event, whilst the other does not, which may create inconsistencies in both the literature and the athlete monitoring process.

Issues surrounding the reliability of threshold-based variables also applies to the acceleration metrics that are measured in terms of distance (metres). Outside of the count-based metrics, distance-based acceleration variables were the third most frequent (18% combined) metric implemented by the included studies in this review. Despite sharing similar advantages to the use of count variables, distance-based metrics are also susceptible to similar issues of inter-unit reliability, particularly at moderate to high acceleration thresholds. A team sport simulation circuit was implemented to identify the inter-unit reliability for three commercially available GPS/GNSS units. For acceleration metrics, software-calculated, moderate acceleration distance for STATSports APEX units were classified as having poor reliability (CV; 90% Confidence Limit: 19.7%; ± 1.5%) whilst GPSports EVO (2.7%; ± 1.5%) and Catapult Sports S5 (3.1%; ± 1.6%) showed greater reliability (Thornton, Nelson, et al., 2019). The substantial variation seen across the results of the three GPS/GNSS manufacturers highlights the potential issues associated with threshold-based variables of acceleration metrics as measured by athlete tracking technology (Thornton, Nelson, et al., 2019). Moreover, interchanging tracking systems (e.g., GNSS & LPS) can also provide reliability issues between technologies for practitioners and researchers (Buchheit, Allen, et al., 2014). Given the increased use of LPS and camera-based systems within outdoor stadiums, practitioners may need to change between technologies depending on their training and competition locations (Thornton, Nelson, et al., 2019). Research. highlighted *small to very large* variation from one LPM system (Inmotio) against GPS (GPSports SPI Pro XII & VX VX340a) and a semi-automated camera system across acceleration efforts (>3 **$m{\cdot}s^{-2}$)** during match play analysis of the study (Buchheit, Allen, et al., 2014). With the results of the study, any variability between tracking systems may then have practical implications for practitioners. Generally, athletes complete the same team drills and therefore have an expectation surrounding the respective exercise volume associated with those drills.

A suggested way to alleviate the concerns with inter-unit variability in count-based approaches is to assign a wearable technology to an athlete for the duration of the season (Delaney, Cummins, et al., 2018; Jennings et al., 2010b). Whilst this suggestion is important to maintain consistency in the volume or intensity reporting for each athlete, it is not without limitation. The wearable device may consistently measure under the count threshold which may have practical implications for the practitioner and researcher (Delaney, Cummins, et al., 2018). Moreover, at the applied level it is not uncommon to group athlete positional data together to gain an understanding of the training and competition activity profile (Delaney, Cummins, et al., 2018). If the combined positional average data has existing variability at the individual athlete level, this may then extend into variation seen in the group average (Delaney, Cummins, et al., 2018). This review anticipates the implementation of count, distance and other threshold-based metrics in the reporting of acceleration will continue in future team sport research. However, it is important that researchers and practitioners understand the respective limitations outlined in these metrics before choosing to incorporate them in athlete monitoring workflows.

3.5.2 Choice of Athlete Tracking System

Whilst this review sought to include all forms of athlete tracking technology that outlined acceleration or deceleration, it is overwhelmingly clear that GPS/GNSS remains the most abundant and popular tracking technology within team sport research. From the results of this review, 113 out of the possible 124 studies (91%) implemented GPS or GNSS technology to track athlete locomotion. This is not surprising given GPS/GNSS technology was initially introduced in ~2003 in elite team sport and as such has seen continued developments as well as improvements in their commercial availability to practitioners (Aughey, 2011a; Edgecomb & Norton, 2006). The continued progressions in the capabilities of GPS/GNSS technology, regarding improvements in samples rates, along with the allowance to wear the technology in most major competitions, have seen these tools become commonplace in the monitoring of team sport athletes (Harper et al., 2019; Malone et al., 2017; Varley, Fairweather, et al., 2012). The wide-spread acceptance of these units (at the applied level) can be attributed to the many benefits GPS/GNSS provide the practitioner. These tools provide objective and unobtrusive data collection from the athlete on their volume and intensity in real time, which can be further analysed to develop training programs and activity profiles aimed at preparation for competition (Scott et al., 2016) . This is aided by the nature of outdoor team sports, particularly those conducted at stadia/practice facilities with no overhanging structures or surrounding infrastructure that may occlude or partially occlude the sky. With minimal occlusion, GPS/GNSS satellite signal connection is maintained and therefore allows for improved athlete tracking data quality. In turn there is no additional GPS/GNSS setup required by the practitioner, which enhances the practicality of tracking athlete movement during training and competition (Aughey, 2011a).

3.5.3 Distribution of GPS/GNSS Technology

The results of this review saw the utilisation of 21 different GPS/GNSS models from seven manufacturers in the outlining of acceleration and deceleration from the study cohort. Whilst the inclusion criteria of this review only included GPS/GNSS technology with sample rates at or above 5 Hz, there was a representation of both 5 Hz and 10 Hz sample rates from manufacturers. It is generally accepted that the use of 5 Hz GPS technology is disadvantaged compared to the greater capacities of 10 Hz technology, particularly for high-intensity acceleration and decelerations (Cummins et al., 2013; Scott et al., 2016). However, in the context of the calculation of acceleration and deceleration, the number of manufacturers and GPS/GNSS devices used, regardless of sample rate raises concern surrounding data consistency in reporting and methodology. The concern surrounding the number of GPS/GNSS devices used stems from the known differences that exist in the data filtering methods and minimum effort durations utilised between manufacturers in the calculation of acceleration (Thornton, Nelson, et al., 2019; Varley et al., 2017). This review is not suggesting that the number of models or manufacturers of wearable technologies is an issue, but rather the issue lies in the differences in their methods to calculate acceleration. With the number of the devices seen in this review, it is anticipated that at least on the manufacturer level, differences exist in acceleration processing (Thornton, Nelson, et al., 2019). The difference in acceleration processing may then extend between unit models, device firmware and between the proprietary software processing acceleration data (Thornton, Nelson, et al., 2019). Ultimately, variation between tracking technology could have the potential to create technology-influenced rather than athlete-driven differences in acceleration/deceleration volume or intensity (Thornton, Nelson, et al., 2019).

3.5.4 Local Positioning Systems in Team Sport Research

3.5.4.1 Background

Historically, it has been difficult for indoor-based team sports to capture the activity profile during training and competition (Hodder et al., 2020; Luteberget et al., 2018). Despite the continued growth of GPS/GNSS technology for outdoor team sports, the obvious limitation of enclosed stadium infrastructure means that GPS/GNSS signals cannot accurately penetrate and track indoor sports (Sweeting, Aughey, et al., 2017). As a consequence, there has been limited technology available to indoor team sport practitioners to adequately capture the activity profile of sports such as basketball, netball, handball and futsal, instead relying upon optical systems to track athlete locomotion (Hodder et al., 2020). However, the introduction of local positioning systems (LPS) or local positioning measurement (LPM) have seen sustained development since the inception of Radio Frequency Identification systems (RFID) (Frencken et al., 2010; Luteberget et al., 2018; Ogris et al., 2012; Sathyan et al., 2012; Stevens et al., 2014). Previously suggested to be the most abundant LPS within applied sport science, RFID systems operate by measuring the distance between anchor nodes at known locations around the field of play with athletes wearing the mobile nodes (Luteberget et al., 2018; Serpiello et al., 2018). Acceptable levels of accuracy exist during locomotion for RFID systems for measuring distance (mean error: 1.26 – 3.87 %) and for average and maximal speed (3.54 % and 13.15 %, respectively) (Ogris et al., 2012; Sathyan et al., 2012; Serpiello et al., 2018). However, RFID systems can be limited by incidents of signal instability and interference (Alarifi et al., 2016; Serpiello et al., 2018). The developments of LPS systems that operate via Ultra-Wideband (UWB) technology have been suggested to overcome the limitations of signal instability in RFID systems (Hodder et al., 2020; Serpiello et al., 2018). The enhanced technology seen in UWB systems allows for greater precision, with signals that can penetrate many structural materials (Alarifi et al., 2016; Hodder et al., 2020). The existing literature evaluating UWB-based LPS systems is limited but two UWB systems (WIMU Pro & Catapult ClearSky T6) are a valid means to assess the positioning of indoor court athletes (Bastida-Castillo, Gómez-Carmona, et al., 2019; Hodder et al., 2020; Luteberget et al., 2018; Serpiello et al., 2018). Operationally, LPS units operate through short-range communication wave generators that are in contact with receivers (Hodder et al., 2020). Local positioning system receivers are fixed to various points around the stadium to maximise full court coverage of the technology (Hodder et al., 2020).

3.5.4.2 Interaction of LPS Systems with outdoor team sport tracking

Whilst LPS-based studies represented a small contribution to the overall review, it is important to discuss the interaction of UWB and radiofrequency technology with outdoor team sport tracking. Given the development of UWB technology, the recent validation studies and the requirement for tracking system technology for indoor-based team sport athletes, it is anticipated that the use of LPS to measure acceleration will continue (Hodder et al., 2020). The prevalence of UWB LPS can be seen in applied sport science with the increasing utilisation of LPS in outdoor-team sport stadia (Aughey, 2011a; Thornton, Nelson, et al., 2019). Except for the use of optical tracking in association football, many outdoor team sports have historically tracked the activity profile in training and competition using GPS/GNSS technology. However, during outdoor-team sport competition in stadiums with obtrusive infrastructure, there may be instances of disruptions in signal quality. The disruptions may occur from overhanging stadium structures which disrupt the signal line of sight with satellites (Aughey, 2011a; Malone et al., 2017). To alleviate signal quality concerns, UWB LPS technology has been erected within outdoor stadia to remove the signal interference seen in GPS/GNSS data

(Thornton, Nelson, et al., 2019). It may be that with further UWB LPS development, these systems will be preferred over the traditional GPS/GNSS technology during competition within large stadiums. Regardless, the development of LPS for indoor-based team sports is important for the analysis of the acceleration of these athletes. However, it must be presented to practitioners that LPS technology is not without limitation. To utilise LPS, stadia must be appropriately fitted with the correct infrastructure before tracking can take place. This cost is expensive and may be problematic with venues that facilitate sporting and entertainment events (Serpiello et al., 2018). Similarly, to utilise this technology for away fixtures, the LPS infrastructure must be installed in the away venue which requires compatible technology to be of use (Thornton, Nelson, et al., 2019).

3.5.5 Alternative Acceleration Metrics.

The results of this review identified metrics outside of the traditional threshold-based variables for quantifying acceleration. This review identified that team sport researchers have implemented an absolute acceleration variable to quantify acceleration. Specifically, 9% of the studies included in this review presented the absolute acceleration metric, with many of the studies originating from the same research group (Brooks et al., 2020; Delaney, Cummins, et al., 2018; Delaney, Thornton, Burgess, et al., 2017; Delaney, Thornton, Pryor, et al., 2017; Delaney, Thornton, et al., 2018; Delves et al., 2019; Duthie et al., 2022; Johnston, Devlin, et al., 2019; Johnston et al., 2022; Johnston, Weaving, et al., 2019; Thornton et al., 2018). Absolute acceleration combines the absolute value of all acceleration data, (regardless of the magnitude) and is averaged over the given period (e.g., drill or match) (Delaney, Duthie, et al., 2016). The use of absolute acceleration avoids the issue of dichotomising a continuous variable into acceleration thresholds, as all acceleration events are included and are not subject to reliability issues that are seen with threshold-based metrics (Douglas & Patrick, 2006). For athlete monitoring, incorporating all acceleration events may be beneficial as all acceleration events carry a physiological and mechanical cost that needs to be accounted for (Delaney, Cummins, et al., 2018). At the research level, the reliability of this method was also found to be *good* to *moderate* in both 5 Hz (CV: 5.7%) and 10 Hz (CV: 1.2 %) technology (Delaney, Cummins, et al., 2018) when compared to VICON (Delaney et al., 2019), rendering the variable suitable for team sport monitoring.

Since the introduction of the absolute acceleration metric, there have been derivative metrics of this variable introduced into research (Delaney, Duthie, et al., 2016). Firstly, acceleration density index (ADI) (avg Acc/Dec per 10 m; $m \cdot s^{-2}$) incorporates the absolute acceleration metric, but is calculated as absolute acceleration performed per 10-metres of distance covered (Brooks et al., 2020). In essence, ADI is analysing acceleration volume relative to distance (Brooks et al., 2020). At the applied level, ADI may provide benefit to court-based sports such as netball or basketball where athletes may not accumulate high acceleration volume relative to total activity time (subject to rest), but accumulate substantial acceleration intensity during locomotion (e.g., goal shooters/goal keepers in netball or centres/power forwards in basketball) (Brooks et al., 2020). Secondly, volume measures calculated from absolute acceleration were evident in this review. Acceleration total load (total Acc/Dec; $m \cdot s^{-2}$) summates the accumulation of all acceleration events over an analysed time period (Brooks et al., 2020). For athlete monitoring, total acceleration load can be implemented as a standalone metric or it can be used as a supplementary variable which summates the information in threshold-based acceleration metrics (Brooks et al., 2020). Similarly, acceleration load (arbitrary units; AU) featured in this review, which was quantified by calculating absolute acceleration over the analysed period before multiplying the value by duration to convert to load (AU) (Thornton et al., 2018). With the growth of the absolute acceleration metric and the subsequent derivate metrics, the implementation of these variables both practically and in research is likely to continue.

3.5.6 Limitations of Included Studies

With the increasing prevalence of athlete tracking technologies in applied sport science there has been a requirement for standardised processes when collecting and reporting upon athlete datasets (Harper et al., 2019; Malone et al., 2017). The basis for a standardised collecting and reporting process is to ensure greater consistency and transparency when reporting activity profiles in research. In keeping with previous recommendations, this review attempted to extract values surrounding the quality of satellite data when tracking athletes over the analysed period (Malone et al., 2017) . Specifically, this review analysed the HDOP, and the number of satellites during the analysed activity. The horizonal dilution of precision provides a value of the accuracy of the GPS/GNSS horizontal positional signal as determined by the geographical positioning of the satellites (Hsu, 1994) Generally, when satellites are spread out, HDOP is low which enhances data quality (Williams & Morgan, 2009; Witte & Wilson, 2004). To rank HDOP quality, a scale of 1-50 is implemented (Malone et al., 2017; Witte & Wilson, 2004). Any HDOP value below 1 is considered optimal for HDOP readings with at least four to six satellites being required to capture human movement (Malone et al., 2017; Witte & Wilson, 2004). Despite the importance of these metrics pertaining to the data quality of each individual study, this review was limited by a lack of information surrounding HDOP and the number of satellite details. For HDOP, only 24% of the eligible GPS/GNSS studies specified a HDOP value for their respective study. Similarly, only 27% of studies outlined the mean number of satellites during the analysed periods. Consequently, it is difficult to make inferences regarding the studies included in this review without sufficient information regarding their data quality. Moreover, at an applied level it is then difficult for practitioners to make judgements regarding activity profiles. However, the researcher does acknowledge that whilst all GPS/GNSS units are capable of collecting HDOP and information on the number of satellites, the access to this information may be limited by EPTS providers, which in turn may not have been made available to researchers (Malone et al., 2017). However, with the availability of GNSS planning tools, researchers and practitioners are still to be able to obtain information relating to the availability of satellites and HDOP measures during data collection. Planning tools should be consulted to document the satellite activity during the data collection to supplement the satellite information from GPS/GNSS technology. Future research should endeavour to specify HDOP and satellite information where possible to allow researchers and practitioners a wholistic opportunity to evaluate research data quality.

Despite the potential differences that may exist between EPTS hardware and specifications (e.g., sample rate), the way in which acceleration events are calculated can result in substantial variation in the quantification of acceleration (Malone et al., 2017; Thornton, Nelson, et al., 2019; Varley et al., 2017). It is accepted that different EPTS manufacturers process acceleration events in different ways. Firstly, acceleration is not directly measured by the tracking technology. As a result, acceleration is calculated as a derivative measure of speed (for GNSS) (Akenhead et al., 2014; Winter, 2009). Secondly, there is a sweeping issue with the reporting of athlete tracking data in which there is no consensus method to process acceleration events. These two points coupled with the increasing amount of wearable tracking manufacturers available to practitioners has potentially created technology-influenced variations in acceleration volume and intensity between units (Malone et al., 2017; Thornton, Nelson, et al., 2019). Variations include the filtering of speed and/or acceleration data by EPTS manufacturers and also the selection of minimum effort durations (MED) for acceleration events (Harper et al., 2019; Varley et al., 2017).

The filtering of athlete tracking data can directly influence acceleration, regardless of the magnitude or metric used to quantify the event (Harper et al., 2019; Malone et al., 2017; Thornton, Nelson, et al., 2019; Varley et al., 2017). The purpose of filtering extends to maintaining data quality, removing poor signals and to decrease the noise content of the signal (Carling et al., 2008; Rader & Gold, 1967; Sweeting, Cormack, et al., 2017; Winter, 2009; Winter et al., 1974). In human movement, there are many different types of filters which have been introduced to process athlete data (Sweeting, Cormack, et al., 2017). In LPS, common filtering methods include, but are not limited to, Kalman and Butterworth filters, whilst GPS/GNSS technology can also utilise Butterworth as well as moving average, moving median, median or exponential filters (Couderc et al., 2019; Furlan et al., 2015; Malone et al., 2017; Sathyan et al., 2012; Stevens et al., 2014; Sweeting, Aughey, et al., 2017; Sweeting, Cormack, et al., 2017; Winter, 2009). However, the process by which manufacturers select their filtering process is arbitrary and can vary from manufacturer to manufacturer (Malone et al., 2017). In research and for applied sport science practitioners, this is problematic as there are many different manufacturers commercially available. As such there are many different types of filters that can be modified, potentially altering the magnitude of an acceleration event (Thornton, Nelson, et al., 2019). For example, manufacturers may elect to filter the speed trace using a determined filter and then calculate acceleration from the speed trace. Manufacturers may also filter the speed trace and then filter the calculation of acceleration using a predefined filter. Therefore, consistency in the reporting of filtering methods is required when processing athlete acceleration data. In this review, only 13% of studies detailed the filter used when processing athlete movement data. This detail includes proprietary filters as defined by the manufacturers and custom filters applied by researchers. The lack of information surrounding the filtering processes in these studies then raises questions as to any identified differences between research. Are these differences driven by the discrepancies between athlete-based external outputs or are they located from technology-driven influences from the use of different data processing methods (Thornton, Nelson, et al., 2019)? However, in posing this question, the researchers do acknowledge that in similar regard to satellite and HDOP information, the filtering process used in the calculation of acceleration via the manufacturer's proprietary software may not be made available.

With the lack of critical information on filtering and signal quality, the researcher was limited in the ability to make judgments and comparisons on acceleration. It is difficult to assess the activity profile without knowing how the acceleration data was processed, given the known influence these processes have on athlete volume and intensity (Harper et al., 2019; Malone et al., 2017; Thornton, Nelson, et al., 2019). Therefore, it is important that future research outlines the filtering processes used in the calculation of acceleration to ensure appropriate comparisons between tracking technology and the activity profile. However, if future research begins to improve the reporting process on filtering in the calculation of acceleration, there may still be issues surrounding the comparability of acceleration load between athlete tracking technologies and manufacturers. There may still be technology-driven discrepancies between activity profiles and validity and reliability studies of wearable technology (Thornton, Nelson, et al., 2019). Following on from previous summations, this review contends that future research should be centred towards a consistent method to process acceleration (Thornton, Nelson, et al., 2019). Despite the majority of the discussion surrounding GPS/GNSS technology, it is anticipated that these same difficulties would occur with local positioning systems and optical systems (Thornton, Nelson, et al., 2019).

The minimum effort duration (MED) is a qualifying criterion in which acceleration events need to be sustained for a specific time frame for the effort to be acknowledged as an event (Harper et al., 2019; Varley et al., 2017). For instance, if a MED of 0.5 s was chosen, the athlete would need to maintain the acceleration for at least 0.5 s for it to qualify as an event (Varley et al., 2017). However, the selection of the MED is problematic as the MED and any accompanying speed threshold and filter (where applicable) is generally arbitrary. The arbitrary selection of the MED may be due to many factors including the inconsistency in the selection of the MEDs within previous team sport research and the use of different EPTS manufacturers. Currently there is no consensus or consistent MED outlined in athlete tracking-based studies and as such, there has been a wide variety of different MEDs presented to calculate athlete acceleration (Harper et al., 2019; Varley et al., 2017). In this review there were six different MEDs selected, ranging from 0.2 s to 2 s, with the 0.5 s threshold being the most frequent. Moreover, approximately 68% of the included studies in this review did not specify their MED for acceleration or deceleration events.

The variation in MEDs between studies is problematic, as the calculation interval as well as the filter used directly influences the magnitude of an acceleration (Harper et al., 2019; Varley et al., 2017). In a previous review, the study made the point that small fluctuations between MED intervals (i.e., 0.1 s) can result in differences in the number of high-intensity acceleration efforts (Harper et al., 2019). The suggestion is based on original research which quantified the impact of differing MEDs (from 0.1 s to 1.0s (0.1 s increments) upon acceleration counts (Varley et al., 2017). In this research, the authors concluded that during an elite Dutch association football match, there was an exponential decline in the number of observed acceleration efforts as the MED increased, across all filtering methods (Varley et al., 2017). In essence, this finding confirmed that the selection of a lower MED of 0.1-0.3 seconds is more appropriate for capturing short and discrete GNSS acceleration events (Harper et al., 2019). However, MEDs of 0.1-0.3-seconds in length are also more susceptible to any error in measurement that may be as a result of numerous repeat accelerations that occur too closely together (Harper et al., 2019). Conversely, a MED of longer duration (> 0.5 s) may have a smoothing effect on the acceleration datapoints for GNSS-based technology, which in turn may dampen the magnitude of higher acceleration events or may underestimate the number of efforts (Varley et al., 2017). Moreover, the impact of any applied filter may also have implications on the magnitude of the acceleration count in conjunction with the defined MED. Longer MEDs may be more suitable for certain filter types compared to short MEDs. For example, a 2 s MED is substantially longer than a 0.5 s MED, which could impact filter use or MED selection. It may be that the choice of filter should align with the choice of MED duration to better handle acceleration data. It should be stressed that this research is GNSS based and may have different implications for LPS/LPM technology.

There is no one ‘perfect’ MED for the calculation of athlete acceleration (Varley et al., 2017). However, it is prudent for practitioners to realise the implications of the selection of a MED and how this may be compared with similar team sport activity profiles (Varley et al., 2017). It is also recognised by the researchers that the choice of a MED may be dictated by the EPTS manufacturer. Similar to the choice of filtering applied to acceleration data, practitioners may be limited to the MED specifications outlined by the manufacturer, whilst other manufacturers may allow complete customisation of the process. Regardless of the situation, differences in MED settings can still lead to differences in acceleration between research studies.

To alleviate the potential differences in volume or intensity as a result of different MED settings, previous research has highlighted the use of a threshold inclusion criteria (Harper et al., 2019; Varley et al., 2017). The inclusion criteria suggested that a qualifying threshold standard for an acceleration effort could be implemented alongside a MED. For example, the acceleration must eclipse 1 $m.s^{-2}$ for the effort to be counted. Moreover, to establish an acceleration endpoint for an effort, this could be implemented when acceleration falls below 0 $m.s^{-2}$ (Harper et al., 2019; Varley et al., 2017). However, the issue of varied MEDs in research still exists with this method. With inconsistencies seen between MEDs in this review, future research may then look to identify appropriate MEDs with respect to each team sport. The presence of MEDs with respect to each team sport would then create a more consistent approach to acceleration/deceleration reporting.

3.5.7 Future Research

To improve future research, studies should attempt to improve the consistency in the processing and reporting of team sport acceleration and deceleration. Specifically, future research should be guided by the following recommendations:

- Report the HDOP and number of satellites during data collection (satellite-based technology only).
- Report the acceleration processing method, including any filtering methods and the minimum effort duration (if known and applicable). Consideration of how the filtering method and MED align in the data handling process should also be recommended.

- Utilise GNSS planning tools (where applicable) to evaluate the performance of their respective wearable tracking system relative to the available satellites (satellite-based technology only).
- Move towards the determination of a common acceleration filter that can be used practically and within research that may be sport specific.

When reporting acceleration from tracking technology it is important that future studies attempt to outline the HDOP and the average number of satellites during analysis. Satellite information can be used by researchers and practitioners as an indication of signal quality and can aid in the evaluation of the quality of the acceleration/deceleration datasets. In terms of acceleration metrics, future research should also endeavour to outline the acceleration filtering used to process the acceleration data and the MED to quantify any threshold-based metrics (if known and applicable).

Future research should attempt to introduce a common acceleration filtering technique for the processing of athlete acceleration and deceleration. A common filtering technique that is sport specific may be appropriate. However, the number of tracking devices, manufacturers and systems seen in this review highlights the importance of having a consistent process to handle and process acceleration data. Without a consistent process and with the known influence filtering methods have upon acceleration/deceleration data, future research will continue to question whether differences in acceleration/deceleration volume and/or intensity are athlete or technology driven (Thornton, Nelson, et al., 2019).

3.6 Conclusions

Acceleration metrics are important components in the exercise monitoring process of team sport athletes. The ability to quantify acceleration events allows practitioners to understand the energetic (acceleration-focused) and eccentric stimulus placed upon the athlete during training and competition (Delaney, Cummins, et al., 2018). With athlete acceleration information, acceleration-specific volume and intensity can be accounted for in the athlete preparatory process.

Acceleration events in team sport research have been predominately quantified via the use of effort counts, including counts related to time. Other 'traditional' metrics in terms of acceleration being quantified via distance remains a relevant selection, as does average intensity by practitioners.

Global Positioning Systems and now GNSS, are the most common tracking systems utilised in the quantification of acceleration in the team sport athlete. However, despite the widespread use of GPS/GNSS technology in tracking athlete locomotion, there is a lack of information surrounding the signal quality via the HDOP and number of satellite metrics. Future research should aim to outline HDOP and the number of satellites where possible, to allow researchers to evaluate the quality of the athlete tracking data.

The calculation of acceleration is influenced by MEDs and the specification of data filtering processes. Despite the influence and variation of data filtering and MEDs between EPTS manufacturers, these metrics have not been consistently published in research. This review concludes that even if future studies outlined the acceleration data filtering process, the anticipated variation between tracking manufacturers may highlight technology-influenced variation in acceleration/deceleration outputs. Therefore, a consistent and potentially sport specific acceleration filtering process and reporting structure needs to be developed and introduced within applied team sport research.

CHAPTER 4 - A QUANTITATIVE SURVEY TO WEARABLE TECHNOLOGY MANUFACTURERS ON THE PROCESSING OF ATHLETE SPEED AND ACCELERATION DATA

4.1 Directions from Chapter 3

The systematic review on the quantification of acceleration in elite team sports in Chapter 3 showed a lack of information on the filter settings of athlete tracking technology. Approximately 13% of studies within the review detailed the filter settings that underpinned the calculation of athlete speed and/or acceleration. However, within activity profile research, it is not uncommon for practitioners and/or researchers to be unaware of the filter settings applied upon their proprietary tracking systems (Malone et al., 2017). For some athlete tracking system manufacturers, this information may not be made accessible to the end-user, which can translate to a lack of filter information circulated within research (Thornton, Nelson, et al., 2019). A lack of understanding on how acceleration is ultimately filtered/processed could contribute to some of the differences in the acceleration component of team sport activity profiles. To identify filter settings and to attempt to fill the gap in understanding of common filtering practices, this thesis proceeded to extend a quantitative survey to athlete tracking system manufacturers to outline how speed and subsequently acceleration is processed within their respective technologies.

4.2 Introduction

The use of electronic performance and tracking systems (EPTS) to track and measure athlete volumes and intensity in training and competition has become commonplace (Malone et al., 2017; Scott et al., 2016; Sweeting, Cormack, et al., 2017). Incorporating the Global Navigation Satellite Systems (GNSS), as well as local positioning systems (LPS) and optical camera systems, EPTS technologies provide information on external volume and intensity metrics of athletes (Linke et al., 2018; Sweeting, Cormack, et al., 2017; Taberner et al., 2020). The locomotion information provided by EPTS allows for the objective collection of athlete movement data, including information on athlete distances, velocities and accelerations which forms the basis of activity profiles of respective sports (Aughey, 2011a; Malone et al., 2017). For conditioning and support staff, details of the activity profile in training and in competition allows for appropriate training and rehabilitation program prescription (Aughey, 2011a; Malone et al., 2017).

Acceleration is an important variable for successful team sport performance and for athlete monitoring in team sport competition (Delaney, Cummins, et al., 2018; Lockie et al., 2011; Young et al., 1995). For team sports such as rugby league, rugby union and American football, the importance of acceleration is heightened, given the close proximity of attacking and defending players, which limits the ability to attain maximum speed (Duthie et al., 2006; Lockie et al., 2011; Young et al., 1995). Subsequently, rugby league has been identified has having the highest mean peak acceleration intensity of various football codes (rugby league; 1.25 $m{\cdot}s^{-2}$, Australian rules football; 1.01 $m{\cdot}s^{-2}$, rugby union; 0.96 $m{\cdot}s^{-2}$, association football; 0.85 $m{\cdot}s^{-2}$) (Delaney, Duthie, et al., 2016; Delaney, Thornton, Burgess, et al., 2017; Delaney, Thornton, Pryor, et al., 2017). Similarly, at peak competition intensity (1-minute epochs), average acceleration ($m{\cdot}s^{-2}$) intensity is greater than 1 $m{\cdot}s^{-2}$ across each rugby league position which equates to 60

$m \cdot min^{-2}$ (Delaney, Duthie, et al., 2016). Practically, this means that over each peak 1-minute interval, where speed intensity averaged 180 $m \cdot min^{-1}$, the speed changed by 60 $m \cdot min^{-2}$. Given the speed changed (in this example) by 33% of the mean speed intensity every second, the ability to facilitate rapid changes in intensity is necessary for the activity profile of competition (Delaney, Duthie, et al., 2016). From a physiological standpoint, accelerations and decelerations that occur during competition can have the potential to incite muscle damage (through increased creatine kinase [CK]) and neuromuscular fatigue in the athlete post-competition (Gastin et al., 2019; Harper et al., 2019; Nedelec et al., 2014; Russell, Sparkes, Northeast, Cook, Bracken, et al., 2016). Therefore, given the energetically demanding nature of accelerations and the eccentric demand on the athlete when decelerating, it is important to measure these events as part of the overall athlete and team management practices (Delaney, Cummins, et al., 2018).

However, the ability to effectively measure acceleration via EPTS has been scrutinised within research (Buchheit, Al Haddad, et al., 2014; Thornton, Nelson, et al., 2019). Since the initial validity study on a commercially available Global Positioning System (GPS) device for use in sport was completed in 2006, there has been a rapid rise in the number of publications pertaining to research surrounding the use of wearable technologies in human movement (Edgecomb & Norton, 2006; Malone et al., 2017). However, in terms of the measurement of acceleration, the continued development in wearable technology has become problematic. Given acceleration is not directly measured from wearable technologies (e.g., GNSS or LPS units) and is derived from doppler shift speed calculations, acceleration commonly undergoes filtering by the EPTS manufacturer to preserve data quality and to smooth erroneous datapoints (Malone et al., 2017; Thornton, Nelson, et al., 2019; Varley et al., 2017). A filter is required as the amount of noise in the signal increases with each calculation of a derivative. As acceleration is a second derivative, the noise has been stated to have the potential to increase up to nine times the original signal (Campbell et al., 2020; Winter, 2009). As a result, the time-interval over which acceleration is calculated can impact the data initially, with a smoothing effect created as the duration of the time-interval increases (Varley, Fairweather, et al., 2012; Varley et al., 2017). Typically, 10 Hz GPS technology will see time-intervals between 0.2 – 0.7 seconds, however, this can vary between units and manufacturers with no consensus time-interval currently in practice or in research (Varley, Fairweather, et al., 2012; Varley et al., 2017). Consequently, after acceleration has been calculated, data may then be filtered by methods determined by the manufacturer (Malone et al., 2017; Thornton, Nelson, et al., 2019; Varley et al., 2017). Both points are important as currently there are no consensus filtering methods in applied practice or research and information pertaining to acceleration filtering methods by manufacturers is not readily available (Malone et al., 2017; Thornton, Nelson, et al., 2019). For example, a previous systematic review on acceleration metrics identified that less than a quarter of all included studies (n = 124) identified the acceleration filtering process used in the formation of activity profiles from various team sports (Chapter 3). Subsequently many different types of filters could be applied to volume and intensity data, such as Butterworth, moving average, moving median, or exponential which all process tracking data differently, thus returning different outputs of acceleration (Campbell et al., 2020; Sweeting, Cormack, et al., 2017). Moreover, the cutoff frequency of the filter can impact acceleration. If the cutoff frequency is too low for a dataset, then some of the "true" signal may be removed, whilst if the cutoff frequency is too high, too much noise will be kept (Campbell et al., 2020; Erer, 2007).

At the applied level, comparisons between acceleration-based demands in team sport research becomes problematic, as activity profiles outlining competition are largely dependent on the EPTS manufacturer used (Thornton, Nelson, et al., 2019; Varley, Fairweather, et al., 2012; Varley et al., 2017). For example, in GPS research, it was suggested that given the different filtering techniques employed by manufacturers, differences in athlete volume during locomotion may be as a result of the influence on how the data is processed rather than differences between athlete outputs (Thornton, Nelson, et al., 2019). This point was further highlighted when reporting upon threshold-based acceleration and deceleration events of different intensity (e.g., low-intensity decelerations/high-intensity acceleration)(Thornton, Nelson, et al., 2019). In three commercially available, 10 Hz GPS devices (STATSports Apex, Catapult Sports S5 and GPSports EVO), the study found a *most likely* to *very likely* difference between manufacturers (S5 – EVO: Effect Size (ES) −1.9; ± 0.3, S5 – Apex: 1.2; ± 0.6, EVO – Apex: 1.7; ± 0.4) for high deceleration distance (measured in metres) and a *most likely* difference in high acceleration (m) events (S5 – EVO: −1.9; ± 0.1, S5 – Apex: -1.9; ± 0.2, EVO – Apex: -1.9; ± 0.1). Moreover, the study compared the demands calculated from each devices' raw processing and manufacturer-applied filters (Thornton, Nelson, et al., 2019). It was determined that the software-calculated acceleration demands across all thresholds were *most likely* (acceleration: −1.95; ± 0.04 to 1.93; ± 0.12) greater across all devices than compared to the respective demands determined by raw filtering. Additionally, deceleration (−1.94; ± 0.08 to 1.94; ± 0.06) demands across all thresholds were higher in the raw filtering for all units compared to the demands processed by the respective-manufacturer settings (Thornton, Nelson, et al., 2019). These findings highlight the influence of filtering methods on the exercise volume and intensity of athletes and the importance of knowing how athlete data is being processed to achieve the specified outputs.

However, the research did not provide or were not given access to the filtering methods used by each manufacturer (Thornton, Nelson, et al., 2019). This is important as given the inevitable growth of tracking technology used in applied sport science practice, and the variety of units used, it is prudent to know if/how athlete volume and intensity data is processed by commercial technology, as activity profiles are directly impacted which influences athlete training programs and protocols (Aughey et al., 2022; Sweeting, Cormack, et al., 2017). Given the importance of acceleration in team sport monitoring, the wide variation in activity demands found between tracking technology manufacturers and the lack of information surrounding filtering settings in research, it is prudent to analyse the current filtering techniques employed by EPTS manufacturers for greater clarification on how athlete data is handled. Therefore, the primary aim of this research is to anonymously outline the different acceleration filtering processes implemented by commercial EPTS manufacturers. Specifically, the study aimed to outline the filter types and cutoff frequencies implemented in the processing of athlete acceleration.

4.3 Methodology

4.3.1 Design and Participants

Twenty EPTS manufacturers were directly invited to participate in the study as part of an anonymous survey. The manufacturers who were invited to participate provided either GPS/GNSS, LPS and/or optical tracking systems. Tracking technology providers were identified from reliability and validity research articles, activity profile research, professional networks and through various sporting organisations globally. The invited manufacturers supplied tracking technology to team sport governing bodies, competitions and/or individual clubs/organisations. All participating manufacturers provided informed consent to participate in the study which was obtained electronically prior to the commencement of the questionnaire. Institutional ethical approval was granted prior to the commencement of the study (Victoria University Human Research Ethics Committee: HRE-21-011).

4.3.2 Procedure

An invitation to participate in the study was extended to EPTS manufacturers via email, direct website enquiry and through advertisements on institutional social media platforms. Emails and direct website enquiries to the manufacturers were directed to the sport scientist or sport science department of each manufacturer. If no response was received following the first two weeks of delivery of the first email, a second reminder email was sent. In the case of no response following this email, a third email was sent two weeks after delivery of the second email. If no response was received following the third reminder email, the manufacturer was excluded from participation in the study. Advertisements on social media platforms (Twitter™ & LinkedIn™) including personal accounts of the research group and institutional groups were displayed. Advertisements featured brief information regarding the study's background, aims and information to participants' document. The direct and anonymous electronic link to the survey was also provided.

To elect to participate in the study, representatives of each EPTS manufacturer were required to confirm their participation via selecting the participation option on the first page of the questionnaire. Manufacturers were required to submit their answers via a commercially available online survey provider (Qualtrics™, Sydney, Australia). The online survey did not require manufacturers to reveal their identities. However, in order for manufacturers to have the ability to withdraw from the study, manufacturers were asked to create a unique, eight-digit code that could be used to identify them to remove their responses. Researchers were not notified of which manufacturer had completed the survey; notification only detailed that a survey attempt had been completed. The electronic link to the survey was deactivated 12 weeks after the initial invitation emails had been sent.

The questionnaire contained 31 questions, all pertaining to the specific properties chosen by each manufacturer in processing speed and acceleration data for human movement. The questions asked in the survey were both open and closed in nature. Manufacturers were initially asked for details surrounding their tracking technology products and clientele, including the array of team sports in which they supplied their products. Specific questioning was directed towards their filtering process of acceleration data through segmented questioning, before asking for their reasoning for selecting this process and how they believed this was optimal for processing acceleration data.

4.3.3 Statistical Analysis

Due to the lack of survey responses received no statistical analysis was implemented on the survey datasets.

4.4 Results

Of the 20 direct invitations to manufacturers, two manufacturers fully completed the survey (10% participation). Five surveys were incomplete and were subsequently deemed not useful to the results of this study (25%). Two manufacturers declined to participate on grounds of commercial risk to their intellectual property (10%). Eleven manufacturers did not respond to any direct invitation correspondence (55%).

4.5 Discussion

The aim of the current study was to anonymously outline the range of acceleration filtering techniques used by EPTS manufacturers who supplied tracking technology to team sport clubs and competitions. Specifically, this study aimed to provide information on the filter types and cutoff frequencies used by manufacturers to improve the significant gap in the knowledge base within applied sport science research. Unfortunately, due to the low participation rates from EPTS manufacturers (2/20 complete survey results), this study was unable to achieve its aim. The current study cannot outline the range of filters and cutoff frequencies implemented across EPTS manufacturers.

It is difficult to attribute the low response rate from EPTS manufacturers to one explanation. The nature of the survey, structure, questions or recruitment could have limited the response rate. However, given two manufacturers (2/20) had declined to participate upon either direct invitation or within the survey itself, citing reasons surrounding commercial risk, it is believed by the researcher that the potential impact to the manufacturer's intellectual property may have hindered participation. This is not surprising given the commercial incentives that exist to EPTS manufacturers to secure contracts to provide clubs and governing bodies with their respective technologies (Aughey et al., 2022). Specifically, it is expected that the competitiveness of the EPTS market will continue to grow, with estimates of market worth increasing towards $7 billion USD by 2023 (MarketsandMarkets, 2019). Moreover, as currently there is limited independent certification of the validity and reliability in EPTS manufacturers from governing bodies and regulatory leagues/associations, there is a lack of incentive for EPTS manufacturers to supply their technology and software for assessment within research. However, the Fédération Internationale de Football Association (FIFA) has introduced the FIFA Quality Program which provides certification for EPTS manufacturers involved within association football. The Quality Program is intended to establish the validity and reliability in EPTS from different manufacturers by comparing EPTS manufacturer data against the criterion three-dimensional motion capture system (Aughey et al., 2022; Oliva-Lozano & Muyor, 2021). However, whilst the validity of EPTS technology can be evaluated in the FIFA Quality Program, as manufacturers are required to send their data for comparison against the criterion, the filter and processing settings may still remain confidential which hinders comparison between EPTS manufacturers at the research and applied level (Oliva-Lozano & Muyor, 2021).

The results of this study may indicate the unwillingness of EPTS manufacturers to provide information surrounding how they process athlete tracking data. At the research level this is a disappointing result, particularly for EPTS validity and reliability research. It is difficult to compare between units or manufacturers, particularly for derivative measures such as acceleration, given the lack of knowledge surrounding how acceleration has been calculated initially (Malone et al., 2017; Thornton, Nelson, et al., 2019; Varley, Fairweather, et al., 2012; Varley et al., 2017). Any differences identified between validity and research studies may be as a result of how acceleration is calculated rather than hardware and technology sample rate specifications (Thornton, Nelson, et al., 2019). Moreover, the existing validity and reliability research has generally provided an overview of how athlete tracking data can be filtered by manufacturers, but without any specific information regarding cutoff frequencies and filter types for manufacturers (Malone et al., 2017; Stevens et al., 2014; Sweeting, Cormack, et al., 2017; Varley et al., 2017). Research has compared raw GNSS files to the manufacturer's filter, but without knowledge of the specific manufacturer filtering settings (Thornton, Nelson, et al., 2019). Moreover, with continued development in EPTS technology and in particular, improvements in sample rates, it is believed that without greater transparency surrounding how EPTS manufacturers filter their data, the issue of inconsistency in validity and reliability research will continue.

Moreover, at the applied level, practitioners may also be impacted by a lack of transparency surrounding filtering processes. Practitioners are regularly required to compare training or competition activity profiles longitudinally across playing seasons/competitions (Aughey, 2011a; Bradley et al., 2009; Jennings et al., 2012a). Given the inevitable hardware, software or firmware upgrades in EPTS technology, longitudinal analysis would be impractical given the likely differences that would exist in the processing of derivative measures such as acceleration (Thornton, Nelson, et al., 2019). Without consistent processing of athlete acceleration data, information on the volume and intensity of training drills and match play may become varied which directly impacts upon athlete training program and rehabilitation prescription (Aughey, 2011a; Boyd et al., 2013; Sweeting, Cormack, et al., 2017).

Given that there may be a financial/commercial interest from EPTS manufacturers supplying tracking technologies to team sports and governing bodies, the withholding of filtering information to protect tracking products may continue. Consequently, for researchers and practitioners, it may be that if manufacturers are unable to outline the filtering settings for their technology, the development of a consistent filter may be required for individual or organisational use (Thornton, Nelson, et al., 2019). Specifically, the introduction of a consistent filter type with an appropriate cutoff frequency that can be implemented across an EPTS for use in either research or the applied setting. The use of a consistent filter and cutoff frequency could alleviate the current levels of variation seen in acceleration between EPTS manufacturers, with reference to longitudinal comparison.

If a common filter can be generated for the processing of acceleration, then researchers and practitioners could see greater levels of consistency in their various environments. For example, practitioners could elect to apply the filter when assessing the validity and reliability of acceleration metrics in new tracking technologies in comparison to existing technologies. At the applied level, practitioners may be required to upgrade their wearable tracking technologies or swap manufacturers. If practitioners can implement a common method to process acceleration outside of the manufacturer's processing (i.e., their own filtering), then there may be greater consistency in their acceleration metrics longitudinally. Greater consistency across multiple seasons worth of data would allow for improved decision making surrounding the acceleration-based volume and intensity of athletes and the respective demands associated with individual drills and sessions.

Future research should endeavour to determine the influence of applying a common acceleration filtering process to multiple wearable tracking technologies (from different manufacturers) during the same bout of locomotion. If a common filter can improve the agreement in acceleration between manufacturers there may be potential to further develop a common filter to be used within the applied and research environments. If a common filter does improve the variation seen in acceleration metrics between technology, it should be then validated against criterion technology to assess the validity of a common metric for future applications.

4.6 Conclusion

The current study could not sufficiently outline the acceleration processing techniques of wearable technology manufacturers. This study received two responses, potentially indicating the unwillingness of wearable technology manufacturers to reveal information surrounding how they process their athlete tracking data and the potential impact on external metrics. Given the commercial interests and continued development into wearable technologies for team sport performance, it may be researchers and practitioners should look towards the development of a consistent filter that can be applied between EPTS devices and manufacturers in both the research and applied environments.

CHAPTER 5 - APPLYING COMMON FILTERING PROCESSES TO GNSS-DERIVED ACCELERATION DURING TEAM SPORT LOCOMOTION

5.1 Declaration of co-authorship and co-contribution

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

This declaration is to be completed for each conjointly authored publication and placed at the beginning of the thesis chapter in which the publication appears.

1. PUBLICATION DETAILS (to be completed by the candidate)

Title of Paper/Journal/Book: Title: Applying common filtering processes to Global Navigation Satellite System-derived acceleration during team sport locomotion
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Accepted and in press: ☐ Date:
Published: ☑ Date: 13/03/2022

2. CANDIDATE DECLARATION

I declare that the publication above meets the requirements to be included in the thesis as outlined in the HDR Policy and related Procedures – policy.vu.edu.au.

[redacted] Digitally signed by Robert Delves
Date: 2023.01.21 14:24:08 +11'00' 05/07/2022

Signature **Date**

3. CO-AUTHOR(S) DECLARATION

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

The undersigned certify that:

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

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

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3. There are no other authors of the publication according to these criteria;
4. Potential conflicts of interest have been disclosed to a) granting bodies, b) the editor or publisher of journals or other publications, and c) the head of the responsible academic unit; and
5. The original data will be held for at least five years from the date indicated below and is stored at the following **location(s)**:

All electronic data will be stored on the Victoria University R Drive. This drive is the central storage facility maintained by Victoria University.

Name(s) of Co-Author(s)	Contribution (%)	Nature of Contribution	Signature	Date
Robert Aughey	5	Assisted with study design, feedback and revisions	[redacted]	20/01/2023
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5.2 Directions from Chapter 4

The results from Chapter 4 in this thesis did not update the current knowledge base on the filter processes implemented by EPTS manufacturers. The lack of survey responses in Chapter 4 could suggest that the filter settings used in processing athlete speed and/or acceleration are protected by manufacturers to maintain any perceived competitive or commercial advantage. However, for the practitioner and researcher, a lack of clarity on how speed and/or acceleration is calculated can hinder longitudinal comparisons of activity profiles across different units, software, firmware, both internally and towards published literature. Due to the unwillingness of manufacturers to provide information on their filter settings, this thesis then pivots to investigate the use of a common filter process to apply on GNSS technology from different manufacturers during team sport training sessions. Firstly, the thesis will begin to outline whether manufacturers process acceleration in different methods via Chapter 5, before beginning to analyse how a common filter could improve the comparison of athlete acceleration in a range of different experimental settings.

5.3 Introduction

Through the continued development of athlete tracking systems, team sport practitioners have increasingly elected to monitor their athlete's locomotion during training and competition with the Global Navigation Satellite System (GNSS) (Buchheit, Al Haddad, et al., 2014; Cummins et al., 2013; Jackson et al., 2018; Malone et al., 2017; Scott et al., 2016). Typically worn in either custom-made undergarments or jersey pouches, GNSS units are positioned near the scapulae and allow for the objective collection of an athlete's position and speed during training and competition (Aughey, 2011a; Malone et al., 2017). The tracking of positional and time data from the GNSS unit allows for the subsequent calculation of other variables, including acceleration (Aughey, 2011a, 2011b; Varley & Aughey, 2013). Information outlining the different locomotion variables then allows for the creation of activity profiles for respective sports, which detail the different volumes and intensity experienced when competing within that sport (Aughey, 2011a). For performance staff, information on activity profiles enables prescription of athlete training programs that are centred towards competition (Aughey, 2011a; Jackson et al., 2018; Jennings et al., 2010a; Malone et al., 2017; Petersen et al., 2009).

The ability to accelerate, decelerate and change direction are important attributes for successful performance in many team sports (Delaney, Cummins, et al., 2018; Hoffmann Jr et al., 2014; Lockie et al., 2011; Young et al., 2018). For example, running speeds for many team sport athletes may be limited due to opponent movements and space limitations in invasion sports (Delaney et al., 2019). Space limitations may prompt the need to both accelerate and negatively accelerate (decelerate) in order to penetrate defensives lines and to capitalise on scoring opportunities (Delaney et al., 2019). For example, the nature of rugby league and rugby union competition promotes accelerations and decelerations through the proximity of the attacking and defending lines (Delaney, Cummins, et al., 2018; Delaney et al., 2019). Mean peak acceleration intensity across rugby league positions and phases of play have ranged from 1.00 to 1.46 $m{\cdot}s^{-2}$, which is comparatively higher to values reported in other football codes such as association football (~0.75 – 0.86 $m{\cdot}s^{-2}$) (Delaney, Duthie, et al., 2016; Delaney, Thornton, et al., 2016; Delaney, Thornton, et al., 2018; Whitehead et al., 2021). The differences in acceleration intensity between team sports indicates the importance of the assessment of acceleration in the determination of team sport activity profiles.

The quantification of acceleration is central to athlete management (Harper et al., 2019). Accelerations incorporate a significant portion of the activity profile during competition (de Hoyo et al., 2016; Gastin et al., 2019; Harper et al., 2019; Russell, Sparkes, Northeast, Cook, Bracken, et al., 2016; Young et al., 2012). However, both accelerations and decelerations provide a different stimulus on the body. Accelerations have a greater metabolic cost and can contribute to neuromuscular fatigue, whilst decelerations are known to be eccentrically demanding (Clarkson & Newham, 1995; Newham, McPhail, et al., 1983; Newham, Mills, et al., 1983). The eccentric loading from decelerations creates a greater mechanical load from high force rates and subsequent braking which is dampened by soft-tissue structures (Clarkson & Newham, 1995; de Hoyo et al., 2016; Gastin et al., 2019; Harper et al., 2019; Newham, McPhail, et al., 1983; Russell, Sparkes, Northeast, Cook, Bracken, et al., 2016; Young et al., 2012). Consequently, in team sport athletes, muscle damage (quantified by increased creatine kinase [CK]) post competition has been identified from high-intensity accelerations and decelerations (Gastin et al., 2019; Harper et al., 2019; Oxendale et al., 2016).

To quantify acceleration during training or competition, GNSS technology is frequently utilised (Akenhead et al., 2014; Buchheit, Al Haddad, et al., 2014; Harper et al., 2019). Commonly, acceleration in team sport has been quantified via threshold-based variables, where counts, time or distance spent in certain thresholds (e.g., > 3.5 m·s^{-2} for high-intensity accelerations) have been analysed (Chapter 3). However, threshold-based measures are limited by the efficacy and processing settings of the tracking technology measuring the event (Delaney, Cummins, et al., 2018; Thornton, Nelson, et al., 2019). For example, the very large variations seen in a team sport simulation circuit during positive (CV = 10–43%) and decelerations (CV = 42–56%) could be attributed to the between-unit reliability (Buchheit, Al Haddad, et al., 2014).

Before the interpretation of activity profile variables such as acceleration, tracking technology validity and reliability should be established. Previous research has detailed that tracking technology is evaluated at three levels (Linke et al., 2018). These levels include positional accuracy (spatial domain) followed by the accuracy of instantaneous speed and acceleration and lastly, the accuracy of individual variables (i.e., max speed, high-speed distance). Previous research reported inferior validity in the measurement of positional accuracy in GPS (96 ± 49 cm) technology compared to a local positioning system (LPS) (23 ± 7 cm) against VICON (Linke et al., 2018). However, for measures of instantaneous speed (0.28 ± 0.07 m·s^{-1}) and subsequently, acceleration (0.67 ± 0.21 m·s^{-2}), GPS was identified by the authors as valid with improved root mean square error (RMSE) against VICON, potentially due to the lack of "cycle slips" associated with doppler shift derived speed (Linke et al., 2018). Research indicates that GPS/GNSS technology has the potential to be valid for instantaneous speed measures which then allows for acceleration to be calculated (Linke et al., 2018). However, the initial process in quantifying acceleration is immediately influenced by any pre-processing and data filtering from the EPTS manufacturer (Carling et al., 2008; Delaney et al., 2019; Linke et al., 2020; Stevens et al., 2014; Sweeting, Cormack, et al., 2017; Wundersitz et al., 2015). Data from wearable technology may be pre-processed in what would be considered raw manufacturer data, which may alter the magnitude of outputs to some degree (Malone et al., 2017). Speed is then initially filtered via various mathematical algorithms to maintain data quality and to smooth erroneous points (Malone et al., 2017; Sweeting, Cormack, et al., 2017; Wundersitz et al., 2015). However, the process in the selection of the respective pre-processing, filter and the associated cutoff frequency is generally arbitrary (Malone et al., 2017; Wundersitz et al., 2015). The arbitrary selection of any imposed filter is problematic, as currently, there is no consensus method in the processing of speed data prior to the calculation of acceleration (Linke et al., 2018; Malone et al., 2017; Sweeting, Cormack, et al., 2017; Thornton, Nelson, et al., 2019). Further, once acceleration is calculated, it is not known if it is then filtered again. Processing methods may vary from manufacturer to manufacturer, resulting in differences in acceleration that could be influenced by a filter. However, it must be stressed that differences in acceleration could also be influenced by the accuracy of instantaneous speed data, as well as hardware specifications (Thornton, Nelson, et al., 2019; Varley et al., 2017). However, hardware specifications (i.e., sample rate, satellite system, magnetometer) are commonly provided in research or accessible from the manufacturer, promoting direct comparison between manufacturers. Filtering details, however, are not (Chapter 3). In Chapter 3, 13% of studies included information regarding the filter of their speed or acceleration data. The result from Chapter 3 may be due to the lack of information from manufacturers on their filtering settings, hindering direct comparisons between manufacturers. The limited information from manufacturers may be due to the protection of commercial interests in not wanting to divulge intellectual property that directly influences their product (French & Ronda, 2021; Malone et al., 2017).

Comparisons between GNSS-based results in team sport research are problematic as practitioners are unable to compare units from different manufacturers due to potential differences in processing methods and hardware specifications (Linke et al., 2020; Thornton, Nelson, et al., 2019). Despite the ability to smooth affected data points during times of poor signal, it is the presence of filters that can influence measured activity profile variables (Delaney et al., 2019; Malone et al., 2017; Sweeting, Cormack, et al., 2017; Thornton, Nelson, et al., 2019). For example, three commercially available, 10 Hz, GNSS devices (Catapult Sports S5, GPSports EVO, STATSports APEX) were used to measure activity during a team sport simulation session (Thornton, Nelson, et al., 2019). The study concluded that standardized data processing methods were recommended which was in part, due to the large differences found between acceleration outputs from the three manufacturer-based filters (Thornton, Nelson, et al., 2019). The differences found between the manufacturers could indicate that the filtering applied to any one of these units was substantially different to the other (Thornton, Nelson, et al., 2019). Knowledge of the filtering settings between manufacturers is important irrespective of similar sample rates and other hardware specifications. It is of interest to assess whether the filter settings are influencing the variation in activity profile results between GNSS units (Thornton, Nelson, et al., 2019). Furthermore, with the sustained development in GNSS tracking technology, it is imperative that as tracking technology evolves, researchers and practitioners understand the role of data filtering in quantifying the activity profiles of athletes.

Given the lack of knowledge surrounding manufacturer filters in research, it is prudent to examine the effect of applying a common filter on different GNSS units during the same testing bout (Thornton, Nelson, et al., 2019). It is of interest to examine whether data from GNSS technology from different manufacturers can be filtered with a similar process to render comparable acceleration outputs during team sport locomotion. Therefore, the aim of this study was twofold. Firstly, the study aimed to observe whether there were substantial differences in acceleration between GNSS manufacturers as extracted from the proprietary software. Subsequently, this study then aimed to apply common filtering properties to acceleration to enable more appropriate comparison between GNSS manufacturers for acceleration outputs.

5.4 Methods

5.4.1 Design and Participants

An observational study design was implemented to examine acceleration data from different GNSS manufacturers during elite rugby league training sessions. Seven, elite male rugby league athletes (mean ± SD; 22 ± 3 years, age range; 18 to 26 years, 1.86 ± 0.09 m, 94 ± 10 kg) who were all contracted full time during the 2018 National Rugby League (NRL) season participated in the study. All participants provided informed consent to researchers. Institutional ethical approval was granted for the commencement of the study (Victoria University: HRE21-017).

5.4.2 Procedure

During analysed training sessions, athlete movements were tracked with two different, commercially available 10-Hz GNSS units (GPSports EVO, firmware: 1.158, Catapult Sports, Melbourne, Australia, and STATSports APEX, firmware: 2.45, Newry, Ireland) that were positioned between the athlete's scapulae, worn in a custom-made undergarment. GNSS units were placed in the same pouch in each participant's vest. It is acknowledged that wearing two units in one undergarment is not standard practice. However, given the obtrusive nature of wearing two undergarments in training sessions featuring ground-based contacts, this was not feasible. Moreover, GNSS units in these pouches were facing with their antenna in the correct position to promote satellite connectivity. The combined average number of satellites (mean ± SD; 9.3 ± 0.9) and horizontal dilution of precision (HDOP) (1.06 ± 0.07) were acceptable for human locomotion (Malone et al., 2017) Additionally, through the use of online GNSS planning tools (gnnsplanning.com), the expected satellite availability and HDOP over the course of all testing sessions was retrospectively recorded (satellites; 11.3 ± 0.5, HDOP; 0.92 ± 0.08). The outdoor training facility for the observed team was free from any surrounding and overhanging infrastructure that could obstruct satellite signals. Importantly, for the calculation of acceleration, both GNSS models, (including previous models) in this research have been previously accepted for variables of either speed or acceleration.(Beato et al., 2018; Delaney et al., 2019; Linke et al., 2018)

GNSS data was collected during 13 selected training sessions with a total of 34 training observations collected by both GNSS manufacturers (GPSports: 34 observations, STATSports: 34 observations: 68 in total). During training, the commencement and finish time of each drill was recorded. Each training file was included in the analysis regardless of how many drills had been completed by that athlete during the given session.

The accompanying proprietary software from both respective manufacturers was used (GPSports Console; version 1.5.0 and STATSports APEX console; version 2.0.2.4) to extract the athlete GNSS files for further analysis of movement variables in Rstudio software (version 1.1.419). Speed traces from the manufacturers for each athlete and session were synchronised using cross correlation via the *ccl* function within the *stats* library in Rstudio (Linke et al., 2020). The cross correlation of the speed traces resulted in a single data frame for each athlete and each session that contained both sets of the manufacturer's speed data. As per Figure 5-1, the data handling methodology followed several steps. From the extraction of the manufacturer's speed data, acceleration was calculated. To determine the appropriate cutoff frequency for processing athlete speed data, a residual analysis was implemented using a range of cutoff frequencies within a 4th

order low-pass Butterworth filter (Linke et al., 2020; Winter, 2009). To plot the differences between the filtered and software exported (raw) GNSS speed traces, 100 different cutoff frequencies (0.1 – 10.0 Hz) at 0.1 Hz increments were implemented. From this analysis and by following the processes outlined previously, a 1 Hz cutoff frequency was determined as being the most appropriate for handling speed (Winter, 2009). Following the formation of the filtered speed variable, acceleration was then calculated using finite differentiation (central difference) of the filtered speed, resulting in the filtered acceleration variable. At this point, another residual analysis identified the most appropriate cutoff frequency for the filtered acceleration variable was at 1 Hz. Filtered acceleration was then filtered again (twice filtered) using the optimal cutoff frequency (1 Hz) and experimental filter (4^{th} order Butterworth). Following the filtering and calculation of the athlete GNSS data, all session data was trimmed to only include drill time, where athletes were actively participating in the training drill. The mean speed ($m \cdot s^{-1}$) and acceleration ($m \cdot s^{-2}$) for each athlete within each drill were established, along with the total high-speed distance (m; > 5 $m \cdot s^{-1}$) and total acceleration counts (n; > 2 $m \cdot s^{-2}$). Total acceleration counts were calculated by the researchers in R Studio software for the software exported as well as filtered and twice filtered conditions to enable appropriate comparison between conditions and manufacturers. For example, if an acceleration occurred > 2 $m \cdot s^{-2}$, during an instance, this would be classed as a count provided it was of minimum duration. An MED time of 0.4 seconds was used in the calculation of acceleration counts which is similar to that used in previous research (Chapter 3). The 0.4 second MED time was selected given the common use of this MED time within team sport activity profile research, as found within the results section of Chapter 3.

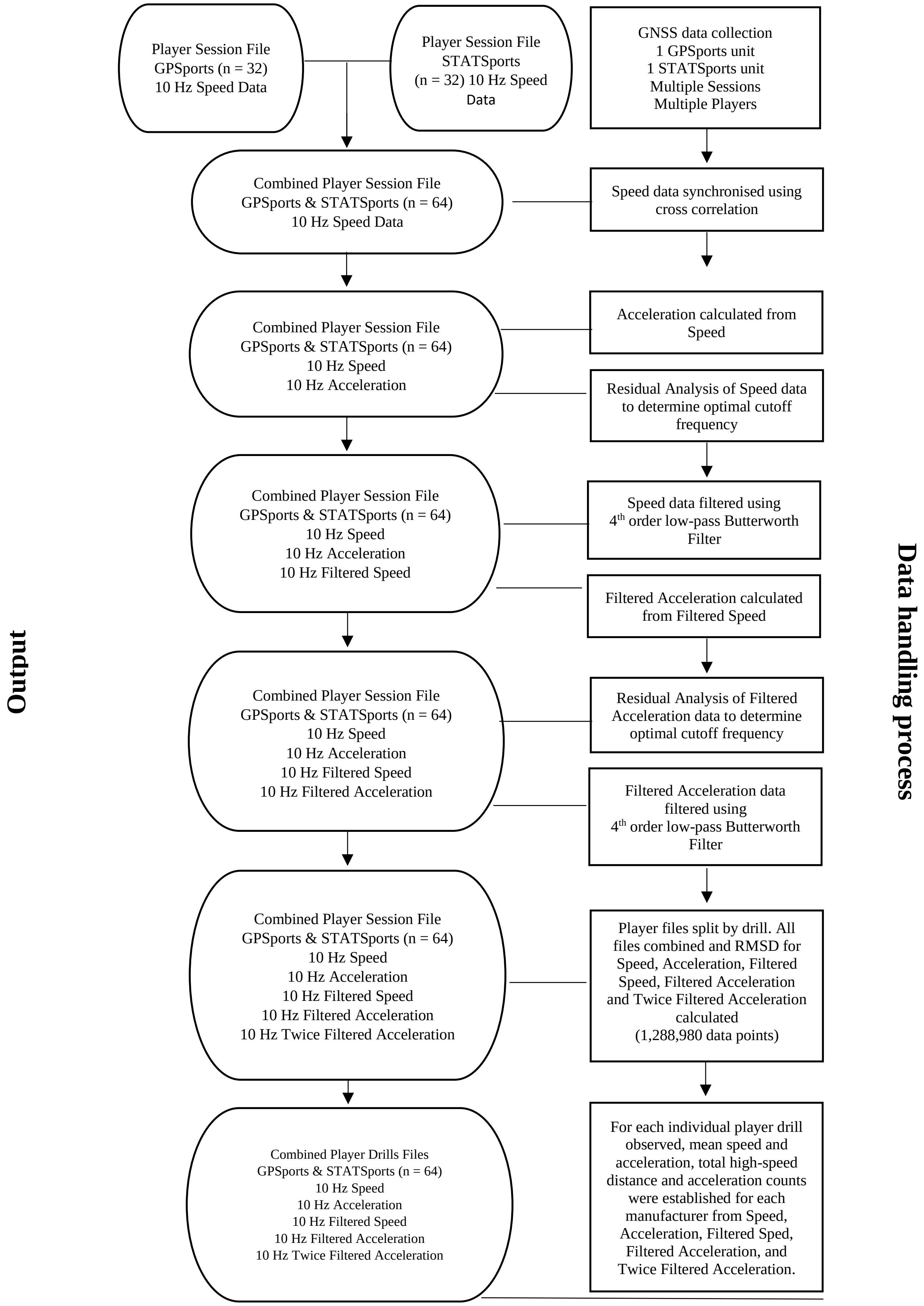

Figure 5-1. Data processing flowchart depicting order of events for handling GNSS data.

5.4.3 Statistical Analysis

To determine the difference between each GNSS device and their respective speed and acceleration values, a root mean square deviation analysis (RMSD) was used. Raw data from each manufacturer was assessed both before and after the application of a 1 Hz Butterworth filter. Athlete values from one GNSS manufacturer across all drills from each training session were compared against the other manufacturer with a resulting RMSD provided for each drill, variable and filtering condition.

To determine the difference in RMSD values and summary values between GNSS models, this study implemented a linear mixed model approach. For the RMSD analysis, a separate linear mixed model was constructed for speed and acceleration and included fixed and random effects. Each athlete was designated as a random effect in both models to account for any error associated with recurring values from the same athlete (Delaney, Thornton, Burgess, et al., 2017; Delves et al., 2019). Each drill was included as a random effect, whilst each filter setting was designated as a fixed effect. Linear mixed models were also used for the analysis of the summary variables and included the same random and fixed effects as used for RMSD analysis, except the GNSS manufacturer, rather than the filter type, was included as a fixed effect. Using similar methodology published previously, the linear models then provided resultant standard deviations (SD) and mean differences that were implemented to determine standardised effect sizes (ES), which were classified as; <0.20 trivial; 0.21- 0.60 small; 0.61 – 1.20 moderate; 1.21 – 2.0 large and >2.01 very large (Hopkins et al., 2009; Johnston et al., 2022; Thornton, Delaney, et al., 2019). Real effects were required to be at least 75% greater than a moderate ES (Johnston et al., 2022). The definition of a real effect was based on a moderate worthwhile difference, in keeping with rationale from previous GNSS technology research (Delaney et al., 2019; Johnston et al., 2022).

5.5 Results

The RMSD in raw, filtered and twice filtered for speed and acceleration is outlined in Table 5-1. The RMSD for acceleration substantially decreased in the filtered (ES; CI: 4.84; 3.23 to 6.46) and twice filtered (ES; CI: 4.94; 3.29 to 6.58) variables compared to the raw variable. The residual analysis of speed and acceleration is shown in Figure 5-2.

Table 5-2 presents the summary values (Mean ± SD) from this study. Raw average acceleration was substantially higher in STATSports APEX units compared to GPSports EVO (ES; CI: 0.82; 0.84 to 0.80). Similarly, in raw acceleration counts, STATSports APEX recorded greater counts compared to GPSports EVO (ES; CI: 6.18; 6.88 to 5.48**)**. There were no differences in speed, high-speed distance or filtered and twice filtered acceleration variable.

Athlete speed and acceleration encompassing all data points from each drill across both GNSS manufacturers is presented in Figures 5-3 and 5-4 respectively. The difference in speed between the two systems relative to the speed measured by the GPSports EVO is displayed in Figure 5-3. Similarly, Figure 5-4 presents the difference in acceleration between systems relative to the acceleration measured from the GPSports EVO.

The distribution of all summary values in this study is presented in Figure 5-5. All boxplots feature the raw and filtered processing of the combined athlete data from both GNSS models.

Table 5-1 Observed Root Mean Square Differences between analysed variables across both GNSS units in Raw, Filtered and Twice Filtered Settings.

	Filter settings (Mean ± SD)			Effect Size (90% Confidence Interval)		
Variable	Raw	Filtered	Twice filtered	Raw – Filtered	Raw – Twice Filtered	Filtered – Twice Filtered
Speed ($m{\cdot}s^{-1}$)	0.35 ± 0.43	0.28 ± 0.44	-	0.16 (0.11 to 0.21)	-	-
Acceleration ($m{\cdot}s^{-2}$)	1.77 ± 0.37	0.27 ± 0.23*	0.24 ± 0.23*	4.84 (3.23 to 6.46)	4.94 (3.29 to 6.58)	0.10 (0.09 to 0.29)

*Denotes substantially different compared to raw values. All observed differences are >75% likelihood of being greater than the smallest worthwhile change (calculated as 0.6 x between-subjects SD).

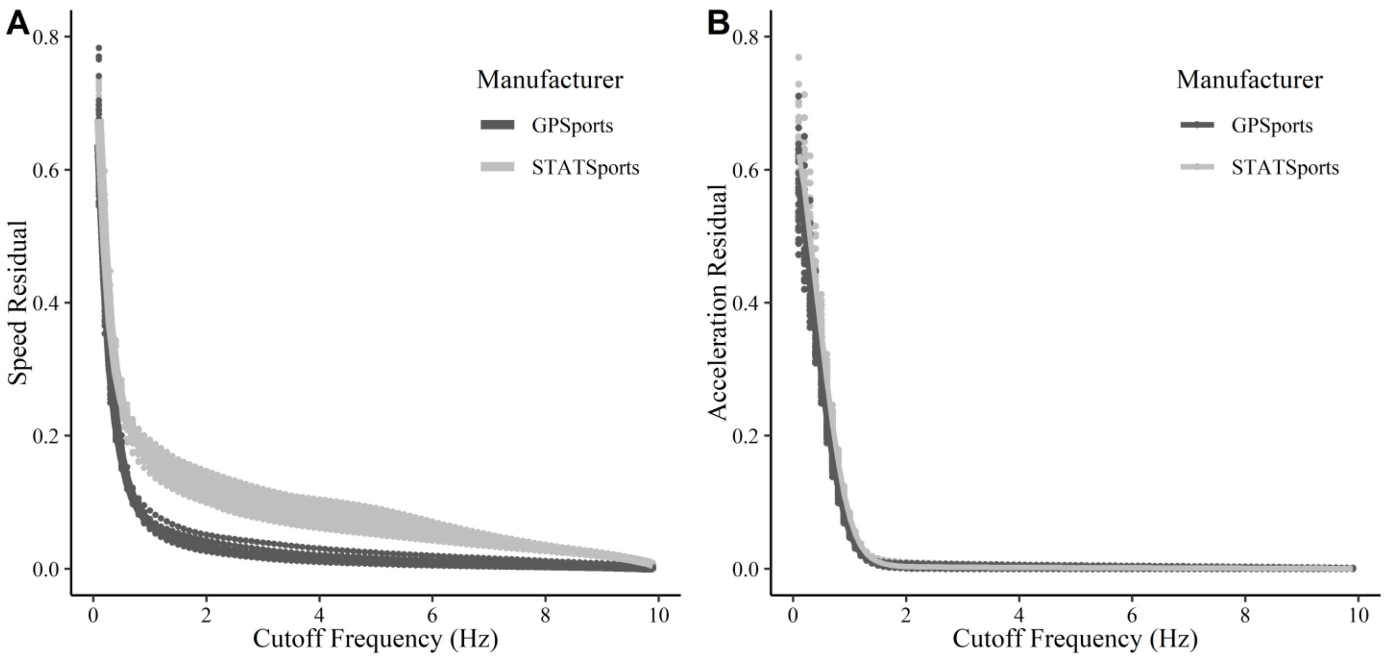

Figure 5-2. GNSS manufacturer residuals to determine the appropriate cutoff frequency for speed (A) and acceleration (B).

Table 5-2. Summary values (Mean ± SD) of GPSports EVO and STATSports APEX units during Elite Rugby League Training Sessions as processed by Raw, Filtered and Twice Filtered properties. Differences between units and corresponding effect sizes outlined as Diff/ES; 90% CI.

Condition	GPSports EVO	STATSports APEX	Difference	Effect size
	Mean ± SD	Mean ± SD	Diff 90% CI	ES 90% CI
Speed ($m \cdot s^{-1}$)				
Raw	1.19 ± 0.36	1.22 ± 0.35	-0.03 -0.04 to -0.02	-0.09 -0.12 to -0.06
Filtered	1.19 ± 0.37	1.22 ± 0.35	-0.03 -0.04 to -0.02	-0.09 -0.12 to -0.06
High-Speed Distance (m)				
Raw	8.22 ± 5.62	9.05 ± 5.19	-0.83 -1.00 to -0.66	-0.18 -0.23 to -0.12
Filtered	8.16 ± 5.69	8.64 ± 5.59	-0.48 -0.62 to -0.33	-0.09 -0.12 to -0.06
Acceleration ($m \cdot s^{-2}$)				
Raw	0.37 ± 0.11	1.19 ± 0.27	-0.82 -0.84 to -0.80*****	-3.72 -4.95 to -2.50
Filtered	0.38 ± 0.12	0.42 ± 0.12	-0.04 -0.04 to -0.04	-0.31 -0.41 to -0.21
Twice Filtered	0.37 ± 0.11	0.41 ± 0.12	-0.03 -0.04 to – 0.03	-0.25 -0.33 to -0.17
Acceleration > 2 $m \cdot s^{-2}$ (n)				
Raw	3.8 ± 2.8	10.0 ± 7.6	-6.2 -6.9 to -5.5*****	-1.1 -1.4 to -0.7
Filtered	4.2 ± 3.0	5.3 ± 3.8	-1.1 -1.3 to -1.0	-0.3 -0.4 to -0.2
Twice Filtered	3.8 ± 2.7	4.7 ± 3.3	-0.9 -1.1 to – 0.9	-0.3 -0.4 to -0.2

*****Metric values substantially different between GNSS models.

All observed differences are >75% likelihood of being greater than the smallest worthwhile change (calculated as 0.6 x between-subjects SD).

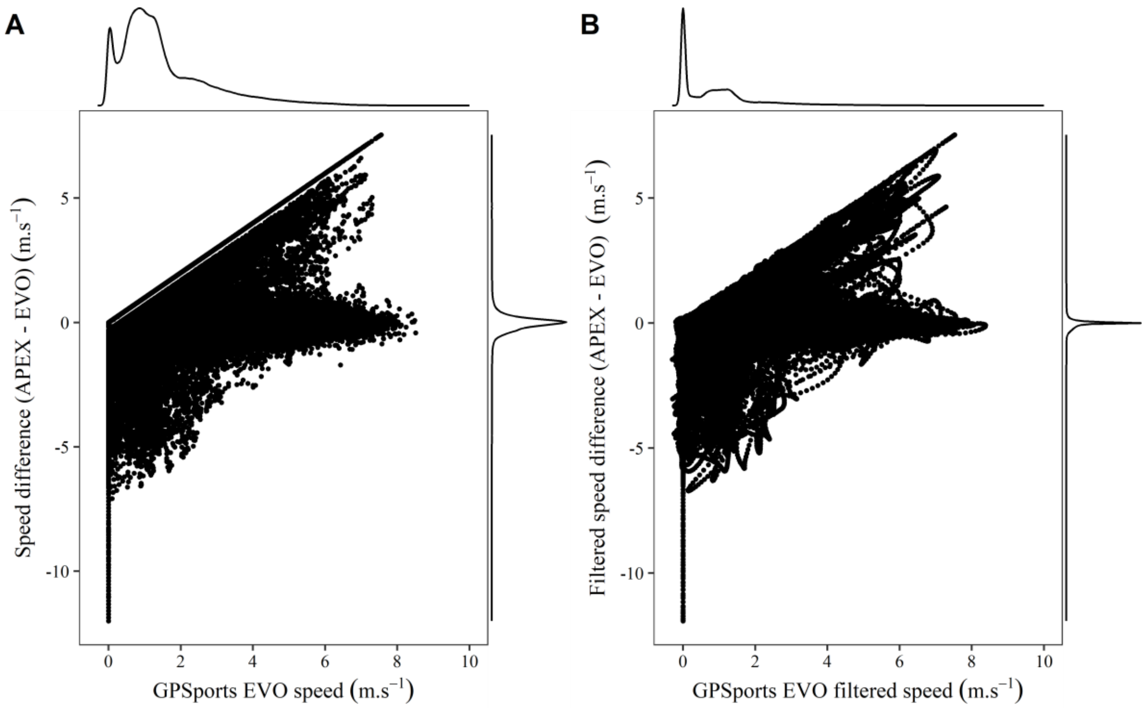

Figure 5-3. Combined athlete speed from GNSS units expressed as a difference between manufacturers. A = GPSports speed compared against speed difference (including STATSports speed). B = Filtered GPSports speed compared against filtered speed difference (including STATSports filtered speed).

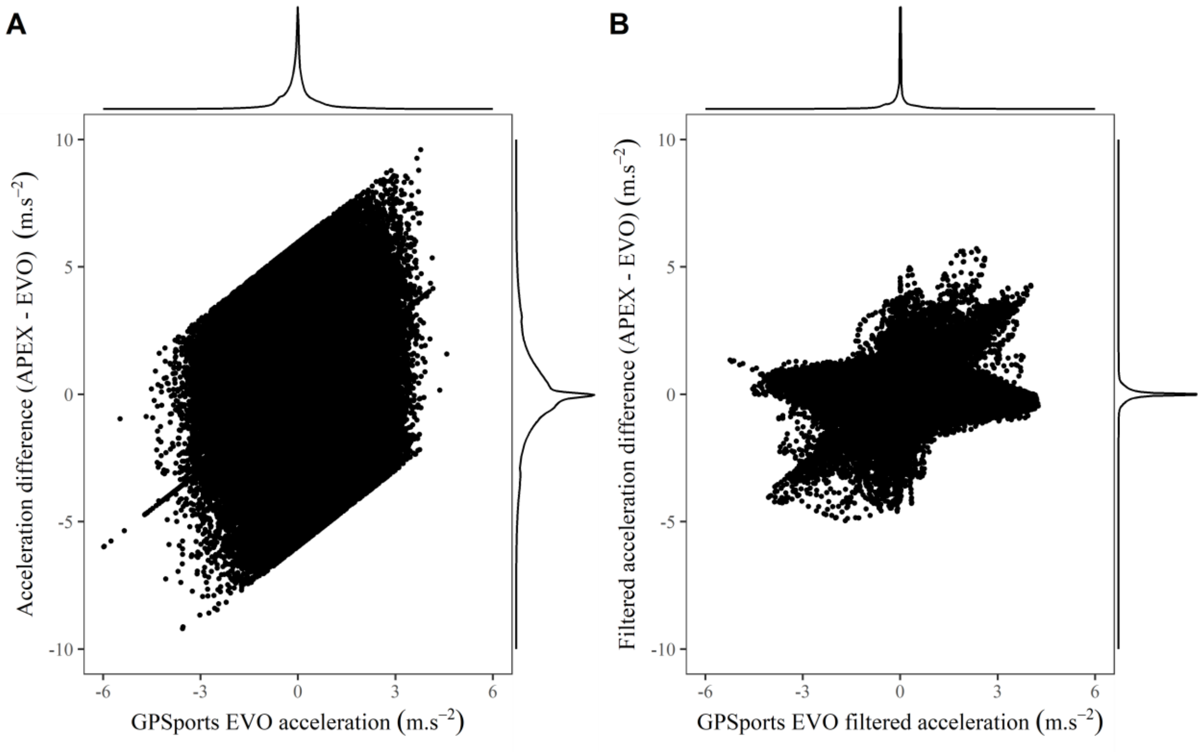

Figure 5-4. Combined acceleration across athletes. Expressed as GPSports versus acceleration difference (including STATSports). A = GPSports acceleration versus acceleration difference (including STATSports acceleration). B = GPSports filtered acceleration versus filtered acceleration difference (including filtered STATSports acceleration).

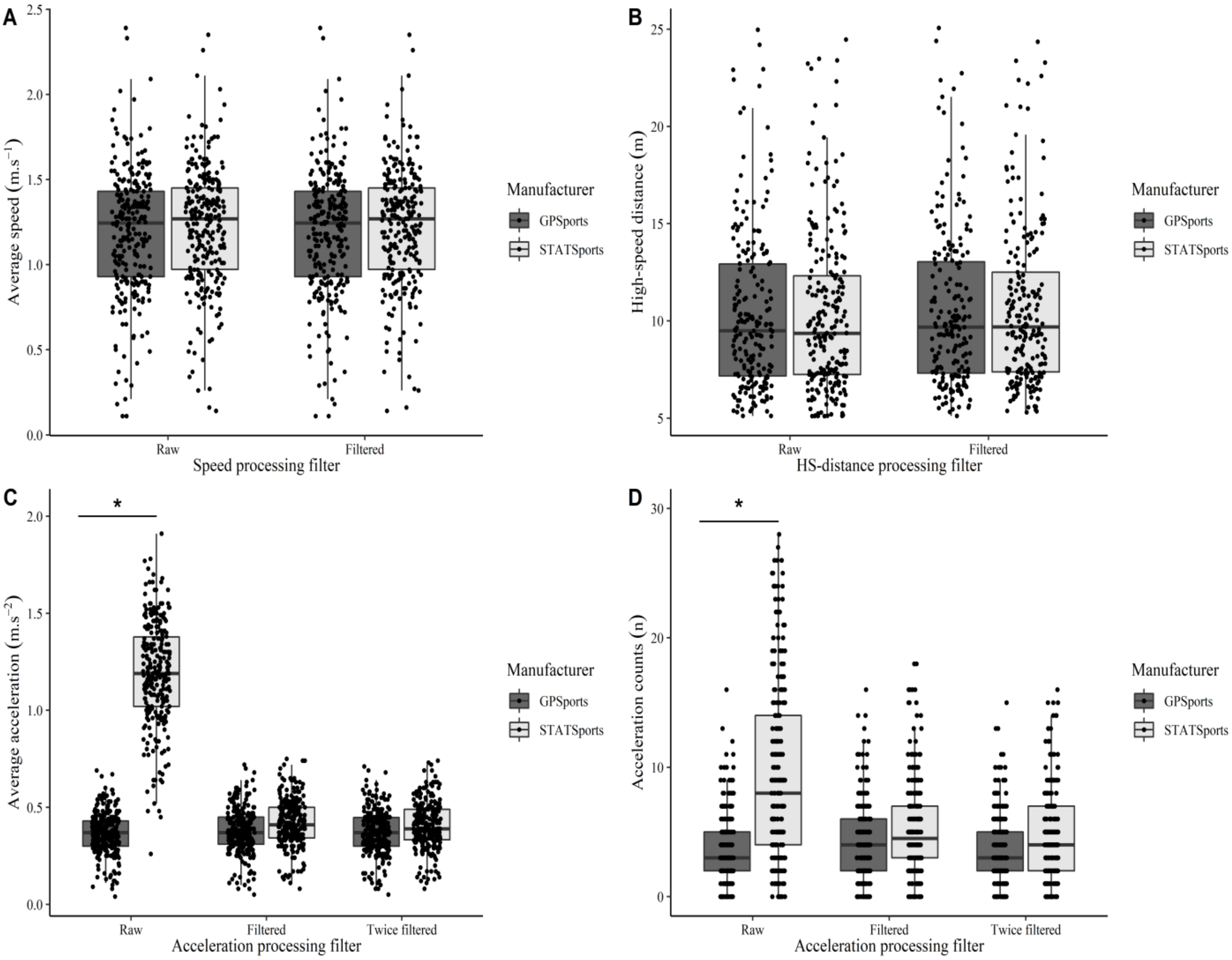

Figure 5-5. Distribution of summary values in the analysed study outlined in raw, filtered and twice filtered variations by GNSS manufacturer. A = average speed ($m·s^{-1}$), B = high-speed distance (> 5 $m·s^{-1}$; m), C = average acceleration ($m·s^{-2}$), D = acceleration counts (> 2 $m·s^{-2}$; n). * Denotes substantially different between raw filter settings.

5.6 Discussion

This study aimed to observe whether there were substantial differences in acceleration during team sport locomotion between GNSS manufacturers. This study then aimed to apply common filtering properties to acceleration to enable more appropriate comparison between GNSS manufacturers for acceleration outputs. This study observed that the RMSD for average acceleration ($m{\cdot}s^{-2}$) decreased from raw outputs (RMSD: 1.77 ± 0.37 $m{\cdot}s^{-2}$) to those observed at the filtered (RMSD: 0.27 ± 0.23 $m{\cdot}s^{-2}$, ES; (CI): 4.8; 3.2 to 6.5) and twice filtered (0.24 ± 0.23 $m{\cdot}s^{-2}$, ES; CI: 4.9; 3.3 to 6.6) variables. Similarly, for summary acceleration variables in average acceleration ($m{\cdot}s^{-2}$) and acceleration counts (n), there were no substantial differences found between APEX and EVO in the filtered (speed) and the twice filtered (acceleration) parameters. The RMSD and summary variable results suggest that the GNSS manufacturers derive acceleration data in different ways which influences the calculation of acceleration. Moreover, the use of a common filter improved the difference in acceleration between unit models. The improved difference suggests that future research should investigate the development of a common acceleration filtering method that can be reported upon in research. A common filter could be implemented by practitioners at the applied level to maintain consistency in tracking data longitudinally and by researchers in activity profile and validity and reliability research (Linke et al., 2020; Thornton, Nelson, et al., 2019).

Despite the continued development of GNSS technology within applied sport science, the processing of acceleration between manufacturers continues to be of concern (Delaney et al., 2019; Linke et al., 2020; Thornton, Nelson, et al., 2019). The raw acceleration-based results from manufacturers in this study were substantially different. STATSports APEX raw average acceleration ($m{\cdot}s^{-2}$) was noticeably higher compared to GPSports EVO, but there was a greater difference in acceleration counts (n: > 2 $m{\cdot}s^{-2}$), where APEX counts

(10.0 ± 7.6) presented a substantially higher amount compared to EVO (3.8 ± 2.8). In similar research, software and raw-derived acceleration data showed consistent differences in variables between STATSports APEX and GPSports EVO (Thornton, Nelson, et al., 2019). In absolute acceleration ($m{\cdot}s^{-2}$), both the raw and proprietary software-derived values in STATSports APEX and GPSports EVOs were *most likely* different (ES; confidence limits: 1.9; ± 0.1), which is consistent with the average acceleration findings in the current study. Whilst the current study opted to analyze acceleration counts (n: > 2 $m{\cdot}s^{-2}$) instead of distance-based thresholds, similar differences were seen to that of previous research with the application of threshold-based variables (Thornton, Nelson, et al., 2019). Despite the difference in study designs, it may be that the results from the controlled, sled-based trials from previous research are confirmed by results from the team sport locomotion patterns seen in the current study (Thornton, Nelson, et al., 2019).

It is important to state that the validity of the measurement of instantaneous speed is vital to the subsequent validity for derivative measures such as acceleration (Linke et al., 2018, 2020). Moreover, both GNSS models in this study have been previously validated for either speed or acceleration variables (Beato et al., 2018; Delaney et al., 2019). The results from the current study indicate that there were no substantial differences seen in average speed variables in both raw and filtered variations according to the study's statistical criteria (Figure 5-3). However, the resulting speeds in both filtered and raw conditions were extremely similar between the manufacturers. The lack of substantial difference in average speed variables and the RMSD results indicates the differences seen in raw acceleration variables are most likely due to the processing and/or filtering at the calculation stage of determining acceleration. Despite both GPS/GNSS models in this study possessing similar sample rates (10 Hz), it is clear one of these systems calculates acceleration differently to the other, which contributed to the discrepancies seen in the raw acceleration-based results. Moreover, Figure 5-4 highlights that the shape of the scatterplot changes substantially in plot B compared to plot A as it appears that one manufacturer in plot A applies a greater filter setting compared to the other. However, when the same filtering is applied as seen in plot B, the errors appear to be more evenly distributed in plot B compared to the skewed differences in plot A. The researcher, however, does not know how raw acceleration from each manufacturer was processed as this information is not made readily available by manufacturers and is not commonly published within research (Harper et al., 2019; Varley et al., 2017). For practitioners, the lack of clarity surrounding the processing of acceleration, as well as the inconsistency in the reporting of acceleration in research, hinders the ability to compare the acceleration-based activity profiles of their athletes to that published in research (Linke et al., 2020). Given the findings of this study, it is prudent that future research attempt to report the filtering processes surrounding their acceleration/deceleration data where possible, to ensure practitioners are aware of any differences that may be technologically influenced (Linke et al., 2020; Thornton, Nelson, et al., 2019).

This study applied a common filter between two GPS/GNSS manufacturers to compare acceleration outputs more appropriately between models. A 1-Hz low-pass Butterworth filter was selected by following the process outlined previously (Winter, 2009). The use of a 1-Hz low-pass Butterworth filter is not uncommon in team sport research, with variants being previously applied to variables in rugby league and rugby sevens (Couderc et al., 2019; Cummins et al., 2018; Ellens, Hodges, et al., 2022; Furlan et al., 2015). The subsequent results of applying the 1-Hz Butterworth filter to the datasets improved the difference in acceleration across all acceleration variables, to a point where there were no substantial differences in average acceleration or acceleration counts and the RMSD decreased from the raw values for acceleration. It should be noted that despite acceleration values becoming similar following data handling, this does not mean that both are valid or reliable outputs of acceleration. However, the results of this portion of the analysis highlights the influence of applying a common filter to GNSS data from different manufacturers and the ability to obtain comparable results. Practically these results should be seen as what could be achieved with further development into the application of a common filtering process. For practitioners, the development towards such a filter would allow for appropriate comparison between the activity profiles published in research and those seen within their own athletes (Linke et al., 2020).

It should also be stated that future wearable tracking research into acceleration processes not only impacts GNSS technology but also local positioning systems (LPS) and optical camera systems (Thornton, Nelson, et al., 2019). Given the growth of tracking installations in outdoor stadia, practitioners may be required to swap in and out of tracking systems whilst on the training field (i.e., GNSS) and the competition arena (i.e., LPS or optical systems) (Buchheit, Allen, et al., 2014; Thornton, Nelson, et al., 2019). This would prompt the need to filter acceleration in similar ways between these two technologies to maintain athlete data longitudinally. Similarly, for researchers, the use of a common acceleration filter may also enhance the quality of validity and reliability trials of future technology by providing a reference point to compare already established technologies (Hodder et al., 2020).

It may also be pertinent that in the research setting, all future research on athlete wearable tracking data be processed by the researchers themselves, rather than the proprietary software. If researchers can process wearable tracking data independently of the proprietary technology, there may be greater clarity (within research) surrounding the methodology in the processing of the athlete data. As seen in the results of this study, the method in which athlete tracking data is processed has a bearing on the activity profiles of training and competition. In terms of acceleration, this importance is further magnified as it is a calculated variable that is a derivative of speed. In turn, with the enhanced availability of data processing information (i.e., filtering properties) more appropriate comparisons and conclusions could be made by researchers and practitioners.

This study was not without limitation. Firstly, training data was collected on one NRL team. The activity profile during training is representative of the athletes in the analysed team and may not be representative of all other teams within the NRL. Training data was also collected on outdoor training surfaces. The results of this study are therefore applicable to these conditions but may not be applicable to events held within stadium structures.

Although the selection of the 1-Hz low-pass Butterworth filter was appropriate for the constraints of this research, for other team sports, this filter may not be appropriate. It could be that a different filter may be optimal for sports. For example, practitioners in individual sports such as track sprinting in athletics may require analysis on inter-stride acceleration, whilst team sport practitioners may require a gross assessment of acceleration over the training session or match (Linke et al., 2018). Both practitioners would then require a different processing method or tracking technology to accommodate such analysis (Linke et al., 2018). Regardless, the findings of this study promote further research into the development of a common approach to processing acceleration-based data of team sport athletes. The researcher suggests researchers conduct a residual analysis on the effects of different filters to ensure that the correct filter is applied to the respective athlete tracking data (Winter, 2009).

This study also analysed two GPS/GNSS models from two manufacturers. The results from this study are relevant to the models and firmware analysed. Whilst this does not provide a representation of GNSS technology that is commercially available to practitioners, practically it is the most that could be worn by an athlete during training sessions. It should be emphasised that having two systems capturing athlete locomotion during training is of practical benefit, given the unscripted nature of movement and with reference to acceleration intensity noted in rugby league (Delaney, Duthie, et al., 2016; Delaney, Thornton, et al., 2016).

5.7 Practical Applications

- Despite similarities in sample rate, average acceleration and acceleration counts that were calculated from each manufacturer's proprietary software were substantially different when compared against each other. This indicates that the calculation of acceleration between manufacturers is different.
- The common filter applied to both GNSS models improved the difference between the manufacturers in acceleration variables.
- The introduction of a common filtering process for calculating acceleration across wearable technologies may be required. The adoption of a common filtering method could alleviate concerns surrounding data variability and the influence of the technology upon activity profiles.

5.8 Conclusions

The results from this study indicate that GNSS technology from different manufacturers derive acceleration data differently. Additionally, technologically influenced variations may exist in the acceleration of athletes. For practitioners and researchers, it is important to standardize the processes in the calculation of acceleration to outline how acceleration events are calculated in each research study. Ultimately, the findings of this study suggest that the development of a common acceleration filtering process for different technologies and manufacturers may be required in team sport research.

CHAPTER 6 - VALIDITY OF GNSS FOR QUANTIFYING MOVEMENT IN TEAM SPORTS

6.1 Directions from Chapter 5

Chapter 5 built upon Chapter 4 by indicating that GNSS technology from different manufacturers can process acceleration data differently which could impact the overall magnitude of acceleration within the activity profile. For practitioners and researchers, the results are problematic, both when assessing the validity and reliability of different tracking technologies, and when evaluating activity profiles for training program prescription. The use of 1 Hz Butterworth filter upon GNSS technology in Chapter 5 improved the comparison in acceleration between manufacturers, to a point where there was no significant difference in acceleration. Whilst the between-model comparison was improved with a common filter in previously validated technology, the filter settings must still be evaluated by a criterion measure before further application could take place both in research and in the applied setting. Chapter 5 is required to evaluate the device settings against three-dimensional motion capture in provisions for use as a possible common filter.

6.2 Introduction

The Global Navigation Satellite System (GNSS) has been used to determine athlete position and speed during training and competition in team sports (Aughey, 2011a; Delaney et al., 2019; Johnston et al., 2020). Athlete tracking via GNSS technology can provide information on movement variables such as speed and acceleration which can underpin the activity profile for training and/or team sport competition (Aughey, 2011a; Sweeting, Cormack, et al., 2017). The GNSS is an advancement in satellite system technology, with increased access to satellite systems such as the Global Positioning System (GPS), BeiDou, GLONASSS and Galileo systems for athlete wearable technology (Chahal et al., 2022; Delaney et al., 2019; Johnston et al., 2020). With increased satellite coverage accessible to athlete wearable tracking technology, there could be further improvements in the validity and reliability of measures such as instantaneous speed, as a lesser number of connected satellites has been associated with greater error rates across distance and speed variables (Aughey, 2011a).

Global Positioning System research has identified that technology that samples at 10 Hz can provide valid reports of distance, speed and maximum speed (Aughey, 2011a; Beato et al., 2018; Jennings et al., 2010a; Jennings et al., 2010b; R. J. Johnston et al., 2014; Johnston et al., 2013; Malone et al., 2017; Scott et al., 2016; Varley, Fairweather, et al., 2012). However, greater variation exists with high-intensity locomotion, such as high-speed distance, and high-intensity acceleration and deceleration events (Akenhead et al., 2014; Aughey, 2011a; Buchheit, Al Haddad, et al., 2014; Crang et al., 2021). For GNSS technology, average speed and average acceleration have been validated as locomotion variables, with small differences found in average speed ($m \cdot s^{-1}$; 0.19–0.25; ± 0.21) and small to moderate differences found in raw acceleration data ($m \cdot s^{-2}$; 0.25–0.35; ± 0.24) against a three-dimensional motion capture system (VICON) at the centre of mass and at the C7 vertebrae (Delaney et al., 2019). For GNSS-derived peak speed and distance, there has been mixed validity and reliability results. Total differences of 1-2% were reported across 400 m bouts, 128.5 m circuits, 20 m trials and max speed efforts in GNSS technology compared to a criterion (Beato et al., 2018). However, a similar study found that seven out of eight devices overestimated distance during sprint trials (Chahal et al., 2022). Given the differences in criterions and GNSS technology used in these studies it is difficult to make conclusions regarding the validity of GNSS technology, particularly with a lack of research surrounding the validity of instantaneous speed data, which can underpin derivative metrics such as acceleration.

To establish GNSS validity, tracking technology should be evaluated against a criterion. The use of three-dimensional motion capture systems (i.e., VICON) have been recommended as the most appropriate criterion to assess the validity of tracking systems such as GNSS technology (Duffield et al., 2010; Linke et al., 2018; Vickery et al., 2014). Specifically, positional and instantaneous speed and acceleration data from GNSS should be directly compared against a motion capture system to establish tracking system validity (Linke et al., 2018; Luteberget & Gilgien, 2020). However, it should be noted that GNSS models typically determine athlete position and speed in different ways compared to a motion capture system. For example, three-dimensional motion-capture systems (e.g., VICON) determine athlete position via the use of X, Y coordinates, from which, athlete speed can be derived (Linke et al., 2018, 2020). Tracking systems such as GNSS, however, determine position and speed via positional differentiation and doppler shift, respectively (Aughey, 2011a; Malone et al., 2017). However, the existing research analysing the validity of either instantaneous positional or speed data in GNSS technology against a three-dimensional motion capture system is limited (Delaney et al., 2019; Linke et al., 2018; Luteberget & Gilgien, 2020). In GPS technology, it has been reported that a

5 Hz GPS (96 ± 49 cm) had inferior positional accuracy results compared to an LPS system (23 ± 7 cm) in a validity study against a three-dimensional motion capture system (VICON) during a series of movement circuits and small-sided games (SSGs)(Linke et al., 2018). However, despite an inferior level of positional accuracy, both instantaneous speed and acceleration from the GPS device showed improved levels of validity with no substantial difference found in GPS outputs against the other tracking systems examined (Linke et al., 2018). The authors suggested that the improved results in instantaneous speed and acceleration were due to the impact of calculating athlete speed via doppler shift, which is more resistant to “cycle slips”, potentially enhancing the validity of instantaneous speed measures (Linke et al., 2018). The cited research would then suggest that determining the validity of instantaneous speed is of importance before analysing derivative variables in team sport activity profiles. Moreover, given that 5 Hz GPS technology is largely superseded by the current standard of 10 Hz technology, the validity for instantaneous speed during team sport movements should be established for this sample rate (Aughey, 2011a; Malone et al., 2017).

Importantly for team sport activity profiles, instantaneous speed can be used to calculate locomotion variables that are commonly assessed by practitioners (French & Ronda, 2021; Linke et al., 2018). For example, acceleration-based metrics such as average acceleration ($m \cdot s^{-2}$) or acceleration distance (m) as well as metabolic variables such as metabolic power ($W \cdot kg^{-1}$) are subsequently calculated from the initial instantaneous speed trace. Variables such as average acceleration ($m \cdot s^{-2}$) or metabolic power ($W \cdot kg^{-1}$)could also be then categorised further into thresholds indicating the distribution of each variable (Linke et al., 2018). However, the validity of any derived metric is subject to the validity of instantaneous speed as measured via the tracking technology (French & Ronda, 2021; Linke et al., 2018). In the existing literature there is limited research on the validity of instantaneous speed measures for GNSS technology (Delaney et al., 2019; Luteberget & Gilgien, 2020). Previous research has validated the use of average speed and acceleration in GNSS technology against a three-dimensional capture system (Delaney et al., 2019). Average speed and acceleration was associated with at least a moderate bias compared to the criterion (Delaney et al., 2019). However, as the cited study did not evaluate instantaneous measures of speed or acceleration, it is difficult to determine the initial levels of error at the instantaneous speed level (Delaney et al., 2019). Moreover, the instantaneous acceleration root mean square error (aRMSE) in GPS technology is similar to the error in instantaneous speed (vRMSE) (Linke et al., 2018). Due to acceleration being a derivative of speed and a second derivative of displacement with time, the initial error at the speed level has previously been magnified in the calculation of acceleration (French & Ronda, 2021; Linke et al., 2018). Acceleration error in GPS technology during a sport-specific course (1.18 ± 0.14 m·s^{-2}) was double compared to the shuttle run condition (0.56 ± 0.17 m·s^{-2}). Additionally, in the same research. the variables of high acceleration (m) (RMSE:50.3%) and deceleration distance (m) (RMSE: 93.3%) exhibited small and medium effect sizes respectively during small-sided games with 5 Hz GPS technology (Linke et al., 2018). Despite the results from the summary metrics, it should be noted that 5 Hz technology has been accepted within research has having limited validity for high-intensity movement compared to the current standard of 10 Hz technology (Malone et al., 2017; Scott et al., 2016). Determining the validity of instantaneous speed is thus important to subsequently calculating derivative metrics.

Therefore, it is of interest to establish the existing levels of error calculated at the instantaneous speed level before deriving GNSS metrics such as acceleration or metabolic power. As the origin of error in calculated acceleration metrics mainly derives from the level of error at the instantaneous speed level, this research will establish that future validity studies should assess the accuracy of variables at the instantaneous speed level. For example, instantaneous speed for GNSS systems should be assessed for validity, whilst the validity of position for X, Y coordinates for LPS and optical systems should be assessed. This study aims to highlight the existing levels of validity for instantaneous speed during team sport movements via GNSS technology. Subsequently this research will aim to establish that future research on wearable technology validity should focus assessment on the validity of instantaneous values of speed rather than derivative variables from speed.

6.3 Methods

6.3.1 Design and Participants

Ten elite youth academy and community-level football athletes participated in the study. Prior to the commencement of the study, all athletes, or their parents (for youth athletes) provided informed written consent to participate and to wear GNSS devices and VICON markers. Institutional ethics committee approval was obtained prior to the commencement of the research to conduct the study (HRE: 16-278).

6.3.2 Testing Environment

Testing was completed in a stadium that featured a full-sized, regulation football pitch. The testing stadium was used for national level competition and featured grandstand infrastructure that seated approximately 15,000 people. The testing area was a 30 x 30-m section where athletes were captured with both GNSS technology and via a three-dimensional capture system simultaneously.

6.3.3 Movement Protocols

To assess the validity of GNSS technology in quantifying team sport movement, athlete movement was assessed via a sport-specific movement circuit and two small-sided game variations. All 10 subjects in the research participated in the movement protocols, which were deemed to be representative of movement patterns closely associated with football. Movements included self-paced walking, jogging, changes of direction and maximal accelerations. All movement protocols took place inside the testing area. The design and operation of the sport-specific movement circuit was replicated based on previous research (Aughey et al., 2022). The movement circuit in the current research was completed first in two sets of 4-minute bouts. Five players participating in the first set of the 4-minute circuit, followed by the other 5 players in the second set. Small-sided games were structured in a 2v2 and a 5v5 format. One, 4-minute 2v2 game was played by four participants, which was followed by a 4-minute 5v5 game featuring all participants.

6.3.4 Tracking Systems

6.3.4.1 Global Navigation Satellite System

During testing, each athlete was tracked with commercially available 10-Hz GNSS technology (Optimeye S5, firmware: 7.42 Catapult Sports, Victoria, Australia) that was positioned between the scapulae, worn in a custom-made undergarment. GNSS devices were turned on at least 10-minutes prior to the commencement of testing to enable maximum satellite connectivity. GNSS devices were positioned in the undergarment to ensure the antenna was in the optimal position for satellite connectivity. Athlete tracking quality during testing was assessed with the number of satellites in connection with the device and via the horizontal dilution of precision (HDOP) (Malone et al., 2017). The mean number of satellites (mean ± standard deviation; 12.0 ± 0.14) and HDOP (0.93 ± 0.23) were acceptable for tracking human locomotion (Aughey, 2011a; Malone et al., 2017).

Following completion of the movement circuit and small-sided games, 24 individual GNSS files were downloaded (movement circuit = 10 files, 2v2 game = 4 files, 5v5 game = 10 files) using the GNSS proprietary software (Catapult Openfield, version 2.3.0, build 52085). GNSS files were trimmed to only include each activity in the movement protocol. GNSS files were then exported as comma-separated files (.csv) and imported into R Studio software (version 1.4.1717) for further analysis. Each raw export contained time, speed and acceleration values. Speed data was filtered in this research by a 1 Hz fourth-order, low-pass Butterworth filter. Butterworth filters have been deemed as being appropriate for processing human locomotion data due to human movement (i.e., running) tending to occur at the low end of the frequency spectrum (Ellens, Middleton, et al., 2022; Wei-zhong et al., 2011; Winter, 2009). Butterworth filters are commonly used in biomechanics as these filters attenuate high frequency noise whilst attempting to maintain the true signal as it passes over lower frequencies (Campbell et al., 2020; Winter, 2009). The cutoff frequency (1 Hz) in this study was selected following the application of a residual analysis on speed data residuals (Campbell et al., 2020; Winter, 2009). Selecting the cutoff frequency is important as selecting a frequency that is too high for the dataset may cause too much noise to pass through, whilst a cutoff frequency that is too low may compromise the true signal as typically the signal and noise would not be separate (Campbell et al., 2020; Winter, 2009). A residual analysis has been previously used in similar research despite concerns surrounding the underestimation of the optimal cutoff frequency (at frequencies well greater higher than 10 Hz) (Campbell et al., 2020; Yu et al., 1999). The residual analysis for this study can be seen in Figure 6-1 which outlines 1 Hz to be most appropriate for the current dataset. Following this methodology, the variables of mean speed and acceleration via GNSS were determined.

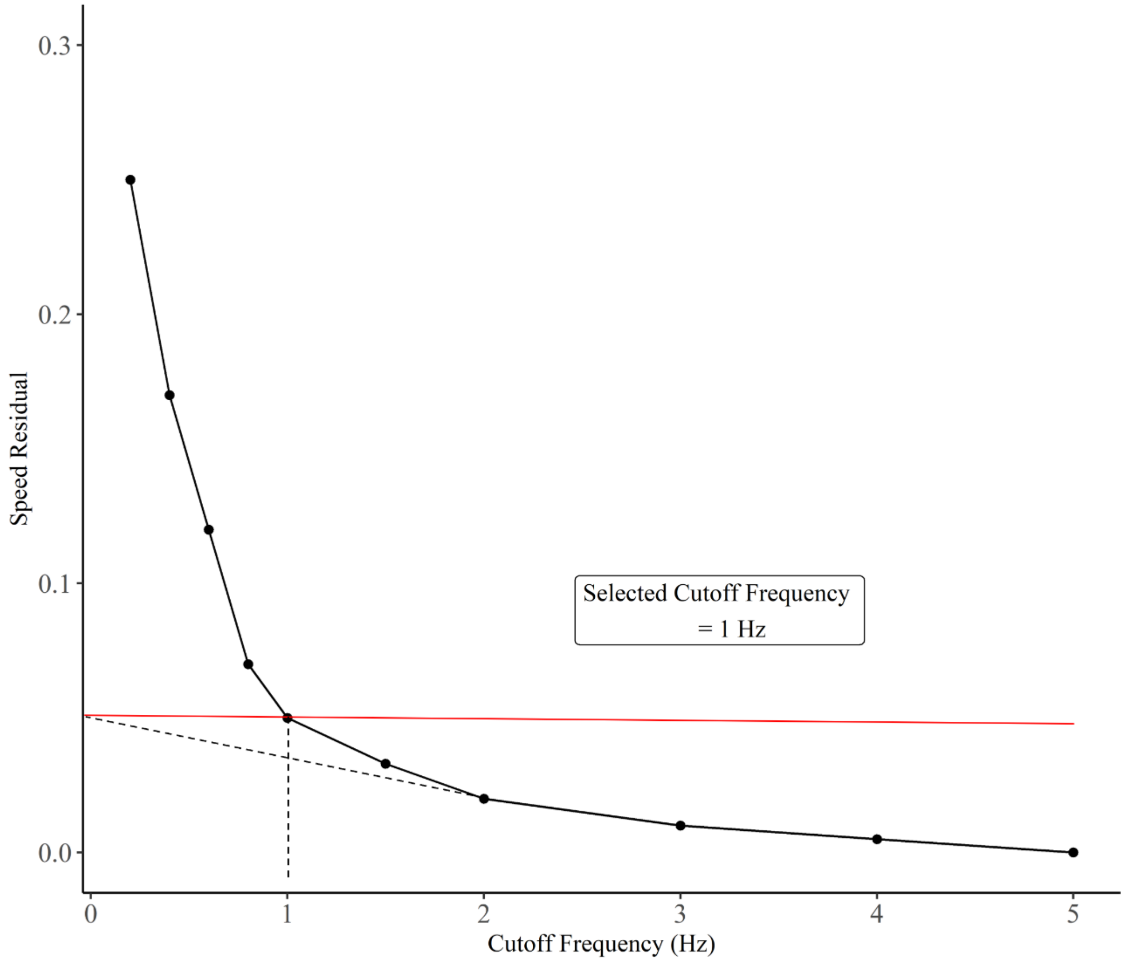

Figure 6-1 Residual analysis performed on the participant GNSS data.

6.3.4.2 Three-dimensional Capture System

The criterion measure of athlete locomotion was a three-dimensional motion capture system (VICON Vantage; Oxford Metrics, Ltd, Oxford, United Kingdom) that featured 36 VICON Vantage cameras (Oxford Metrics Group Plc [OMG], Oxford, UK) with a sampling frequency of 100 Hz. The cameras were placed around the 30 x 30-m testing area for both the small-sided games and the movement circuit as used previously (Aughey et al., 2022; Linke et al., 2018). To track athlete locomotion during testing, participants wore five 38-mm retro-reflective spherical markers that were placed on anatomical landmarks following similar methodology from previous research (Aughey et al., 2022).

One marker was placed on each shoulder, with three markers placed on the pelvis (left-anterior superior iliac spine, right anterior superior iliac spine and sacrum) (Linke et al., 2018). Data for each athlete's markers was labelled with the VICON Nexus software before being exported for further analysis.

6.3.5 Data Processing

To make appropriate comparison between the GNSS technology and the criterion, athlete locomotion data was processed using the following methodology. Firstly, speed was determined via doppler shift speed in GNSS technology and from the rate of change in horizontal X, Y position coordinates in the criterion measure. Acceleration was calculated as the rate of change in each respective technology's speed outputs. Positional data were exported in X, Y coordinate form from VICON. To obtain horizontal plane speed, raw positional data (X, Y coordinates) from the three-dimensional capture system were differentiated using a three-point finite central difference formula (Delaney et al., 2019; Gilat, 2013). As VICON sampled at 100 Hz and the GNSS technology sampled at 10 Hz, VICON data was down sampled to 10 Hz to align with GNSS technology as that is the primary tracking system of interest in this research. Once the data was processed to sample at 10 Hz, a residual analysis was performed on the X, Y and speed export data from VICON where a 1 Hz cutoff was selected (Campbell et al., 2020; Winter, 2009). Following the selection of the 1 Hz cutoff frequency, the fourth order, low-pass Butterworth filter was applied to the VICON X, Y and speed data (Chapter 5, Chapter 7 & Chapter 8). Once the VICON speed data was processed, acceleration was calculated. The above process was replicated for the GNSS dataset before a cross correlation was performed to synchronise both datasets using speed data. GNSS data was subsequently shifted forward and back by 10 seconds to obtain an optimal synchronisation to minimise the root mean square deviation (RMSD) in speed. Once data was aligned, the difference (error) between GNSS and VICON for speed and acceleration was calculated. A rolling three-point RMSD was then calculated and subsequently plotted to examine the magnitude of error in acceleration in relation to the magnitude of error in speed. All data processing following the export from the respective proprietary software was performed in R Studio software (version 1.4.1717).

6.3.6 Statistical Analysis

Following the processing of the GNSS and criterion data, the validity of GNSS for quantifying team sport movement was assessed via RMSD. Both speed and acceleration variables were compared against the criterion (24 total observations, 52178 data points) with the RMSD determined. Root mean square deviation analysis depicts the standard deviation of the differences between the GNSS calculated speed or acceleration against the respective variable from the criterion (VICON) (Aughey et al., 2022). The relationship between speed and acceleration error was then observed. The maximum absolute acceleration error that occurred as the speed error increased up to 0.4 $m \cdot s^{-1}$ (0.02 $m \cdot s^{-1}$intervals) was calculated, which resulted in 20 data points. The resulting 20 data points were plotted as a solid line in Figure 6-4 via a linear model, with the model returning a coefficient of determination of 0.98. Figure 6-4 shows the output from the linear model, with the solid line depicting maximal acceleration error occurring in 0.1 m/s speed error increments. The process in describing the maximal acceleration error against the speed error was not designed to be comprehensive, but rather to demonstrate that maximal acceleration error is related to the magnitude of the speed error.

6.4 Results

The results of the residual analysis are outlined in Figure 6-1. Upon completion of the residual analysis, a 1 Hz cutoff filter was selected. The RMSD for speed and acceleration (RMSD ± standard deviation [SD]) was 0.17 ± 0.04 $m \cdot s^{-1}$ and 0.55 ± 0.17 $m \cdot s^{-2}$ respectively. The speed error from GNSS and VICON speed is plotted in Figure 6-2. The acceleration error from GNSS and VICON acceleration is plotted in Figure 6-3. Speed error is plotted against acceleration error in Figure 6-4. Figure 6-4 shows an increase in the maximal acceleration error as the speed error increased.

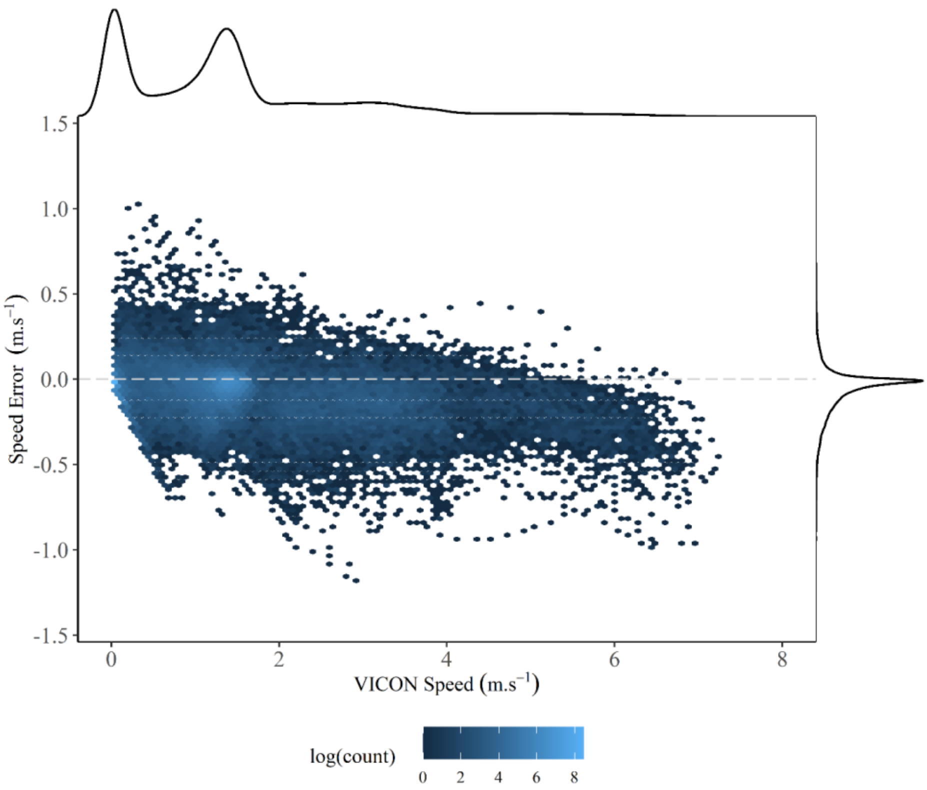

Figure 6-2 Speed ($m \cdot s^{-1}$) error derived from GNSS against the criterion speed. Density determined by a log of the instances.

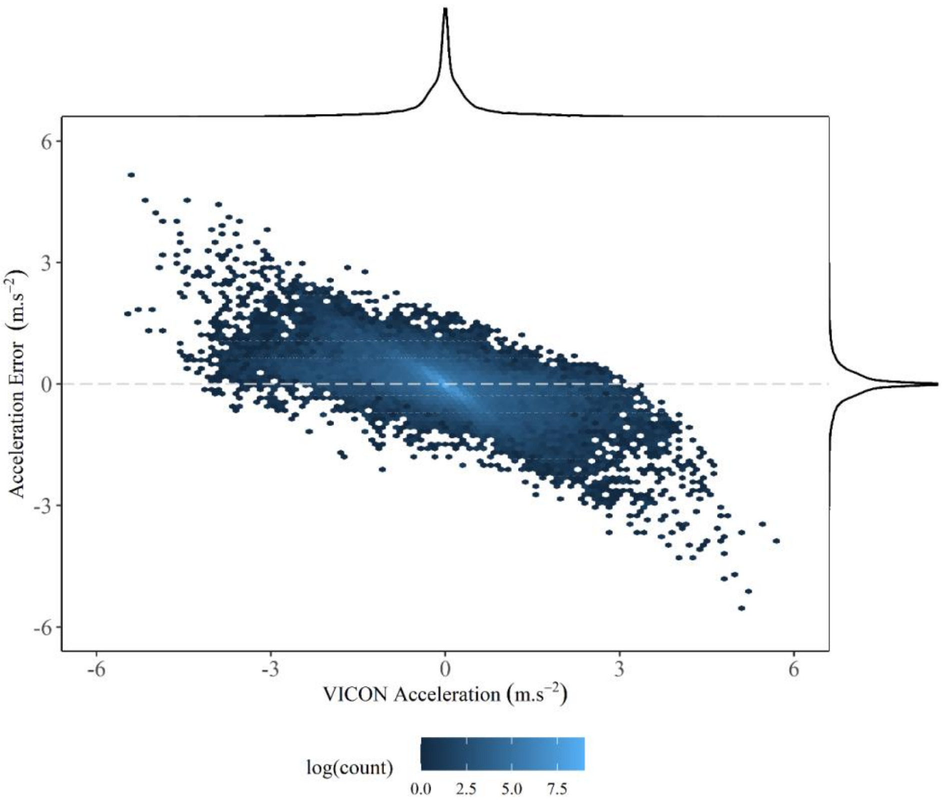

Figure 6-3 Acceleration ($m \cdot s^{-2}$) error derived from GNSS against the criterion acceleration. Density determined by a log of the instances.

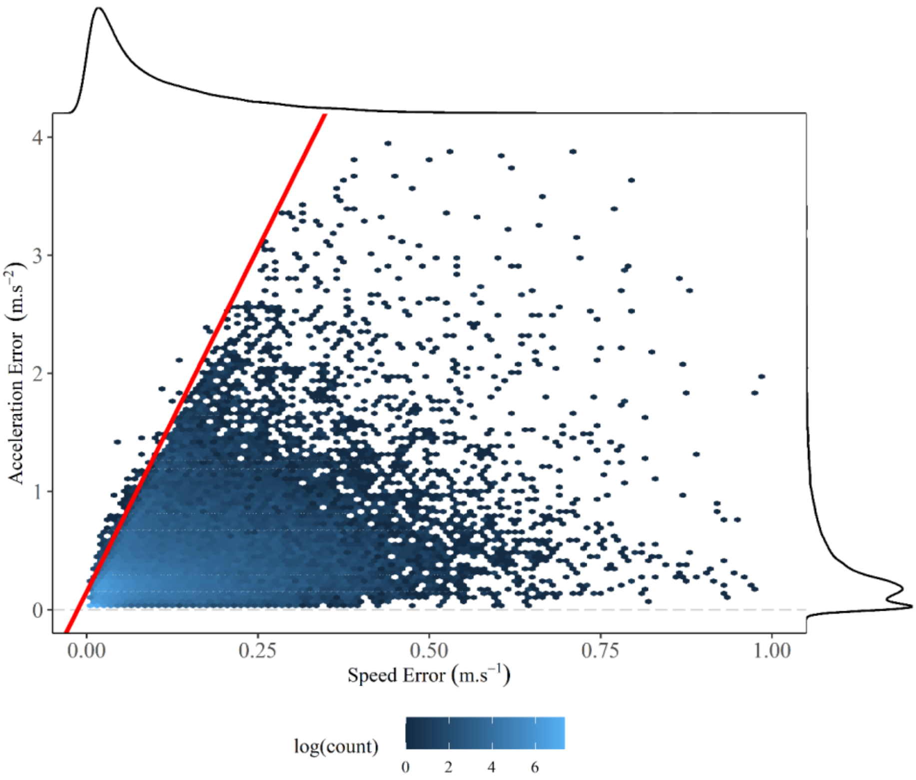

Figure 6-4 Speed error ($m \cdot s^{-1}$) derived from GNSS against the criterion acceleration plotted against Acceleration error ($m \cdot s^{-2}$). Density determined by a log of the instances.

6.5 Discussion

This study identified the validity of a GNSS device against a three-dimensional motion capture system during team sport movements. The GNSS device had strong agreement in speed and acceleration across a team sport movement circuit and multiple small-sided games when compared to the three-dimensional motion capture criterion.

The results from the current study showed a RMSD for speed and acceleration of 0.17 $m \cdot s^{-1}$ and 0.55 $m \cdot s^{-2}$ respectively. Currently there is limited research comparing GNSS technology validity against a three-dimensional motion capture system in a stadium environment (Aughey et al., 2022; Delaney et al., 2019). However, speed accuracy less than 0.50 $m \cdot s^{-1}$ is likely to be satisfactory in practical applications (i.e., team sport training and competition) as long as the error and subsequent impact on the athlete activity profile is understood (Aughey et al., 2022). Whilst the speed accuracy in the current study is considerably less than 0.50 $m \cdot s^{-1}$, it is difficult to make direct assessment as to the level of validity of the GNSS technology in this study with limited comparisons within research. In the limited research available, the validity of various EPTS in a stadium environment against VICON has been assessed (Linke et al., 2018). Global Positioning System technology reported a RMSD for speed of 0.28 $m \cdot s^{-1}$ which increased to 0.67 $m \cdot s^{-2}$ for acceleration (Linke et al., 2018). The reported results showed greater error compared to the GNSS results in the current study. However, the GPS technology used in the cited research, sampled at 5 Hz (interpolated to 15 Hz) which would be considered inferior to the 10 Hz GNSS technology used in the current study and as such may have contributed to the stated differences.

The results from this study also highlighted the importance of minimising speed error on the subsequent validity of derivative variables. Acceleration is a common variable for analysis in team sport activity profiles, but acceleration is also a second derivative of displacement and time and a first derivative of speed (Aughey, 2011b; Aughey et al., 2022; Delaney, Cummins, et al., 2018). As such, any existing error at the speed level may be magnified when acceleration is derived (Delaney et al., 2019; Duran & Earleywine, 2012; Thornton, Nelson, et al., 2019). The results from this study indicated that RMSD for speed (0.17 $m \cdot s^{-1}$) further increased when acceleration was subsequently derived (0.55 $m \cdot s^{-2}$). The influence on the existing levels of error in speed upon acceleration is illustrated in Figure 6-4 and shows high levels of density below the speed error threshold of 0.5 $m \cdot s^{-1}$. Moreover, Figure 6-4 indicates that as the magnitude of the speed error increased, the magnitude on acceleration error also increased. It should be noted as Figure 6-3 illustrates, the majority of acceleration error in the current study occurred at approximately 0 – 1 $m \cdot s^{-2}$. This finding is not novel given the results from previous research, where existing levels of speed error have been further magnified when derivative variables have been formulated (Linke et al., 2018). However, there are practical instances within applied team sport where the GNSS-calculated speed error could be high whilst the acceleration error remains low. For example, an attacking player breaks through the defensive line in rugby league and sprints towards the try line uncontested at a 9 $m \cdot s^{-1}$ as tracked by an optical system or 3D motion capture system. The GNSS technology records the effort at 8 $m \cdot s^{-1}$, which results in a speed error of approximately -1 $m \cdot s^{-1}$. If the speed within this effort isn't changing substantially (which minimises changes in acceleration) and both tracking models record acceleration at 0 $m \cdot s^{-2}$, the resulting acceleration error is still 0 $m \cdot s^{-2}$. Regardless, the results from this study indicate that establishing the validity of instantaneous speed is important before attempting to produce derivative variables for analysis, such as acceleration. Specifically, acceleration metrics in team sports can be quantified using discrete variables that rely upon thresholds (i.e., counts, distances, time in zones) and as such, the validity for these measures should be established before practitioners make informed decisions on activity profiles (Chapter 3). Additionally, metrics such as metabolic power have become common in team sport activity profiles, which is also partly derived from acceleration data, again highlighting the importance of not only establishing the validity for acceleration but for the initial validity of speed (Delaney, Duthie, et al., 2016; Delaney, Thornton, Burgess, et al., 2017; Delaney, Thornton, et al., 2018; Delves et al., 2019; di Prampero et al., 2005; Osgnach et al., 2010).

The choice of filter and cutoff frequency can have an influence upon the validity of speed and acceleration data as calculated from GNSS technology (Delaney et al., 2019; Malone et al., 2017; Thornton, Nelson, et al., 2019; Winter, 2009). This study largely performed the handling and processing of the participant data independently of the GNSS manufacturer's proprietary software. Firstly, the researchers selected a Butterworth filter given most human locomotion is undertaken at lower frequencies (Campbell et al., 2020; Winter, 2009; Yu et al., 1999). As a result, the researchers performed a residual analysis on the instantaneous speed data to identify the optimal cutoff frequency for this dataset (Campbell et al., 2020; Winter, 2009). A residual analysis was performed as the effectiveness of the Butterworth low-pass filter can depend upon the appropriateness of the cutoff frequency selected (Campbell et al., 2020; Yu et al., 1999). The results of the study showed that despite the researchers processing the participant data independently of the GNSS proprietary software, instantaneous speed was identified as being valid against the criterion. The researcher suggests that the use of the fourth-order 1 Hz Butterworth filter used in the current study is suitable for processing athlete GNSS data, with respect to team sport athletes, given the completion of the team sport movement circuit and series of SSGs completed within the study.

6.6 Practical Applications

The practical application of a residual analysis could allow practitioners to begin to process athlete tracking data using their own filtering settings by following a similar methodology to the current study. Practically, this may aid practitioners who may wish to complete longitudinal analysis of athlete tracking data over competitive seasons whilst trying to maintain as much consistency in the data handling process as possible. Greater consistency in the data handling process may improve the ability to make comparisons between seasons, given the potential impact of manufacturer software updates upon variables such as acceleration which are periodically available across seasons. Moreover, the results from this study have shown that the filter chosen for this dataset may have facilitated valid results compared to the criterion. It should be reiterated that Butterworth filters have been widely used throughout research into human locomotion, given human movement occurs at lower frequencies and Butterworth filters typically allow lower frequencies to pass through whilst filtering higher frequencies (Campbell et al., 2020; Couderc et al., 2019; Ellens, Hodges, et al., 2022; Furlan et al., 2015; Winter, 2009). The choice of a common filter may promote greater consistency for practitioners who elect to process athlete tracking data themselves, where typically they may have greater control over the processing methodology (i.e., filter choice and cutoff frequency) as opposed to relying upon the manufacturer processing and any subsequent updates to software or device firmware (Harper et al., 2019; Malone et al., 2017). However, it should be noted that different wearable tracking manufacturers may allow greater access and transparency to practitioners who wish to process tracking data themselves compared to other manufacturers. This may mean that some practitioners or academics may be continually reliant upon manufacturer processing to handle athlete tracking data as the end-users of the technology are generally subject to what the manufacturer provides in terms of processing, filtering and software/firmware updates with little consultation.

6.7 Limitations

Whilst this study assessed the validity of instantaneous speed and acceleration via GNSS technology, the study did not assess the validity of GNSS-calculated athlete position compared to the criterion. However, previous research has indicated that despite GPS technology having inferior levels of positional accuracy compared to LPS systems, GPS, or in the current study's example, GNSS, can overcome positional limitations when calculating instantaneous speed through the avoidance of cycle slips via Doppler measurements (Linke et al., 2018).

Currently it is not feasible to assess the validity of GNSS technology during competitive football matches due to the technological difficulties of creating a capture area so vast and due to the configuration of cameras near the playing surface. Thus, there is no gold standard criterion to assess GNSS technology during competitive, outdoor team sports (Linke et al., 2018). Moreover, whilst the incorporation of a movement circuit in conjunction with the use of SSGs provides an element of game simulation regarding movement patterns, the size of the capture area is not a direct representation of competition movements and work to rest patterns. Lastly, this study assessed the validity of GNSS technology from one model from one manufacturer. Given the growth in GNSS technology in team sports, there are numerous manufacturers across various sample rates that should also be considered (Malone et al., 2017).

6.8 Conclusions

This study established the validity of a GNSS device during a team sport circuit and SSG testing battery against a three-dimensional motion capture system. The results from the study suggest that the GNSS technology, which processed athlete movement data using a fourth order, 1 Hz Butterworth filter was valid for instantaneous speed. The RMSD for acceleration showed to increase as the RMSD for speed increased, indicating that practitioners and researchers should elect to establish the validity of instantaneous speed first before processing derivative measures such as acceleration or metabolic power.

CHAPTER 7 - ASSESSING THE ACCELERATION INTENSITY ACROSS NATIONAL RUGBY LEAGUE SEASONS FOLLOWING THE INTRODUCTION OF THE SIX-AGAIN RULE

7.1 Declaration of co-authorship and co-contribution

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

This declaration is to be completed for each conjointly authored publication and placed at the beginning of the thesis chapter in which the publication appears.

1. PUBLICATION DETAILS (to be completed by the candidate)

Title of Paper/Journal/Book: Title: The introduction of the six-again rule has increased acceleration intensity across all positions in the National Rugby League competition
Journal: Science and Medicine in Football

Surname: Delves First name: Robert

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

Status:

Accepted and in press: ☐ Date:

Published: ☑ Date: 14/03/2022

2. CANDIDATE DECLARATION

I declare that the publication above meets the requirements to be included in the thesis as outlined in the HDR Policy and related Procedures – policy.vu.edu.au.

[redacted] 05/07/2022

Signature **Date**

3. CO-AUTHOR(S) DECLARATION

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

The undersigned certify that:

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

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3. There are no other authors of the publication according to these criteria;
4. Potential conflicts of interest have been disclosed to a) granting bodies, b) the editor or publisher of journals or other publications, and c) the head of the responsible academic unit; and
5. The original data will be held for at least five years from the date indicated below and is stored at the following **location(s)**:

All electronic data will be stored on the Victoria University R Drive. This drive is the central storage facility maintained by Victoria University.

Name(s) of Co-Author(s)	Contribution (%)	Nature of Contribution	Signature	Date
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Kevin Ball	2.5	Assisted with study design, feedback and revisions	[redacted]	17/08/2022
Grant Duthie	2.5	Assisted with study design, methodology, feedback and data analysis	[redacted]	17/08/2022
Heidi Thornton	2.5	Assisted with study design, methodology, feedback and data analysis	[redacted]	17/08/22
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Delves, R. I. M., Thornton, H. R., Hodges, J., Cupples, B., Ball, K., Aughey, R., & Duthie, G. M. (2022). The introduction of the six-again rule has increased acceleration intensity across all positions in the National Rugby League competition. Science and Medicine in Football, 7(1), 47–56. https://doi.org/10.1080/24733938.2022.2051729

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7.2 Directions from Chapter 6

Chapter 6 established the validity of a GNSS device for instantaneous speed against a three-dimensional motion capture system. The filter used in Chapter 6 (and Chapter 5) helped establish validity for instantaneous speed against the criterion measure, indicating a level of appropriateness for practical use on team sport data in the applied setting. Rugby league has experienced rule changes which the governing body in Australia (Australian Rugby League Commission) believed would increase the pace of play (Australian Rugby League Commission, 2020). However, given the notable acceleration component in rugby league, it would be of interest to examine any differences in acceleration in the competition activity profile (Delaney, Duthie, et al., 2016). Updating and reviewing the competition activity profile is a common task performed by sport scientists in ensuring that training and rehabilitation protocols are suitable for the current activity profile (Delves et al., 2019; Sunderland & Edwards, 2017). However, to compare between seasons before and after the implementation of rule changes, consistency is needed in processing of athlete tracking data. To provide a more appropriate comparison, Chapter 7 will process athlete acceleration data from National Rugby League (NRL) competition in seasons before and following the introduction of a rule change with the filter settings used in Chapters 5 and 6. Thus Chapter 7 will build upon the previous chapters by replicating a common scenario faced by applied practitioners in analysing the competition activity profile, but with an improved capacity to compare activity profiles with similar processing settings for athlete acceleration.

7.3 Introduction

Rugby league is a collision-based team sport that features intermittent bouts of repeated high-intensity activity distributed between low-intensity movement (Cummins et al., 2018; Gabbett, 2015; Hausler et al., 2016; R. Johnston et al., 2014; Kempton et al., 2013). In the National Rugby League (NRL), the adoption of GNSS technology has led to substantial research on the activity profile of rugby league competition (Austin & Kelly, 2013; R. Johnston et al., 2014; Waldron, Twist, et al., 2011). Subsequently, speed ($m \cdot min^{-1}$) and acceleration ($m \cdot s^{-2}$) intensity during competition has been quantified across rugby league competition, with whole-match averages described by positional group and for full and modified athlete participation (Cummins et al., 2018; Dalton-Barron et al., 2021; Dempsey et al., 2018; Kempton, Sirotic, & Coutts, 2015; Varley et al., 2014).

Moving average windows ranging from 1 to 10 minutes in duration have been used to investigate the running speed of rugby league competition (Delaney et al., 2015; Weaving et al., 2019; Whitehead et al., 2019; Whitehead et al., 2018). The peak 1-minute speed has been found to range between ~154 to 179 $m \cdot min^{-1}$ across all positional groups within the NRL and Super League (SL), with fullbacks identified as having the greatest intensity (~179 $m \cdot min^{-1}$) (Delaney, Duthie, et al., 2016; Delaney et al., 2015; Weaving et al., 2019). However, the maximal mean speed and acceleration over a given duration only quantifies a small proportion of the game, specifically, 1-minute (Johnston et al., 2022; Novak et al., 2021; Thornton et al., 2020). As such, practitioners also need to have information regarding the distribution of intensity over the duration of games when preparing athletes for the rigors of competition. Data attained from games can be used to monitor drills that are designed to mimic or exceed the activity profile of competition or can be used to inform rehabilitation protocols (Aughey, 2011a; Bradley et al., 2009; Delaney, Duthie, et al., 2016; Jennings et al., 2012a). Further, athlete intensity data from matches can allow practitioners to record and evaluate the intensity of conditioning games and context-specific drills (i.e., 13 vs 13 team drills) relative to competition. However, despite the application of activity profiles to training programs, the findings published in research are relevant to competition rules invoked during the time of publication (Austin & Kelly, 2013; Delaney, Duthie, et al., 2016; Delaney et al., 2015; R. Johnston et al., 2014). Changes in the existing competition rules may alter the activity profile of competition and therefore, may warrant corresponding changes to athlete training programs (Delaney, Duthie, et al., 2016; Sunderland & Edwards, 2017).

The modification of competition rules can impact existing activity profiles (Delves et al., 2019; McMahon & Kennedy, 2019; Sunderland & Edwards, 2017). In 2014, elite field hockey reduced total playing time from 70 minutes to 60 minutes (Delves et al., 2019; McMahon & Kennedy, 2019; Sunderland & Edwards, 2017). This rule change substantially increased the mean speed (across all positions) (McMahon & Kennedy, 2019). In rugby league, the New South Wales Rugby League extended the 5 m retreat by the defensive team after each completed tackle to a 10 m retreat (McLellan et al., 2011; Meir et al., 2001). Via retrospective time-motion analysis, it was determined that due to the extension of the separation between the attacking and defending lines, forwards increased their time jogging (8% increase) (Meir et al., 2001). Importantly, differences in the locomotion pattern of athletes reported in research may prompt practitioners to review and/or alter their training programs to reflect the updated activity profile (McMahon & Kennedy, 2019; Meir et al., 2001) .

Following the initial suspension of the 2020 season due to the COVID-19 pandemic, the NRL implemented changes to the competition rules. The two-referee system was reduced to one referee, whilst adjustments were made to ruck infringements (McLellan et al., 2011). Colloquially termed the “six-again” rule, ruck infringements (area immediately surrounding the tackled player) were changed from the awarding of a traditional penalty, where teams were given the option of kicking into touch, restarting an attacking set from the penalty spot or a penalty shot at goal; to an automatic reset of the team's tackle count to a full six tackle allocation. The six-again rule is believed to increase the speed of the game and promote greater ball-in-play time, which could have ramifications on the activity profile of athletes in competition (Australian Rugby League Commission, 2020). However, there is limited research surrounding the impact of the revised competition rules on the activity profile of NRL matches. Specifically, given the intention of the six-again rule, it is important that research details the changes in intensity under the current competition format.

Therefore, the primary aim of this study was to update and compare the peak movement intensity of NRL athletes via GNSS technology between the 2019 (previous competition format), 2020 and 2021 seasons (current competition format). The secondary aim of this study was to analyse the effect of the six-again rule on athlete mean acceleration and speed relative to ball-in-play times. Lastly, the change in the distribution of running volumes across competition formats relative to ball-in-play times was evaluated.

7.4 Methods

7.4.1 Design and Participants

An observational, longitudinal study design was implemented to investigate the study aims. The mean peak running intensity, mean acceleration/speed and the distribution of volume relative to ball-in-play times between the 2019, 2020 and 2021 NRL seasons were investigated. The activity profile of competition was quantified through GNSS technology worn in competition and ball-in-play times were obtained from NRLPRO (Stats Perform, Sydney, Australia). All experimental data was collected from one participating club. All athletes provided informed written consent to participate, and institutional ethical approval was granted by the Victoria University Human Research Ethics Committee (HRE21-017).

Global Navigation Satellite System data was collected from 42 elite rugby league athletes (mean ± SD; 26 ± 2 years, age range; 18 to 32 years, 185 ± 7.8 cm, 94 ± 4.6 kg) during the 2019, 2020 and/or 2021 seasons. The data collection period took place across the 2019 (20 matches), 2020 (21 matches) and 2021 (15 matches) seasons. The dataset comprised a total of 56 matches with 876 individual athlete competition files analysed. 20 matches were analysed prior to the introduction of the six-again rule change, whilst 36 matches were analysed following the introduction of the rule change. Match files from the 2020 and 2021 seasons were separated due to the interruption of the 2020 season. From the 42 athletes who participated in the study, the mean and SD match observations was 21 ± 14 (range: 1 to 46). To evaluate differences in the activity profile between positions, match files were categorised into their playing positions, determined by where the athlete spent the majority of the time during each match. Athletes (n = 42) were allocated to four positional groups; edge forwards (n = 6), halves and hookers (half-back, five-eighth and hooker; n = 10) outside backs (winger, centre and fullback; n = 14) and middle forwards (middle forward, lock and interchange forward; n = 12). Edge forwards were separated from middle forwards due to their extended match durations compared to middle forwards and wider field positioning. Hookers were grouped with halves due to ball-playing responsibilities and extended match durations, despite generally playing in the middle of the field when defending. Fullbacks were grouped with outside backs rather than halves and hookers due to the field positioning, particularly when defending. Fullbacks do not defend in the defensive line for a full six-tackle set and share similar responsibilities to outside backs on kick returns and first-tackle carries after a defensive possession.

7.4.2 Procedures

During all matches across the 2019, 2020 and 2021 NRL seasons, athlete GNSS data was collected with a commercially available, 10-Hz GNSS (Vector S7, firmware; 8.1, Catapult Sports, Victoria, Australia). The GNSS was worn between the scapulae in either a custom undergarment or within a pouch attached to the athlete's game jersey. Where possible, athletes wore the same GNSS across each respective season to minimise inter-unit variability (Buchheit, Al Haddad, et al., 2014). The quality of data was evaluated via the horizontal dilution of precision (HDOP) and satellite count. No files had a HDOP value >1.5 (typical cut off for removal) (mean ± SD; 0.61 ± 0.22), whilst the satellite count (11 ± 2) was acceptable (Aughey, 2011a; Malone et al., 2017).

Upon completion of each match, athlete GNSS files were downloaded and trimmed using the proprietary software (Openfield, version; 3.3.1, build #68050, Catapult Sports, Victoria, Australia) to only include instances where the player was on field (i.e., excluded bench players). Raw 10 Hz GNSS files were exported as comma-separated files (.csv) from the proprietary software and imported into R Studio software (RStudio v. 1.4.1106, RStudio, Boston, MA) for further analysis. Each raw export included time, speed and acceleration. Units of measure for speed was converted from kilometres per hour ($km \cdot h^{-1}$) to metres per second ($m \cdot s^{-1}$). Speed was processed using a fourth-order, low-pass Butterworth filter with a cutoff frequency of 1 Hz (Delaney, Duthie, et al., 2016). Following the processes outlined previously, a residual analysis was used to determine the appropriate cutoff frequency for the processing of speed (Winter, 2009). Acceleration was then computed using finite differentiation (central difference) of the filtered speed with a 0.4 s dwell time. Following the calculation of acceleration, speed was converted from metres per second ($m \cdot s^{-1}$) to metres per minute ($m \cdot min^{-1}$) to facilitate analysis of the observed metrics. Maximal mean speed ($m \cdot min^{-1}$) and acceleration ($m \cdot s^{-2}$) were included as analysed variables representing the peak intensity in rugby league competition, following on from similar research (Delaney, Duthie, et al., 2016; Delaney et al., 2015). Both maximal mean speed ($m \cdot min^{-1}$) and acceleration ($m \cdot s^{-2}$) were calculated from 10 seconds to 10 minutes in 10-second increments. Following this process, categorising variables such as position and season were included in the dataset.

7.4.3 Peak Intensity Analysis

Using the 10-second to 10-minute maximal mean speed ($m \cdot min^{-1}$) and acceleration ($m \cdot s^{-2}$) data, the relationship between running intensity and duration was observed using a power law relationship (Delaney, Thornton, et al., 2018; G. Rennie et al., 2020). To establish this relationship, a linear model was fitted to the log transformed duration and log transformed intensity (speed or acceleration) to identify the intercept (c) (mean estimates) and slope (n) (rate of decay) for each player file (Delaney, Thornton, et al., 2018; Delves et al., 2019; G. Rennie et al., 2020). An intercept and slope were calculated for each match observation.

7.4.4 Ball-in-play Analysis

Following each match, an export of the ball-in-play phases within the match were downloaded from NRLPRO (official match statistics provider). Within these files, the start and end time of each event within a game was provided. After removing non-ball-in-play phases, this file was imported into the GNSS proprietary software in an extensible markup language (XML) format and were synced to the Openfield cloud-based software. Once on the Openfield cloud, a common separated file of the match was exported, which included each ball-in-play phase and the corresponding GNSS data for each player. Match ball-in-play time was determined through summating the coded ball-in-play phase. Each match total was then averaged against all other matches in the respective season to determine a mean ball-in-play match time. Mean speed ($m \cdot s^{-1}$) and acceleration ($m \cdot s^{-2}$) relative to ball-in-play time were calculated by extracting the mean value respectively for each match and then averaging for each corresponding season. The mean total match time (minutes), mean ball-in-play phase (seconds) as well as mean speed ($m \cdot s^{-1}$) and acceleration ($m \cdot s^{-2}$) relative to ball-in-play time were analysed.

7.4.5 Distribution Analysis

The distribution of acceleration and speed were also assessed relative to ball-in-play time. Distance accumulated at speed thresholds (0.5 $m \cdot s^{-1}$ increments, range; 2 to 9 $m \cdot s^{-1}$) and impulse accumulated at acceleration thresholds (0.25 $m \cdot s^{-2}$ increments, range; 1 to 6 $m \cdot s^{-2}$) were quantified. Individual athlete mass (kg) was included to determine impulse. Unlike the methodology for power law analysis, upon completion of each match, athlete GNSS files were trimmed to reflect athlete locomotion during ball-in-play time. Raw 10 Hz GNSS files were imported into R Studio software as previously mentioned. For each ball-in-play phase, distance (speed x 0.1) and impulse (speed x mass x 0.1) were calculated at each 1 Hz sample. All speed data < 2 $m \cdot s^{-1}$ and all acceleration data <1 $m \cdot s^{-}$

^{2} were removed from analysis. Distances at each speed and impulse at each acceleration increment were summated across all ball-in-play phase during each game to determine individual player totals. Individual game totals for distance and impulse were log transformed. A quadratic model was then fitted to log transformed game totals to derive the quadratic coefficient (a), linear coefficient (b), and intercept (c) coefficients and the coefficient of determination (r^2) for speed and acceleration for each player for each match. The quadratic coefficients describe the relationship between the volume covered in a game, and the intensity of which that volume was completed. Specifically, a represents the overall position of the curve up and down the y axis (i.e., wide or narrow), b reflects the upward or downward linear trend in y values along the x axis, and c is a constant (intercept), representing where the relationship sits on the y axis (Duthie et al., 2021).

7.4.6 Statistical Analysis

7.4.6.1 Peak Intensity Analysis

To investigate any differences between the peak intensity of NRL athletes across the 2019, to 2021 seasons, multiple random intercept linear mixed models were used. The analysed dataset was separated by metric (e.g., maximal mean speed or acceleration), before being filtered by position. Rather than using an interaction between playing position and either speed or acceleration intercept/slope, the dataset was filtered to only include one playing position at a time in separate models, due to overfitting of the models. This process led to the use of 16 separate models (two metrics [speed or acceleration] x four playing positions x two variables [slope or intercept]). In these models, either the speed or acceleration intercept/slope (depending on the model) from the initial power law relationship determined previously was used as the outcome measure (dependent variable; value will depend on the season), whilst playing season was designated as a fixed effect (independent variable). Athlete identification was included as a random intercept. For each model, the least squares mean test was used to determine the differences between playing seasons (fixed effect). The resulting mean, standard deviation (SD) and mean difference for each position, variable and metric were then analysed to establish effect sizes (ES) and confidence limits (CL; 90%). The magnitude of effect sizes was described as previously implemented; <0.20 trivial; 0.21- 0.60 small; 0.61 – 1.20 moderate; 1.21 – 2.0 large and >2.01 very large (Hopkins et al., 2009). Effect sizes were described according to previous research, with any effect deemed to be real if they were at least 75% greater than the smallest worthwhile change (SWC) (calculated as 0.6 x between-athlete SD) (Duthie et al., 2022; Hopkins et al., 2009; Johnston et al., 2022).

7.4.6.2 Ball in Play Analysis

The differences in ball-in-play-based metrics were assessed via the use of random intercept linear mixed models. Mean ball-in-play phase and mean speed and acceleration were log transformed and were included as the model's outcome measure and playing season was included as the fixed effect. The model for mean match duration designated playing round as a random effect as there were no individual players in the dataset. Differences between playing seasons were determined through similar methods for intercept/slope analysis using the least squares mean test. However, effect sizes, for mean match duration and mean ball-in-play phase, were deemed to be real if they were at least 75% greater than the smallest worthwhile change (SWC) (calculated as 0.2 x between-athlete SD). Differences in mean acceleration and speed relative to ball-in-play time were assessed using similar methods for intercept and slope analysis. In keeping with the GNSS related metrics, the SWC was calculated as 0.6 x between-athlete SD.

7.4.6.3 Distribution Analysis

To analyse the difference in the distribution of speed and acceleration intensity across the 2019, 2020 and 2021 seasons, random intercept linear mixed models were also implemented, following similar methods to the previous sections. Coefficients (a, b and c) for distance and impulse were included separately in models as the outcome measure, and season was included as the fixed effect. As per the methods of the peak intensity analysis, the dataset was separated by positional group, whereby a separate model was run for each positional group. Effect sizes were established using the methodology previous stated. Effects for this analysis were deemed to be real if they were at least 75% greater than the SWC (calculated as 0.6 x between-athlete SD). All statistical analysis was conducted using R Studio software (RStudio v. 1.4.1106, RStudio, Boston, MA).

7.5 Results

7.5.1 Changes in Intensity

Compared to the 2019 season, power law-based speed intercepts in the 2021 season were higher for edge forwards (ES = 1.03; ± 0.49) and halves and hookers (ES = 0.78; ± 0.36) (Table 7-1, Figure 7-1). Compared to the 2019 season, speed slopes for outside backs were higher in the 2020 season (ES = 0.86; ± 0.30) as well as the 2021 season (ES = 0.83; ± 0.33).

The power-law based acceleration intercept was substantially different for all positional groups between playing seasons. Compared to the 2019 season, edge forwards had an increase in acceleration intercepts in 2020 (ES = 1.28 ± 0.53) as well as an increase in season 2021 (ES = 2.78; ± 1.14). Compared to the 2019 season, halves and hooker's acceleration intercepts were greater in seasons 2020 (ES = 1.74; ± 0.72) and 2021 (ES = 2.19; ± 0.91). Acceleration intercepts for middle forwards were greater in season 2020 compared to the 2019 season (ES = 1.43; ± 0.60), whilst acceleration intercepts in 2021 were greater (ES = 2.29; ± 0.96) than the 2019 season. Compared to 2019, acceleration intercepts for outside backs were greater in the 2020 (ES = 1.67; ± 0.70) and 2021 seasons (ES = 2.47; ± 1.03). No substantial differences were found in the acceleration slopes across all positional groups between seasons.

Table 7-1. Intercept and slope values (mean ± SD) for speed and acceleration based upon a 1-minute moving average in NRL athletes across the 2019, 2020 and 2021 Premiership seasons.

Position	Intercept			Slope		
	2019	**2020**	**2021**	**2019**	**2020**	**2021**
Acceleration ($m \cdot s^{-2}$)						
Edge Forward	0.94 ± 0.04	1.03 ± 0.09*	1.07 ± 0.05*	-0.26 ± 0.02	-0.25 ± 0.03	-0.25 ± 0.02
Halves & Hooker	0.96 ± 0.06	1.09 ± 0.08*	1.09 ± 0.06*	-0.25 ± 0.03	-0.23 ± 0.04	-0.23 ± 0.03
Middle Forward	0.89 ± 0.05	0.99 ± 0.08*	1.03 ± 0.07*	-0.26 ± 0.03	-0.26 ± 0.03	-0.26 ± 0.03
Outside Back	0.87 ± 0.06	1.02 ± 0.12*	1.05 ± 0.09*	-0.27 ± 0.03	-0.25 ± 0.03	-0.25 ± 0.03
All Positions	0.91 ± 0.07	1.02 ± 0.10*	1.06 ± 0.07*	-0.26 ± 0.03	-0.25 ± 0.04	-0.25 ± 0.03
Speed ($m \cdot min^{-1}$)						
Edge Forward	179 ± 9	182 ± 9	189 ± 11*	-0.24 ± 0.02	-0.24 ± 0.03	-0.23 ± 0.04
Halves & Hooker	180 ± 12	185 ± 11	188 ± 13*	-0.23 ± 0.03	-0.22 ± 0.03	-0.22 ± 0.03
Middle Forward	171 ± 11	175 ± 11	179 ± 10	-0.24 ± 0.03	-0.24 ± 0.03	-0.23 ± 0.04
Outside Back	181 ± 13	184 ± 12	186 ± 12	-0.26 ± 0.03	-0.24 ± 0.03*	-0.23 ± 0.04*
All Positions	177 ± 12	181 ± 12	185 ± 12	-0.25 ± 0.03	-0.23 ± 0.03	-0.23 ± 0.04

*Denotes season being different (at least 75% greater than the SWC (calculated as 0.6 x between-athlete SD) compared to previous rule format (season 2019).

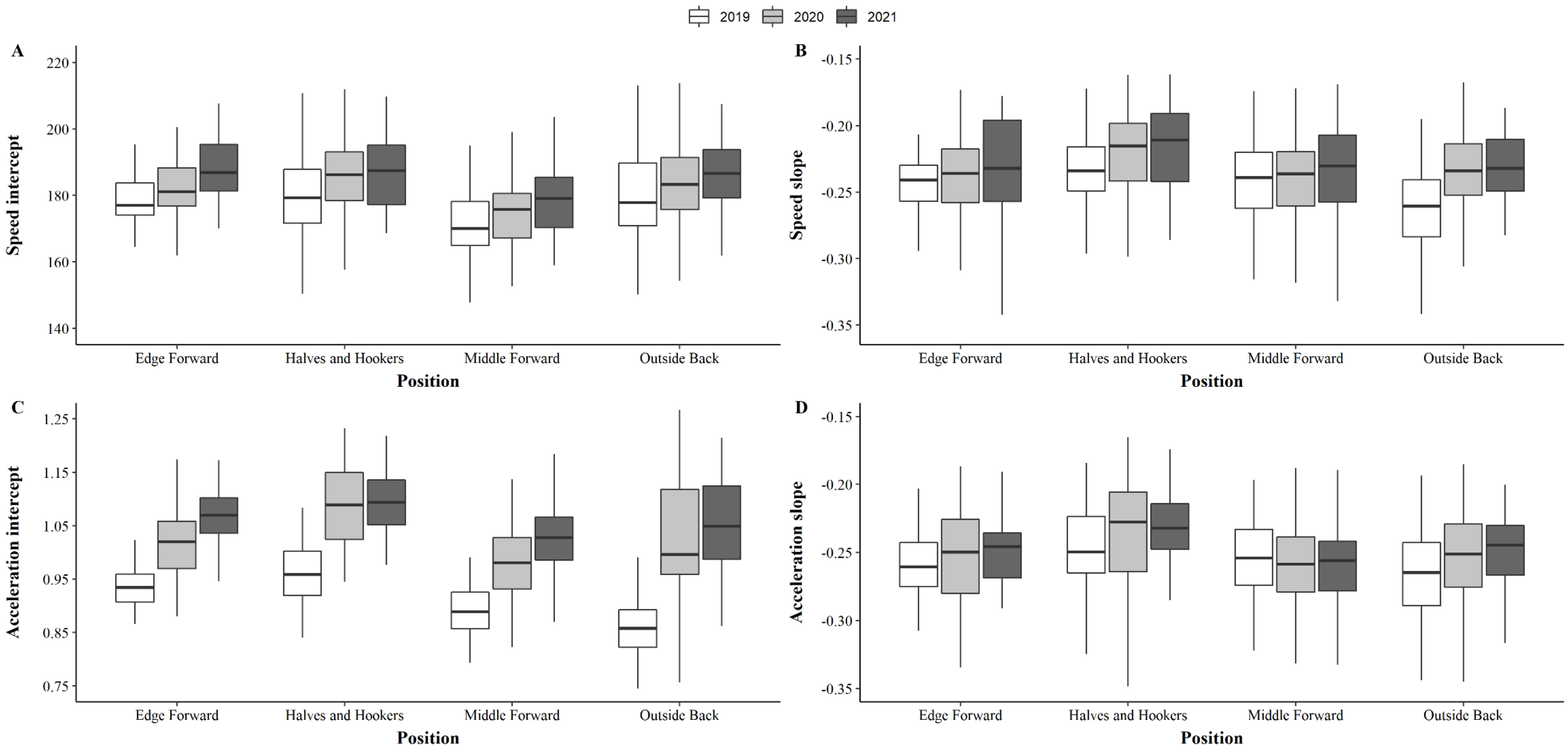

Figure 7-1. Intercept and slope values for speed (A and B) and acceleration (C and D) by position and season. The box plots represented the median, first and third quartiles and the whiskers are 1.5 x interquartile range.

7.5.2 Ball-in-Play

Total match duration relative to ball-in-play time was greater in season 2020 compared to season 2019 (ES = 0.57; ± 0.51) (Table 7-2). Mean ball-in-play phase lengths were greater in both the 2020 (ES = 1.00; ± 0.55) and 2021 (ES = 0.90; ± 0.61) seasons compared with season 2019. Mean acceleration relative to ball-in-play time was greater in season 2020 (ES = 0.75; ± 0.32) compared with season 2019. There was no difference in mean speed relative to ball-in-play across seasons.

Table 7-2. Ball-in-play times (mean ± SD) across NRL competition during the 2019, 2020 and 2021 Premiership seasons.

Ball-in-play metric	Season		
	2019	2020	2021
Total ball-in-play match duration (mins)	53 ± 3	56 ± 5*	55 ± 4
Mean ball-in-play phases (s)	76.6 ± 11.9	90.1 ± 14.9*	89.7 ± 17.5*
Mean speed ($m \cdot min^{-1}$)	111 ± 14	116 ± 13	108 ± 16
Mean acceleration ($m \cdot s^{-2}$)	0.59 ± 0.17	0.67 ± 0.18*	0.63 ± 0.19

*Denotes season being different (at least 75% greater than the SWC (calculated as 0.6 x between-athlete SD) compared to previous rule format (season 2019).

7.5.3 Differences in the Distribution of Intensity

There were no substantial differences between competition formats across all positional groups for acceleration coefficients (Figure 7.2) (Table 7-3). For speed, middle forwards had greater (ES = 0.74; ± 0.24) coefficients in season 2021 compared with the previous competition format in 2019 (Table 7-3). There were no other substantial differences in speed between competition formats and individual positions.

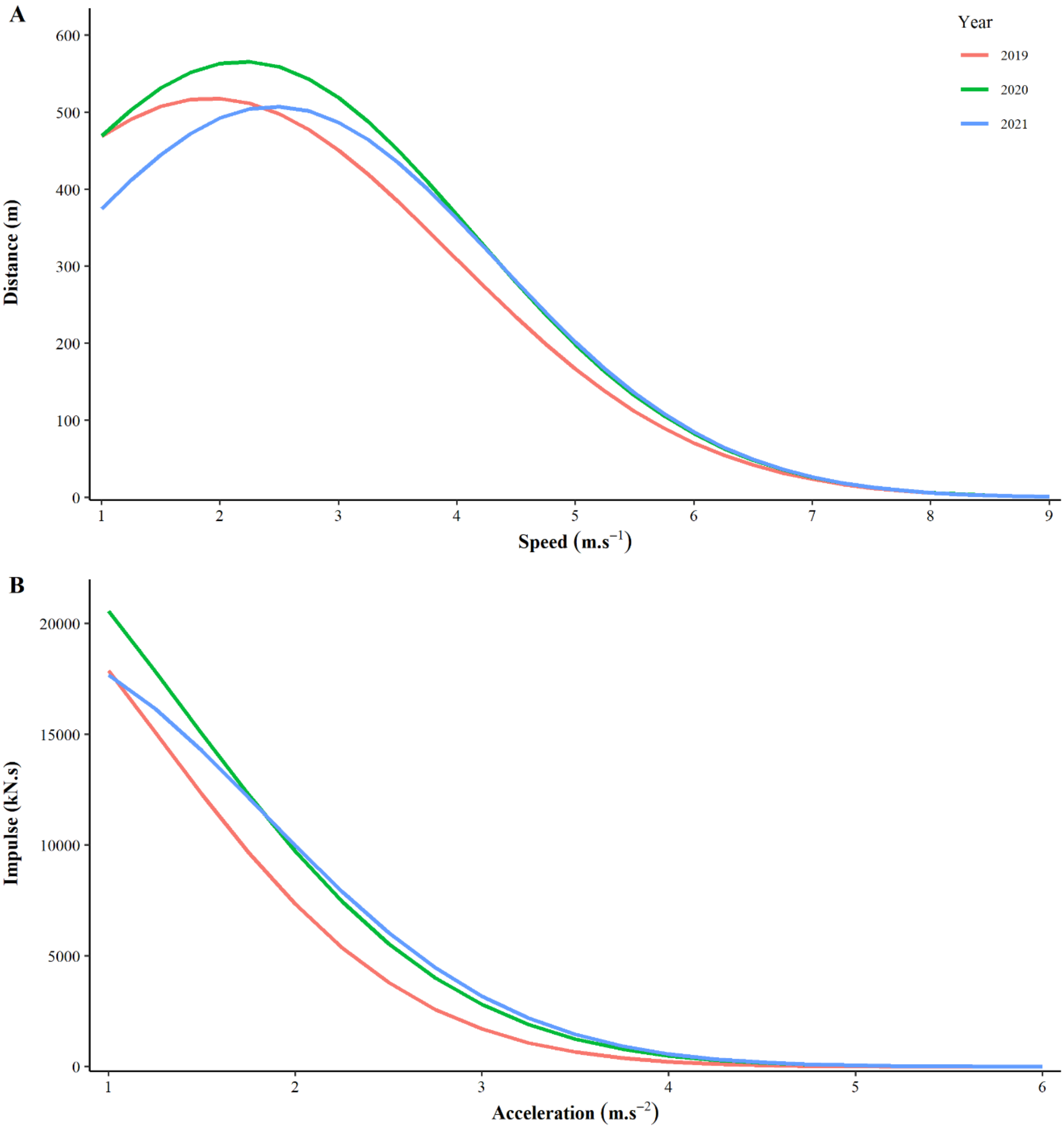

Figure 7-2. Distribution of distance and impulse across the speed and acceleration spectrum.

Table 7-3. Quadratic coefficients (a, b, c) of acceleration ($m \cdot s^{-2}$) and speed ($m \cdot min^{-1}$) (mean ± SD) across each positional group during the 2019, 2020 and 2021 NRL Premiership seasons.

Position	a			b			c		
	2019	**2020**	**2021**	**2019**	**2020**	**2021**	**2019**	**2020**	**2021**
Acceleration ($m \cdot s^{-2}$)									
Edge Forward	-0.29 ± 0.19	-0.29 ± 0.16	-0.28 ± 0.13	0.03 ± 0.96	0.19 ± 0.82	0.29 ± 0.70	10.23 ± 1.13	10.05 ± 0.98	9.77 ± 0.90
Halves & Hookers	-0.31 ± 0.23	-0.27 ± 0.18	-0.32 ± 0.15	0.04 ± 1.04	0.08 ± 0.86	0.39 ± 0.78	10.22 ± 1.14	10.38 ± 0.99	10.07 ± 1.01
Middle Forwards	-0.36 ± 0.28	-0.28 ± 0.21	-0.37 ± 0.14	0.30 ± 1.24	0.17 ± 1.01	0.75 ± 0.65	9.53 ± 1.28	9.67 ± 1.09	8.97 ± 0.84
Outside Backs	-0.18 ± 0.18	-0.17 ± 0.18	-0.20 ± 0.13	-0.57 ± 0.90	-0.45 ± 0.92	-0.18 ± 0.69	10.76 ± 0.96	10.87 ± 1.10	10.61 ± 0.78
All Positions	-0.29 ± 0.24	-0.24 ± 0.19	-0.29 ± 0.16	-0.03 ± 1.12	-0.02 ± 0.94	0.29 ± 0.81	10.11 ± 1.23	10.20 ± 1.12	9.80 ± 1.09
Speed ($m \cdot min^{-1}$)									
Edge Forward	-0.13 ± 0.04	-0.14 ± 0.05	-0.16 ± 0.08	0.59 ± 0.34	0.68 ± 0.43	0.89 ± 0.63	5.68 ± 0.63	5.58 ± 0.80	5.08 ± 1.04
Halves & Hookers	-0.13 ± 0.08	-0.12 ± 0.07	-0.17 ± 0.07	0.45 ± 0.61	0.44 ± 0.53	0.85 ± 0.54	6.06 ± 1.18	6.30 ± 1.05	5.55 ± 0.97
Middle Forwards	-0.12 ± 0.07	-0.16 ± 0.08	-0.17 ± 0.07	0.47 ± 0.55	0.76 ± 0.62	0.92 ± 0.54*	5.53 ± 1.15	5.03 ± 1.15	4.63 ± 1.09
Outside Backs	-0.11 ± 0.06	-0.16 ± 0.08	-0.17 ± 0.07	0.45 ± 0.52	0.49 ± 0.53	0.59 ± 0.33	5.87 ± 1.01	6.00 ± 1.06	5.80 ± 0.66
All Positions	-0.12 ± 0.06	-0.13 ± 0.07	-0.15 ± 0.07	0.46 ± 0.53	0.59 ± 0.56	0.78 ± 0.55	5.81 ± 1.10	5.69 ± 1.17	5.26 ± 1.12

*Denotes season being different (at least 75% greater than the SWC (calculated as 0.6 x between-athlete SD) compared to previous rule format (season 2019).

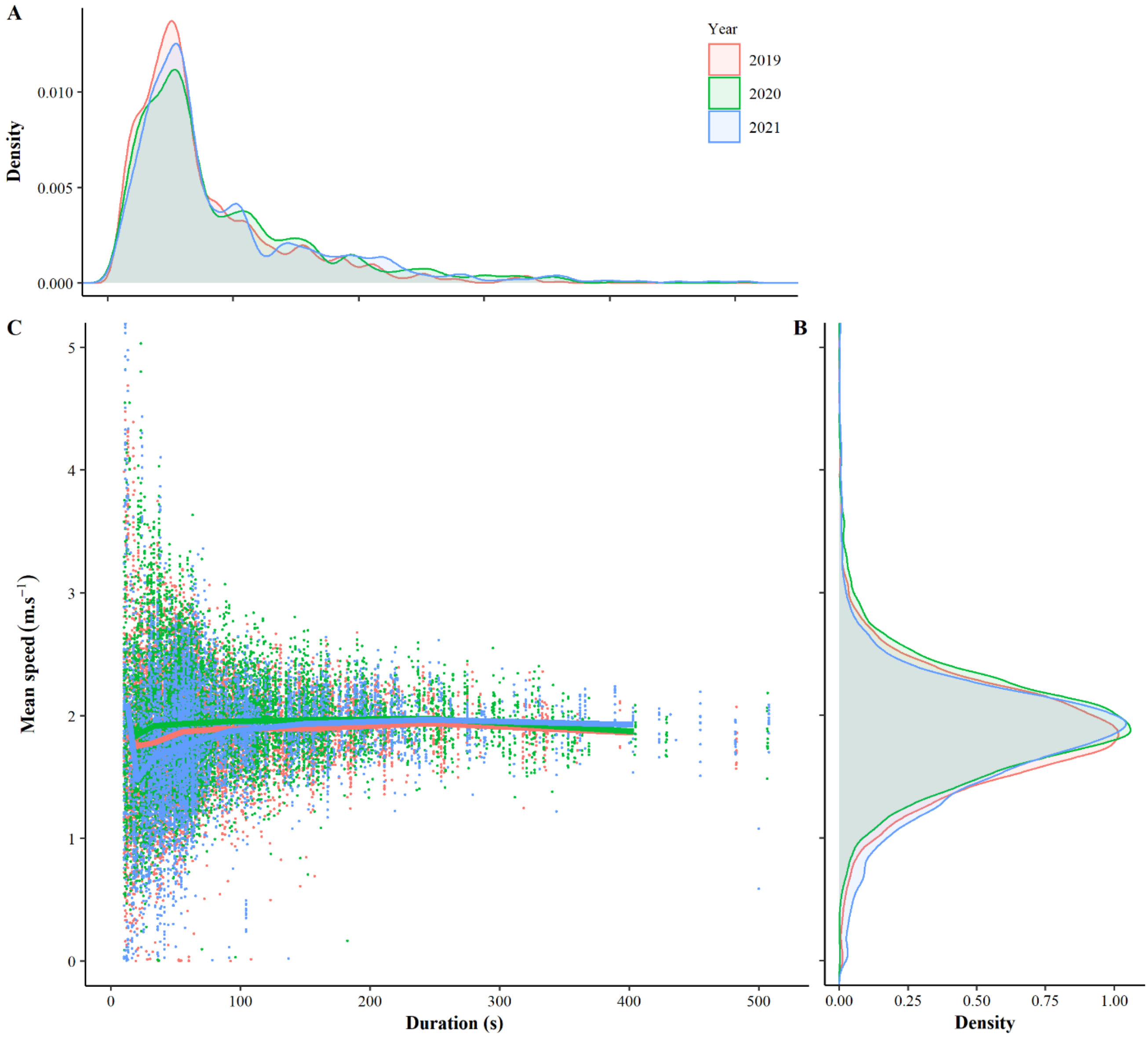

Figure 7-3. A) shows density of the duration of each ball-in-play phase by year, B) shows the density of the mean speed of each ball-in-play phase. C) is mean speed for each duration.

7.6 Discussion

The main findings revealed that the peak acceleration intensity of NRL athletes substantially increased across all positional groups in the 2020 and 2021 seasons (current competition format) compared to the 2019 season (previous competition format). The combined acceleration intercept (power law analysis) encompassing all positional groups substantially increased from the 2019 season compared to the 2020 and 2021 seasons. Moreover, mean acceleration relative to ball-in-play time increased in the 2020 season following the rule change compared to the 2019 season. Additionally, despite the introduction of the six-again rule, there were minor differences between the current and previous competition formats for maximal mean speed. Speed intercepts (power law analysis) for edge forwards and halves and hookers were greater in the 2021 season compared to the 2019 season. Mean match times and ball-in-play phase lengths also increased following the modification of the competition format compared to season 2019. For the distribution of distance, the results from the determination of quadratic coefficients suggests that middle forwards had increased speed intensity in the 2021 season for the b coefficient following the introduction of the six-again rule.

Following collation of player tracking data (from all clubs) from the entire 2020 season and from the first half of season 2021, the NRL published a release contending that the data did not support the assertion that the intensity in athletes was greater compared to the previous competition format (National Rugby League, 2021). However, as depicted in Table 7-1 and Figure 7-1, the results of the current study do not concur with the assessment published by the NRL, albeit with the current data representing only one club in the competition. Specifically, when comparing the intercept and slopes between seasons, maximal mean acceleration intensity was substantially higher in the current study across all positions in both the 2020 and 2021 seasons compared to the 2019 season.

Although, the NRL release was limited in its detail as to the methodologies used in determining the metrics they presented, which may or may not contribute to the differences found between this research and the release. Moreover, the NRL release did not present information relating to changes in acceleration across seasons, which is significant as acceleration is an important metric in assessing the intensity of competition (Lockie et al., 2011; Oxendale et al., 2016; Young et al., 1995; Young et al., 2012).

High-intensity acceleration and deceleration events are associated with increased levels of creatine kinase (CK), which is an objective marker of muscle damage following team sport competition (Gastin et al., 2019; Nedelec et al., 2014; Oxendale et al., 2016; Russell, Sparkes, Northeast, Cook, Bracken, et al., 2016; Young et al., 2012). In rugby league research, a moderate correlation between high-intensity acceleration ($r = 0.44$) and deceleration ($r = 0.48$) efforts and CK concentration was observed (Oxendale et al., 2016). Given the maximal mean acceleration intensity increased across all positions under the revised NRL competition format, the research highlights the importance of not only measuring the intensity of movement (speed), but also the need to account for the change of speed (acceleration) when reporting upon activity profiles (Oxendale et al., 2016). Moreover, the increase in maximal mean acceleration intensity during the 2020 and 2021 competitions could be attributed to the six-again rule where stoppages in play for ruck penalties were replaced with automatic tackle count restarts. Additionally, ball-in-play time before a stoppage increased between competition formats which limits the amount of recovery time and promotes sustained acceleration and deceleration efforts, particularly for the defensive team that is required to retreat 10 m after each completed tackle (National Rugby League, 2021).

The use of power law models for athlete locomotion metrics is established within team sport research (Delaney, Thornton, et al., 2016; Delaney, Thornton, et al., 2018; G.

Rennie et al., 2020). The power law-derived acceleration intercepts from the current study in both competition formats are considerably lower than previous research. (Delaney, Thornton, et al., 2016). For example, the acceleration intercept for halves was previously reported at 1.22 ± 0.13 m·s^{-2}, whilst in the current study, the range for halves and hookers across both competition formats was noticeably lower (2021; 1.09 ± 0.06 m·s^{-2}) (Delaney, Thornton, et al., 2016). However, the differences between the GPS/GNSS technology hardware and processing settings may have contributed to differences in athlete outputs between the two studies (Malone et al., 2017; Thornton, Nelson, et al., 2019). The current study filtered the GNSS speed data which dampened the magnitude of acceleration unlike previous research (Delaney, Thornton, et al., 2016). The filtering processes implemented in the current study were deemed appropriate for the locomotion patterns in rugby league competition. Briefly, the current study selected the filtering processes by implementing a residual analysis on the athlete tracking data across 10 cutoff frequencies (0.1 – 10.0 Hz; 0.1 Hz increments) within a fourth order Butterworth filter (Winter, 2009). From this analysis and the process outlined previously, a 1 Hz cutoff frequency was selected (Winter, 2009).

Power law analysis can provide benefit in athlete monitoring, as practitioners can utilise competition intensity to monitor training intensity through the use of intercept and slope information (Delaney, Thornton, et al., 2018). If a SSG is intended to elicit a stimulus focusing on acceleration (m·s^{-2}), the drill duration and respective intercept and slope for a positional group can be included into an equation to extract the predicted intensity of the drill (Delaney, Thornton, et al., 2018). For example, if outside backs were participating in an SSG for three minutes, the predicted acceleration intensity to replicate competition intensity could be determined using the 2021 results from this study (and current filtering practices):

$$Intensty\ (i) = 1.05\ (3)^{-0.25}$$

The predicted acceleration intensity for the SSG is 0.80 $m \cdot s^{-2}$. Coaches and support staff could then track this information across training sessions or for use in the planning of training sessions for tactical and/or rehab sessions relative to competition intensity. It may be that practitioners could replicate similar power law analysis using their own filtering practices across their longitudinal data (multiple seasons) to replicate such equations derived in this research. This would provide greater accuracy than solely relying upon the information provided in this study. Live tracking of such intensities could be facilitated if similar processing/filtering occurred at the live and post-session downloads, however, this may be challenging at the current juncture depending on the manufacturer, device, software and filter used. Regardless, post-training analysis could be completed to assess training intensity relative to competition intensity on a consistent basis with respect to acceleration variables.

The ball-in-play times of NRL competition have increased following the introduction of the six-again rule in the 2020 season. The average ball-in-play match times released by the NRL are similar to those found in the current study, with the exception of ball-in-play phase times (National Rugby League, 2021). While this study's results are limited to one team and the methodology in determining mean ball-in-play phases may differ, the findings are supported by research in Super League (Rennie et al., 2021). Across 11 Super League teams, the mean ball-in-play phase durations had also increased across all positional groups, following the inclusion of a six-again rule following a COVID-enforced suspension in the season (Rennie et al., 2021). Moreover, similar to acceleration intercept and slope findings, the mean athlete acceleration relative to ball-in-play was also greater in season 2020 compared to season 2019. Practically, the increased mean length in ball-in-play phases and mean acceleration following the six-again rule may have applications for practitioners. Conditioning games may need to feature extended periods of uninterrupted ball-play to better replicate the changes seen in the results of the current study.

The distribution of distance (distance summated into speed thresholds) relative to ball-in-play times was different for middle forwards between seasons. The *b* coefficient for middle forwards saw discrepancies between competition formats, in the 2019 and 2021 seasons, where it was substantially higher in 2021. The *b* coefficient represents reflects the upward or downward linear trend in y values along the x axis, therefore a greater value such as in this context represents that more volume was covered at a higher intensity compared to previous seasons (Duthie et al., 2021). The difference in the distribution of speed for middle forwards could be attributed to the influence of the six-again rule. Generally, middle forwards play centrally in the attacking and defending lines and are frequently involved in active play compared to outside backs (Austin & Kelly, 2013; Cummins et al., 2018). With the automatic tackle count restart in effect after a ruck infringement, play is sustained through the middle of the field with reduced recovery time. With the ball-in-play results of the current study also indicating that match duration and phase time increased after the introduction of the rule change, it may be that there is an increase in the mean speed intensity of middle forwards. Specifically, for both attacking and defending plays, increased mean speed could be as a result of either increased hit-ups (attacking carries) or defensive tackles in repeated succession, potentially promoting a greater overall average intensity during active play (Gabbett et al., 2011).

Observing the distribution of match intensity relative to distance can provide practitioners with information on the volume accumulated across speed thresholds during competition. (Johnston et al., 2022). In isolation, mean peak intensity results do not indicate how much volume is obtained at each threshold (Johnston et al., 2022). To achieve a more wholistic/specific prescription of SSGs, it may be that practitioners can utilise information on the distribution of competition volumes to determine more appropriate programming for training drills and sessions (Johnston et al., 2022).

7.7 Practical Applications

- The increase in acceleration intensity highlights to practitioners the need to tailor training programs that prepare athletes for the changes in competition.
- Through the use of power law analysis, intercept and slope information can be generated by positional group to provide specific information on the mean peak competition intensity for SSG prescription.
- The distribution of distance and impulse provides practitioners with an indication of the volume in intensity attained in competition which can aid in the prescription of SSGs.
- The results from the ball-in-play findings indicate that practitioners may look to program SSGs with longer uninterrupted periods to better replicate the longer ball-in-play phases found under the current competition format.

7.8 Limitations

The current study analysed tracking data from one NRL team. The current results are representative of the activity profile and game style of the analysed team, which may not be representative for other competing teams. Moreover, the strength of opposition/scheduling for the one team could impact the magnitude of the analysed metrics in this study. Practitioners should elect to run similar analysis on their athlete's tracking data to produce specific competitions intensity to facilitate training interventions.

7.9 Conclusions

Following the introduction of the six-again rule during the 2020 season, the activity profile of the NRL has changed. Acceleration intensity has substantially increased across all positions following the introduction of the six-again rule compared to the previous format. Forwards showed an increase in the distribution of speed intensity in season 2021 with the introduction of the six-again rule. Ball-in-play times for match duration and phases of play increased with the introduction of the six-again rule. The increases in acceleration intensity requires specific training program development for athletes to ensure they are adequately prepared for competition. Practitioners can elect to replicate the analysis used in the current study to integrate the use of the power law intercept and slope to predict speed and/or acceleration intensity for the purpose of SSG prescription.

CHAPTER 8 - OUTLINING THE DISTRIBUTION OF ACCELERATION AND SPEED INTENSITY IN NATIONAL RUGBY LEAGUE TRAINING WEEKS RELATIVE TO MATCH TURNAROUND TIME

8.1 Directions from Chapter 7

Chapter 7 outlined the differences in the acceleration activity profile in elite rugby league as a result of the changes in competition rules. The acceleration intensity across all positions increased following the six-again rule change, which may prompt changes in training program prescription from practitioners. However, the ability to compare and evaluate changes in the activity profile of competition was enhanced by being able to compare acceleration more appropriately between seasons and independently of the tracking system manufacturer. With greater independence in data processing to be able to filter speed and derive acceleration with a similar methodology, greater confidence may be had in the overall assessment of any rule changes. Whilst the analysis of competition is vital in understanding the activity profile of team sports such as rugby league, in-season analysis of training volume and intensity with respect to competition outputs may also be important for practitioners (Aughey, 2011a; Bradley et al., 2009; R. Johnston et al., 2014). Having a consistent filtering process can aid the longitudinal analysis of the training activity profile, and through Chapter 8, the research can replicate common workflows practitioners and researchers regularly undertake throughout the competitive team sport season.

8.2 Introduction

Rugby league features efforts of high-intensity activity interspersed with low-intensity movement and physical contacts (Hausler et al., 2016; R. Johnston et al., 2014; Johnston et al., 2022). Using wearable technologies such as Global Navigation Satellite System (GNSS) devices, the activity profile of training or competition can be outlined (Delaney et al., 2015; Hausler et al., 2016; R. Johnston et al., 2014; McLellan et al., 2011). Using these devices, typically, rugby league research has outlined summary values that incorporate whole match averages, typically presenting metrics such as total distance (m) covered, or distances at pre-defined speed thresholds (i.e., $>5\ m\cdot s^{-1}$) (Johnston et al., 2022). For example, Australian elite rugby league athletes generally cover total distances between 5000 and 9000 m, depending on game time or position played, with the average running distance covered as a unit of time (speed) reported between 80 to 100 $m\cdot min^{-1}$ (Austin & Kelly, 2013; Delaney et al., 2015; Hausler et al., 2016; R. Johnston et al., 2014; McLellan et al., 2011). The ability to accelerate is also important in rugby league competition, as the proximity of the defensive and attacking lines limit sustained high-speed running and promote short efforts (Gabbett, 2012; R. Johnston et al., 2014). Acceleration within rugby league research has been typically measured as counts and summarised as the average count attained in matches, or the distance or time spent over the course of the analysed period (Delaney, Cummins, et al., 2018). For example, in the National Rugby League (NRL) competition, maximal accelerations have ranged between 50 and 80 per game ($\geq 2.78\ m\cdot s^{-2}$), with a frequency of 1.1 ± 0.6 per minute (Hausler et al., 2016; Kempton, Sirotic, Rampinini, et al., 2015; Varley et al., 2014).

Analysing the sum of total distance across competition provides limited context comparative to the peak intensity and the distribution of intensity (Johnston et al., 2022). To overcome the limitations of absolute variables, expressing commonly used intensity metrics such as speed and acceleration over rolling time epochs of different durations can be used (Cunningham et al., 2018; Delaney, Duthie, et al., 2016; Delaney et al., 2015; Delaney, Thornton, Burgess, et al., 2017; Delaney, Thornton, Pryor, et al., 2017; Varley, Elias, et al., 2012). A 1 to 10-minute moving mean in elite rugby league outlined the maximal (highest attained intensity) mean 1-minute speed intensity between 154 and 172 $m \cdot min^{-1}$ across positions, which was significantly higher than the absolute estimates of 80 to 100 $m \cdot min^{-1}$ in prior research which used whole match averages (Austin & Kelly, 2013; Delaney et al., 2015).

The maximal mean intensity has been used as a reference point for prescribing and monitoring training intensity with different drill durations (Delaney, Duthie, et al., 2016; Delaney et al., 2015; Delaney, Thornton, Burgess, et al., 2017; Delaney, Thornton, Pryor, et al., 2017). However, the mean peak intensity for both speed and acceleration generally occurs in competition only once per game for very limited durations, and as such do not detail the distribution of intensity throughout competition (Johnston et al., 2022; Thornton et al., 2020). For example, if an athlete spent only 1-minute of a match at an intensity similar to the mean peak, it would be inappropriate and excessive to program small-sided games that require athletes to compete at a similar intensity during 10-minute bouts in training (Johnston et al., 2022). Therefore, without information on the distribution of intensity across various epochs in competition, practitioners have limited information to compare the distribution of intensity completed in training to that in competition.

The maximal mean speed and acceleration, as well as the distribution of speed and acceleration intensity in elite rugby league has been quantified (Chapter 7). Across all positions, the maximal mean speed and acceleration intercepts (estimated peak intensity as time approaches 0s) for the 2021 season were reported as 185 ± 12 $m \cdot min^{-1}$ and 1.06 $\pm$ 0.07 $m \cdot s^{-2}$ respectively (Chapter 7). To assess the distribution of intensity of competition, intensity metrics such as speed and acceleration, are later converted to their volume equivalents (distance and impulse respectively). Specifically in rugby league, across all seasons and positions, the majority of total distance within the NRL competition was distributed across what would be considered low intensity activity, with an average of approximately 1000 - 4500 m covered (depending on playing time) between 1-4 $m \cdot s^{-1}$ per match (Chapter 7). Similarly for impulse, much of the total distribution during competition was at low to moderate acceleration intensity of 1-3 $m \cdot s^{-2}$ across all seasons and positions (Chapter 7). Whilst practitioners have access to improved knowledge surrounding intensity during NRL competition, currently there is limited research examining how rugby league training compares to the distribution of intensity in competition, especially when time between fixtured matches is considered. The current literature has examined the activity profile of NRL and Super League (SL) teams with respect to the length of the microcycle, but not the distribution of training intensity (McLean et al., 2010; Moreira et al., 2015; Parmley et al., 2022). Thus, key gaps in understanding of training versus competition still exist.

Research in association football (soccer) and women's Australian rules football has analysed total distance and impulse within training sessions (Riboli et al., 2021; Thornton et al., 2020). In Australian Woman's Football League (AFLW), training drills were assessed against the 1-minute mean peak intensity for distance and impulse (Thornton et al., 2020). A greater proportion of total distance was accumulated between 70 to 100% of the mean peak in competition compared to skill drills and warm ups (Thornton et al., 2020). For impulse, matches had a greater distribution between 60 to 80% of the mean peak compared to conditioning drills (Thornton et al., 2020). A portion of the AFLW research was conducted during the pre-season, without the constraints of matches, and importantly the number of days available for training between matches. Commonly, the pre-season period has consistent structure week-to-week with less fluctuation in training intensity and volume compared to the in-season phase. It is not currently known how the distribution of intensity for a given impulse and distance changes during the season. Given the limited opportunities for training between matches in-season, maximising the intensity for a given impulse is critical to maintain or enhance fitness and minimise fatigue for matches.

Therefore, the aims of this study were to assess the distribution of distance and impulse in NRL training sessions relative to microcycle length. Further, the distribution of distance and impulse in training relative to the intensity and volume in NRL competition was compared.

8.3 Methods

8.3.1 Design and Participants

An observational, longitudinal study design was used to evaluate the distribution of training intensity across different microcycle epochs in elite rugby league competition. GNSS devices measured running intensity for speed ($m{\cdot}s^{-1}$) and acceleration ($m{\cdot}s^{-2}$) and were used to provide the volume measures of total distance (m) and impulse (kN·s) respectively. Training session data were collected during the 2021 National Rugby League season (NRL). All athletes in the study provided informed consent to researchers to confirm participation. Ethical approval was granted prior to the commencement of the study by the Victoria University Human Research Ethics Committee (HRE21-017).

Athlete tracking data was collected from 35 athletes (mean ± SD; 25 ± 3 years, age range; 18 to 33 years, 186 ± 6.9 cm, 93 ± 5.1 kg) who were all contracted to one team for the duration of the 2021 NRL season. Tracking data was collected from the beginning of the 2021 season, through to the completion of the final game of the season. The dataset consisted of 73 training sessions throughout the home and away season with 1932 individual files (51.8 ± 15.6 files per athlete, range: 20 – 71 files) across the season. Although athletes weren't categorised by playing position for the analyses, the dataset collected represents athletes across all positional groups. Specifically, athletes represented the following positional groups; edge forwards (match files [n] = 405), halves and hookers (half-back, five-eighth and hooker; n = 512), outside backs (winger, centre and fullback; n = 503) and middle forwards (middle forward, lock and interchange forward; n = 512).

8.3.2 Training Activity Profile and Technology

Athlete locomotion was quantified during training sessions via the use of GNSS technology. A 10 Hz GNSS device (Vector S7, firmware: 8.1.0 +f0455e7b, Catapult Sports, VIC, Australia) was worn by each athlete in a custom-made undergarment or in a pouch in the athlete's playing jersey. Athletes wore the same GNSS device across the season (where possible) to maintain inter-unit reliability (Buchheit, Al Haddad, et al., 2014). To assess the quality of each individual GNSS file, the number of satellites and the mean horizontal dilution of precision (HDOP) was determined, and files a HDOP >1.5 were considered inappropriate and were removed from the analysis. The mean ± standard deviation (SD) satellite count (14.7 ± 3.5) and HDOP quality (0.76 ± 0.16) were deemed acceptable for accurate athlete locomotion (Aughey, 2011a; Malone et al., 2017), and as such, no files were removed due to poor satellite connection/HDOP.

8.3.3 Data Processing

Following the completion of each training session, GNSS files were downloaded and trimmed via the GNSS manufacturer's proprietary software (OpenField, version 3.3.1, build 68050, Catapult Sports, Victoria, Australia). Each training session was trimmed to only include instances where the athlete was a full participant in each training drill. GNSS files were exported in their raw 10 Hz form as comma-separated files (.csv) from the manufacturer's software and were imported into R Studio software (version 1.4.1717). Raw exports included time, speed and acceleration. Speed was converted to metres per second ($m \cdot s^{-1}$) and processed with a fourth-order, low-pass Butterworth filter. The current study applied a residual analysis to determine the appropriate cutoff frequency for speed (Campbell et al., 2020; Winter, 2009). Upon inspection of the residual analysis, a 1 Hz cutoff frequency was determined as being appropriate for this dataset (Winter, 2009). The selection of a 1 Hz, Butterworth filter has been previously used in team sport research (Couderc et al., 2019; Cummins et al., 2018; Ellens, Middleton, et al., 2022). Acceleration was calculated via finite differentiation of speed (filtered) and was not filtered again (Linke et al., 2018). Acceleration ($m \cdot s^{-2}$) was made absolute to remove negative values (decelerations) (Delaney, Cummins, et al., 2018; Thornton, Nelson, et al., 2019).

A 1-minute moving average was then applied to speed and acceleration data. Speed was converted to $m \cdot min^{-1}$ and acceleration converted to $m \cdot min^{-1} \cdot s^{-1}$. The volume of speed [distance (m) covered] and acceleration [impulse (kN·s) accumulated] was then established with the distribution of these variables categorised into 10 $m \cdot min^{-1}$ and 10 $m \cdot min^{-1} \cdot s^{-1}$ 'buckets' for speed and acceleration respectively. The total volume of distance and impulse in each 'bucket' across each microcycle was calculated, with the total microcycle volume of each intensity bucket calculated and then expressed relative to the microcycle volume as a percentage. As such, there were four variables obtained from such analyses: distance, relative distance, impulse and relative impulse.

All drills that were scheduled as part of the main skill component of the session were included in the analysis. Drills were labelled as either warm up, 13v13 skills, position specific, small-sided game, conditioning, or game simulation. Each microcycle was filtered to only include athletes who were full participants in all training sessions that week (i.e., non-injured, non-modified athletes). Microcycles were defined as the number of days separating matches from one round to the next. Microcycles were grouped as 5-6 days, 7-8 days and 9-10 days, accounting for the common rest intervals in NRL competition from one round to the next (Moreira et al., 2015). Grouped intervals were used in this analysis as pilot results indicated similar training volumes and intensity in distance and impulse between 5 and 6-day microcycles, 7- and 8-day microcycles and 9- and 10-day microcycles, and further to restrict the number of statistical comparisons made. The phase of the season (early, mid, late etc) was not considered in this study, as training was kept consistent (intensity and volume was not altered) across the duration of the season.

The volume and intensity for both distance and impulse were visually inspected, revealing a quadratic (non-linear curvilinear) relationship. To describe the distribution of distance and impulse across the intensity spectrum, four different quadratic models were established for each player for each microcycle. Quadratic coefficients demonstrate the shape of the data (the relationship). As such, four separate quadratic models developed were, to describe the shape of the distribution for each variable. The quadratic models were:

Distance model: Speed (x) in 10 $m \cdot min^{-1}$ buckets versus the logarithm of accumulated distance (y).

Relative distance model: Speed (x) in 10 $m \cdot min^{-1}$ buckets versus the logarithm of relative accumulated distance (y). Relative was defined as a percentage of the total microcycle distance.

Impulse model: Acceleration (x) in 10 $m \cdot min^{-1} \cdot s^{-1}$ buckets versus the logarithm of accumulated impulse.

Relative impulse model: Acceleration (x) in $m \cdot min^{-1} \cdot s^{-1}$ buckets versus the logarithm of relative accumulated impulse. Relative was defined as a percentage of the total microcycle impulse.

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

8.3.4 Statistical Analysis

The quadratic coefficients that describe the shape of the distribution that were obtained from the quadratic models were statistically analysed. To compare the difference in the quadratic coefficients for the four variables (distance, relative distance, impulse and relative impulse) between microcycles, random slope linear mixed models were used. Separate linear mixed models were run for each of the four quadratic model's (the four variables) coefficient values (12 models). Coefficients (a, b and c) were non-normally distributed, however, residual plots (quantile-quantile plots) demonstrated normality of the residuals, an assumption of linear mixed models. The coefficients were used individually as outcome measures, whilst microcycle length (entered as a categorical variable) was designated as the fixed effect in all models. Athlete identification was included as a random effect, where a random slope design was selected to allow for varying intensity distributions between athletes (varying effects of microcycle length). For each linear mixed model, a least squares means test determined the differences in coefficients between microcycles (fixed effect), with the resulting mean, standard deviation (SD) and mean difference for each athlete analysed to calculate standardised effect sizes (ES) and confidence limits (CL; 90%). The magnitudes of effect sizes were described as; < 0.20 trivial; 0.21–0.60 small; 0.61–1.20 moderate; 1.21–2.0 large and > 2.01 very large (Hopkins et al., 2009; Johnston et al., 2022; Thornton et al., 2020). Effects were deemed real if they were at least 75% greater than the smallest worthwhile difference (SWD), which was calculated as 0.2 x the between-athlete SD (Duthie et al., 2022; Hopkins et al., 2009; Johnston et al., 2022; Thornton et al., 2020). All analysis was completed in R Studio software (version 2021.09.0).

8.4 Results

The results are expressed in Figure 1 and Table 1. Figure 1 depicts the four different quadratic models for each of the different microcycle lengths. Table 1 shows the quadratic coefficients for each of the four quadratic models for the different microcycle lengths.

Table 8-1 Quadratic coefficients (a, b, c) of acceleration ($m\cdot s^{-2}$), relative acceleration ($m\cdot s^{-2}$), speed ($m\cdot min^{-1}$) and relative speed ($m\cdot min^{-1}$) (mean ± SD) across different microcycle lengths (5-6 days, 7-8 days, or 9-10 days) in National Rugby League athletes.

Variable	Coefficient								
	a			***b***			***c***		
	5-6 Days	**7-8 Days**	**9-10 Days**	**5-6 Days**	**7-8 Days**	**9-10 Days**	**5-6 Days**	**7-8 Days**	**9-10 Days**
Acceleration ($m\cdot s^{-2}$)	-0.0056 ± 0.0020	-0.0054 ± 0.0019	-0.0054 ± 0.0016	0.33 ± 0.09	0.32 ± 0.10	0.33 ± 0.09	5.48 ± 1.07	5.93 ± 1.25*	5.99 ± 1.20*
Relative acceleration ($m\cdot s^{-2}$)	-0.0056 ± 0.0020	-0.0054 ± 0.0019	-0.0054 ± 0.0016	0.33 ± 0.09	0.32 ± 0.10	0.33 ± 0.09	-1.73 ± 1.03	-1.77 ± 1.17	-2.02 ± 1.14*
Speed ($m\cdot min^{-1}$)	-0.0007 ± 0.0002	-0.0006 ± 0.0001*	-0.0006 ± 0.0001*	0.11 ± 0.02	0.09 ± 0.02*	0.10 ± 0.02*	2.41 ± 0.86	3.33 ± 0.88*	3.46 ± 0.81*
Relative speed ($m\cdot min^{-1}$)	-0.0007 ± 0.0002	-0.0006 ± 0.0001*	-0.0006 ± 0.0001*	0.11 ± 0.02	0.09 ± 0.02*	0.10 ± 0.02*	-1.23 ± 0.83	-0.80 ± 0.74*	-0.98 ± 0.60*

*Denotes microcycle being different (at least 75% greater than the SWC (calculated as 0.2 x between-athlete SD) compared to 5–6-day microcycle

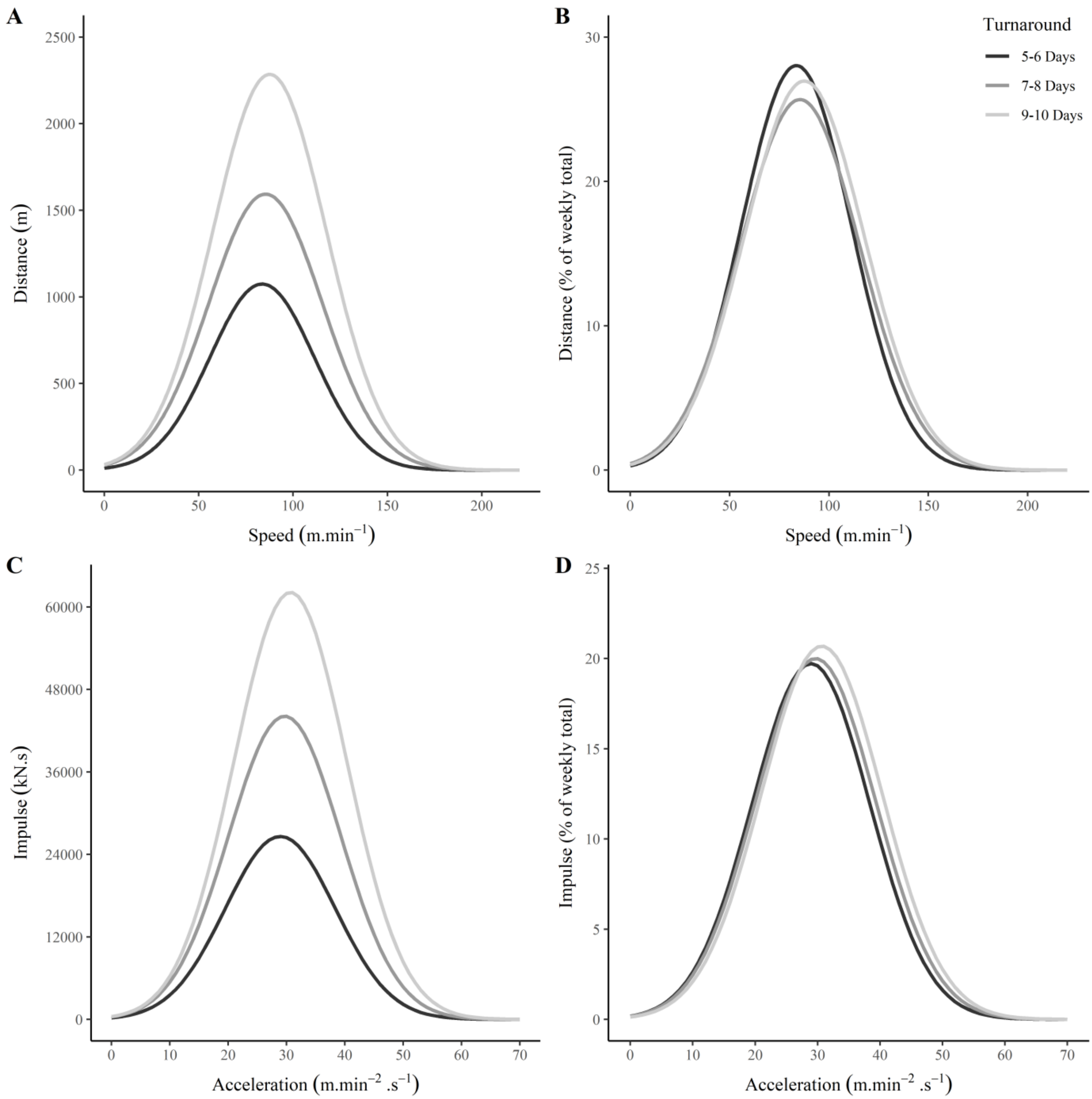

Figure 8-1 The distribution of distance and impulse across different microcycle lengths in both absolute and relative forms during an NRL season. A = weekly distance plotted against speed intensity, b = relative distribution of distance in various speed thresholds, c = weekly impulse plotted against acceleration and d = relative distribution of impulse in various acceleration thresholds across each microcycle length.

For impulse, there were no substantial differences in a or b coefficients between all microcycles (Table 1). The c coefficient in the impulse model for both 7-8 day (ES = 0.37; ± 0.18) and 9-10-day microcycles (ES = 0.44; ± 0.19) was greater when compared with 5–6-day microcycles. The relative impulse model showed no substantial differences in a or b coefficients between all microcycles (Table 1). The c coefficients in the relative impulse model for 9–10-day microcycles (ES = 0.29; ± 0.19) was smaller compared with 5–6-day microcycles.

For the distance model, all coefficients in 7-8 day and 9–10-day microcycles were different when compared with 5–6-day microcycles. The a coefficient in both 7-8 day (0.59; ± 0.22) and 9–10-day microcycles (0.61; ± 0.25), was greater compared to 5–6-day microcycles. The b coefficients were smaller in 7–8-day microcycles (0.63; ± 0.18) and 9-10 microcyles (0.54; ± 0.19) compared to the 5–6-day microcycles. C coefficients were greater in 7–8-day (1.05; ± 0.15) and 9–10-day (1.26; ± 0.17) microcycles compared to 5–6-day microcycles. For the relative distance model, all coefficients in 7-8 day and 9-10 microcycles were different compared to 5–6-day microcycles. The a coefficient was greater in 7-8 day (0.59; ± 0.22) and 9-10-day microcycles (0.61; ± 0.25) compared to 5–6-day microcycles. The b coefficients were smaller in 7–8-day microcycles (0.63; ± 0.18) and 9–10-day microcycles (0.54; ± 0.19) when compared with 5–6-day microcycles. The c coefficient was greater in 7–8-day microcycles (0.54; ± 0.14) and 9–10-day microcycles (0.34; ± 0.16) compared to 5–6-day microcycles.

8.5 Discussion

This study aimed to outline the distribution of distance and impulse in NRL training with respect to match fixture. Additionally, this study also aimed to outline the relative distribution of distance and impulse in NRL training relative to the total volume accumulated for the given microcycle. The main findings of the study revealed that the training distributions of both distance and impulse varied with differences in microcycle length. Specifically, both the distance model and impulse model showed greater distance and impulse values in 7-8 day and 9-10 microcycles respectively compared to 5–6-day microcycles. As depicted in Figure 1, a greater total volume of distance was covered across the intensity spectrum during longer microcycles (7-8 day and 9-10 day) compared to short microcycles (5-6 days). Similarly, the relative distance model (percentage of microcycle distance total) indicated that short microcycles accumulated greater relative distance at a lower speed intensity compared to longer (> 7–8-day) microcycles. Impulse in 7-8 and 9-10-day microcycles indicated greater values compared to 5–6-day microcycles, with slightly greater relative impulse distributions seen at a higher acceleration intensity (% of microcycle impulse total).

As the relationship between both volume and intensity measures were non-linear (quadratic), this study used quadratic models to describe the relationship (shape). The quadratic coefficients which describe the shape of the relationship indicated that all coefficients for speed were substantially different in 7-8 days and 9–10-day microcycles compared to 5–6-day microcycles for both total and relative distance accumulated. Collectively, the results demonstrated that training intensity and volume are manipulated across the various microcycle lengths (as indicated by the coefficients). Although not directly measured or recorded in this study, the manipulation of volume and intensity between each microcycle may have been to allow adequate recovery where needed, or logistical/time constraints of training (short microcycles), and to elicit a positive training response, or longer sessions where time permits (longer microcycles). The results of this study are novel and are highly practical, as no study is yet to provide the distribution of volume across the intensity spectrum specific to rugby league or regarding microcycle length. This data has applications for practitioners in planning training during the in-season period.

When comparing the results from the distance and impulse models between microcycles, the findings from the current study are similar to the limited research available (McLean et al., 2010; Moreira et al., 2015; Parmley et al., 2022). The current study identified that both the 7-8 day and 9–10-day microcycles had greater overall distance and impulse compared to the 5–6-day microcycle (as seen in Figure 1). For example, total distance for training sessions during the 5–6-day microcycle was approximately 7360 m compared to 13000 m of the 9–10-day microcycle, being approximately 43% less volume, due to typically two less field-based training sessions, presumably due to the limited time available to train and the need to adequately recover between matches. Research from SL competition identified similar findings via GNSS technology to the current study with significantly lower total distances found in 5-day microcycles compared to 10-day microcycles, as well as 5-day compared to 8-day microcycles (Parmley et al., 2022). Although, it should be acknowledged that the aforementioned research chose to analyse each microcycle in an individual day context rather than grouping days closer in proximity (i.e., 5-6 days) as in the current study (Parmley et al., 2022).

In similar NRL research, the training activity profile have been quantified using subjective measures such as the session rating of perceived exertion (s-RPE) (McLean et al., 2010; Moreira et al., 2015). The training activity profile (arbitrary units; AU) during shorter microcycles (5-6 days; 209 ± 63 AU) was significantly reduced compared to normal (7-8 days;

235 ± 46 AU) and long (9-10 days; 242 ± 40 AU) microcycles (Moreira et al., 2015). These findings are in agreement with the current study, despite the use of internal metrics rather than the external variables (GNSS technology) such as that used in the current study. The results from the current study and previous literature suggest that the reduction in training volume seen in 5–6 day microcycles may be simply due to the lack of time and logistical constraints (i.e., travel) of completing various training sessions, although the prioritisation of athlete recovery to help maintain performance for the upcoming match (McLean et al., 2010; Moreira et al., 2015; Parmley et al., 2022) is another likely contributor. Facilitating recovery in short microcycle situations is important within NRL competition, as athlete neuromuscular performance and perception of fatigue decline for at least 48 hours post-competition with recovery to baseline levels expected within four days (McLean et al., 2010; Murray et al., 2014). From the results of the current study and when compared with the existing literature, it seems rugby league practitioners promote recovery through manipulation of training program variables such as training volume (Moreira et al., 2015; Parmley et al., 2022).

Whilst training volume decreased as microcycle length between matches reduced, training intensity results were mixed. Firstly, in the relative impulse model, which was expressed as a percentage of the total impulse accumulated during the microcycle was similar between microcycle lengths, indicating limited variability. These results indicate that whilst the overall volume of impulse decreased, the relative distribution of this impulse remained stable, which could suggest an emphasis upon maintaining acceleration intensity irrespective of the microcycle length throughout the season. Perhaps increasing practitioners' understanding of impulse and the important role of periodising acceleration intensity and volume (impulse) will increase the body of research available. Currently, it is difficult to compare impulse-based results to previous literature given the limited research available. The relative distance model conversely showed greater variation in intensity across different microcycle lengths. The results from the current study showed that 28% of the microcycle distance total in 5–6-day microcycles were obtained at speeds of approximately 80 $m \cdot min^{-1}$, whereas the longer microcycle lengths in 7-8 days (26%) and 9-10 days (27%) showed peak distance accumulated around 90 $m \cdot min^{-1}$. However, there were similar distributions at 100 $m \cdot min^{-1}$ across all microcycles with minimal difference between 5-6 day and 7–8-day microcycles. In another study, weekly training intensity was maintained in elite rugby league training programs despite reduced training volume with a shortened microcycle between matches (Moreira et al., 2015). However, intensity was quantified via internal measures (i.e., RPE) and not via external metrics as used in the current study (Moreira et al., 2015). Similarly, in SL research, using GNSS technology, the training duration rather than training intensity was manipulated to facilitate athlete recovery and a maintained level of performance (Parmley et al., 2022). Given the results of the current study, it seems that to facilitate athlete recovery and performance, training volume is reduced as the length between matches is shortened, whilst relative intensity in training sessions is maintained for impulse. This finding is timely, as recent research has outlined the activity profile of NRL competition before and after the inception of the "six-again" rule which is likely to have caused the increase in acceleration intensity in competition (Chapter 7). Potentially, this rule change and greater emphasis on acceleration intensity within training has led to limited variability between match microcycles as shown in the current study.

In the 2021 NRL season, over half (4192 m; 53%) of all match distance attained would be considered low intensity, ranging between 60 and 180 $m \cdot min^{-1}$ (1-3 $m \cdot s^{-1}$) (Chapter 7). Distances obtained at high intensity (> 300 $m \cdot min^{-1}$; > 5 $m \cdot s^{-1}$) accounted for 12% of the entire match distribution (Chapter 7). Moreover, Figure 1 in the current study demonstrates that speed (expressed as a percentage of the microcycle total) peaks at less than 30% for intensity of approximately 80 to 95 m·min^{-1} across each training week, with minimal distribution at higher intensity, indicating that most of the training distribution is attained at lower intensity exercise. This result is not surprising given the composition of rugby league training sessions where drill intensity is dictated by the purpose of the drill. For example, tackling/contact drills in training sessions may be of considerable duration, but may also be of minimal intensity with reference to external running variables such as speed. Similarly, training drills that are based on skill development would be also completed at lower intensity (for the purposes of distributing intensity) when compared to 13v13 match simulation drills. However, it is important that appropriate comparison between competition and training can take place to enable practitioners to tailor training and rehabilitation protocols that are specific to the current competition format (Chapter 7). Specifically, to enable more appropriate comparison, this study processed both distance and impulse using a similar processing methodology (i.e., filter and cutoff frequency) with the same GNSS technology as previous research (Chapters 5 & 7). With acceleration-based metrics such as impulse it is important that acceleration is processed similarly given the potential variance of different filter types from different GNSS manufacturers on the processing of acceleration (Sweeting, Cormack, et al., 2017). By employing a similar processing methodology, the results from both Chapter 7 and current study can be more appropriately compared longitudinally, which may be of benefit to practitioners comparing between seasons.

Whilst the results of this study have outlined the distribution of distance and impulse across in-season training weeks with different microcycle lengths, this data is representative of one single club, given the difficulty and constraints of obtaining multiple clubs data, therefore may not be representative of all other NRL clubs. Further, the current research is also limited by the use of one external device (GNSS) to analyse the training activity profile (Parmley et al., 2022), rather than using a combination of internal measures (i.e., heart rate, RPE) which may also provide a more holistic view of training practices between microcycle lengths during the season (Moreira et al., 2015; Parmley et al., 2022). This study also did not take into account physical contact-based variables such as collisions or tackles which may also account for the activity profile between microcycle lengths (Parmley et al., 2022). Given the association between contacts/tackles in rugby league competition and muscle damage markers such as creatine kinase, future research should consider examining collision-based metrics in conjunction with internal and external activity profile metrics (Murray et al., 2014; Parmley et al., 2022; Twist et al., 2012).

Quadratic coefficients have been used previously in activity profiles for team sport athletes (Duthie et al., 2021). However, it is important to practically outline how activity profile data can be manipulated after the coefficients have been determined. For example, if a practitioner wished to identify the distribution of any given speed intensity across the 7–8-day microcycle they could program this information via the following example:

a coefficient = -0.0006, b coefficient = 0.0976, c coefficient = 3.4629

$$((\mathrm{a} \times \text{speed intensit}y^2) + (b \times \text{speed intensity}) + \mathrm{c})^e$$

$$((-0.0006\ \times \text{speed intensit}y^2) + (0.0976\ \times 100) + 3.4629)^e$$

This information could become useful when practitioners are required to conduct longitudinal comparisons across seasons. The differences in coefficients themselves can also be used as an indication that differences may exist.

The comparison between microcycle lengths in impulse and distance allows practitioners to observe the differences in training volume across different microcycles. This may provide practitioners with an understanding of structuring training sessions regarding volume and intensity, whilst considering available time/logistics, facilitating recovery, and facilitating an adequate training stimulus. As the length of the microcycle deceased (i.e., 5-6 day compared to 7-8 and 9-10 day), the overall training volume for distance and impulse reduced. The relative distribution of intensity for impulse was similar between microcycle lengths, with greater variation seen in the relative distribution of distance, where there was a greater volume accumulated at lower intensity during 5–6-day microcycles compared to 7-8- and 9-10-day microcycles. The results from the study indicate that in shorter microcycles (i.e., 5-6 days), recovery was prioritised and to maintain athlete physical performance in-season, training volume was manipulated, and to a lesser extent, intensity. Further, practitioners can compare the distribution of their training intensity and volume relative to their competition data. Longitudinally, this may enable historical comparisons across seasons to identify trends in training relative to competition data.

8.6 Conclusions

The current study identified that as the length of the microcycle length between matches decreased, the overall training volume for distance and impulse reduced. Specifically, there were lower totals for both distance and impulse in 5–6-day microcycles compared to the longer durations of 7-8 days and 9-10 days. The relative distribution of intensity for impulse was similar between microcycle lengths, however, despite any reduction in microcycle length. For example, a 5-6-day microcycle did not see a commensurate reduction in the relative distribution of impulse compared to a 9-10-day microcycle, indicating that acceleration-based intensity wasn't directly scaled with training volume. Greater variation was seen in the relative distribution of distance, where there was a greater volume accumulated at lower intensity during 5–6-day microcycles compared to 7-8- and 9-10-day microcycles. The results from the study indicate that in shorter microcycles (i.e., 5-6 days), recovery was prioritised and to maintain athlete physical performance in-season, training volume was manipulated. To a lesser extent, training intensity was manipulated, however, acceleration-based intensity was largely maintained despite any decrement in training volume.

CHAPTER 9 - GENERAL DISCUSSION, CONCLUSIONS AND DIRECTIONS FOR FUTURE RESEARCH

9.1 Introduction

This thesis examined the effects of a common filter applied to GNSS technology during team sport movements for the processing of acceleration. Subsequently this thesis then examined acceleration in NRL competition following a rule change and the distribution of training volume and intensity during NRL training weeks. The use of a common filter reduced the differences in acceleration outputs between two GNSS devices during rugby league training sessions before being validated against VICON systems. The common filter was applied practically and helped to determine that the acceleration intensity of NRL competition increased across all positions following the introduction of the six-again rule, before identifying how speed was manipulated whilst impulse was maintained across NRL training weeks in-season. The application of this thesis has identified a method that allows for processing acceleration data in an independent, and importantly, more consistent way to help alleviate discrepancies that exist between player tracking provider processes and with changes in tracking device software and firmware. To process acceleration data with a more consistent methodology, practitioners and/or researchers should firstly consider a desired filter and consequently, a desired cutoff frequency via the use of residual analysis and consider a minimum effort duration. Pending the determination of validity and reliability with the selected processing methodology, practitioners and researchers can elect to process their athlete tracking data independently of proprietary software which may allow for more appropriate longitudinal comparison of acceleration data across important junctures (i.e., season versus season or athlete performance over time). By using this method, this thesis found that the six-again rule change substantially altered the acceleration profile of NRL players across all positions, Moreover, the distribution of volume and intensity for speed and impulse was identified using this method where speed in training was altered depending on the turnaround time between matches whilst impulse was consistent.

9.2 Discussion and Future Directions

The results from the systematic review in this thesis indicated that quantifying acceleration in team sports via counts was selected in well over half (~72%) of the included studies. The selection of counts to express part of the acceleration profile for a team sport is common practice, but the processing of acceleration to derive the count has shown considerable variation (Chapter 5). Chapter 5 in this thesis identified that the counts for the same activities in rugby league training sessions were substantially different, with double the number of counts identified by one device compared to the other (GPSports: 3.8 ± 2.8, STATSports: 10.0 ± 7.6). Given both devices were worn at the same time, the differences suggest that the processing of acceleration can directly impact upon the number of counts for the activity profile. Within rugby league research such discrepancies may already exist. Research from one study has identified that NRL athletes can attain approximately 71 counts during competition, whilst another study identified a range of 50-80 counts across positions (Kempton, Sirotic, Rampinini, et al., 2015; Varley et al., 2014). It should be highlighted that both studies used 5 Hz GPS technology from different providers, which may contribute to the differences and highlights the issue of a lack of information surrounding the processing of acceleration. Importantly, if a practitioner is observing the counts identified within their team versus those in research, it may become difficult to make informed decisions about any training or competition intervention if the difference in counts is substantial. If the practitioner uses a player tracking provider that’s different from the provider within a research article and the counts are substantially different, then this may lead to inappropriate decisions regarding training or load management. For example, if a half-back in rugby league is quoted as completing 100 acceleration counts per match (> 2.5 $m \cdot s^{-2}$) within research, but the practitioner's tracking system has shown an average of only 50 counts across the season average, it becomes difficult to make any decision regarding performance or recovery interventions. Similarly, for comparisons with research, it may be difficult to know if there have been accurate changes in the activity profile if differences in processing are not outlined or established. Specifically, given the relevance of counts and other threshold-based acceleration metrics, it's important that a common process is established or at least reported upon in the research.

The filtering methodology introduced in Chapter 5 showed that the use of a common filtering process reduced the difference in acceleration between two GNSS devices from different providers across a series of rugby league training sessions. The same methodology, being a 1 Hz Butterworth, fourth-order filter, was subsequently validated against a three-dimensional motion capture system (VICON) in Chapter 6. The findings from Chapters 5 and 6 indicated that applying a common filtering process to GNSS devices from different manufacturers can reduce the differences seen in the magnitude of acceleration variables while, crucially, mot altering the data to render it invalid or inaccurate. As a result, the use of a common filtering process can provide a valid approach to improve the consistency in processing athlete tracking data independently of the tracking system provider's software.

Using the common filtered data, differences in acceleration profiles were found between the NRL competition activity profile before and after the introduction of the six-again rule. Commonly, the introduction of rule changes into team sport competition prompts practitioners to review the activity profile of competition over multiple seasons to evaluate the need to alter training and/or rehabilitation programs to reflect the change in the competition activity profile (Delves et al., 2019; Sunderland & Edwards, 2017). However, evaluating athlete tracking data over a longitudinal period can be difficult due to software and firmware updates that are inevitably released by manufacturers over a similar period (Malone et al., 2017). Software or device firmware updates can alter the way tracking data is processed which consequently can alter the outputs for variables such as acceleration. For practitioners it is then difficult to ascertain whether any differences between seasons or phases within a season are driven by changes in competition play or due to changes in the processing and calculation of the athlete tracking data. Chapter 7 in this thesis showed that this research could analyse longitudinal-type studies which had software and firmware updates during the competitive seasons analysed. Moreover, greater confidence could be had that the differences in the acceleration profile were real and not due to differences in processing. Specifically, the use of a standard methodology to process athlete tracking data could help the practitioner to create greater consistency in their analysis longitudinally by enabling clearer analysis surrounding the impact of any rule changes upon the respective activity profile.

Practitioners are commonly required to evaluate the competition activity profile in comparison to their training programs to assess suitability for their athletes (Sweeting, Cormack, et al., 2017). Moreover, practitioners are also required to manipulate training volume, intensity, and recovery periods during the in-season phase of competition to promote training adaption or recovery where required. To enable comparison both distribution of speed and acceleration in competition and between microcycle lengths within season, practitioners should have a consistent methodology in the processing of their athlete tracking data. Without a consistent methodology to process tracking data like in Chapter 8, practitioners may again be subject to device firmware updates or software updates across the season which could influence the magnitude of any acceleration outputs. Any inconsistencies between processing may negatively impact the ability to compare between similar microcycle lengths across the length of the season, or across multiple seasons in relation to competition. Importantly, being able to also consistently complete analysis of training stimuli against competition regularly is enhanced with the use of a reproducible and consistent processing methodology.

The determination of a common filtering method for acceleration could be implemented across a variety of team sports. The validation of GNSS technology for speed in Chapter 6 was processed using the common filter applied in this thesis upon association football athletes, whilst the practical application of the common filter approach was used in training and competitive environments within rugby league. Whilst the validation of this process against the criterion took place in a different sport to the longitudinal application in a practical setting, it's important to note that the initial residual analysis to determine the optimal cutoff frequency for rugby league training data took place in Chapter 5, with respect to the rugby league studies in Chapter 7 and 8. It is also understood that it would be difficult to globally recommend the use of 1 Hz Butterworth fourth, despite the use already within research, in order filter to all team sport practitioners using GNSS technology, given the differences between the activity profiles of most team sports (Ellens, Middleton, et al., 2022). However, tracking system providers may currently apply one filtering process to their tracking device models or systems regardless of the different types of team sports currently using their products. Regardless, what could be generalized across different team sports is the notion of instilling a common filtering process once the analysis and subsequent internal validity and/or reliability is examined.

9.2.1 Future Directions

Future research on the application of a consistent method to process acceleration from athlete tracking devices should extend across to LPS and optical tracking systems. This thesis focused upon GNSS technology, given the widespread use of GNSS devices in outdoor team sport competitions at the elite level (Aughey, 2011a; Malone et al., 2017). However, there is an increasing trend for outdoor team sports such as rugby league and Australian rules football to interchange wearable tracking systems from training to competition (Thornton, Nelson, et al., 2019). For example, an NRL team may train with GNSS devices as their training facility may be outdoors and free from stadium infrastructure. During competition in stadia, a common alternative is for athletes to wear LPS devices with local infrastructure installed within the stadium to maintain or improve signal quality for competition. However, for practitioners and researchers, the interchanging of systems may impact athlete monitoring as the devices may process tracking data differently, with different sample rates and consequently, error rates which may provide incompatible data between training and competition (Buchheit, Allen, et al., 2014; Thornton, Nelson, et al., 2019). Therefore, it would be of interest to analyse the impact of applying a common filter to wearable tracking technology and optical technology to identify the levels of compatibility between the datasets with identical processing methodologies.

In the applied setting, within elite team sports, it may be pertinent for practitioners to analyse longitudinal athlete tracking data over several seasons (Dalton-Barron et al., 2021; Rennie et al., 2021). Currently, it is difficult for practitioners to analyse longitudinal data as inevitably there are device changes/upgrades, firmware updates, software updates or filtering changes that occur at regular intervals across a season or multiple seasons which can inhibit valid comparisons across seasons (Brosnan et al., 2021; Malone et al., 2017; Thornton, Nelson, et al., 2019). Any changes or updates to tracking device technology can lead to differences in the outputs of athlete tracking metrics such as acceleration (Brosnan et al., 2021). For team sport practitioners, it may be valuable to analyse their longitudinal data over seasons to enhance their decision-making processes surrounding athlete management and the prescription of training interventions. It may be that the requirements of competition have changed for the respective team and perhaps different training interventions may be required. (Chapter 7) Practitioners could improve their ability to conduct longitudinal analysis of their tracking data by following the methodologies outlined in this thesis. For example, practitioners could firstly identify an appropriate filtering method that is valid against a criterion measure to begin processing their data, similar to the methods outlined in Chapters 5 and 6. After this point, practitioners could then apply a consistent filter with similar rationale to that in Chapters 7 & 8, with a longitudinal project that could be applied across a season or multiple seasons with analysis on training and/or competition. Future applied research from elite team sports could also follow a similar process in the outlining of activity profiles or comparing activity profiles from previous seasons. Reanalysis of historical activity profiles from respective sports could be examined and processed using a consistent methodology to make more appropriate comparison between seasons. Commonly, the updating of activity profiles following the introduction of competition rule changes are required and could be appropriate to apply some of the methods used in this thesis (Delves et al., 2019; McMahon & Kennedy, 2019; Meir et al., 2001; Sunderland & Edwards, 2017).

For team sport practitioners, the introduction of rule changes within team sports can prompt the need to revaluate the potential changes in the competition activity profile (Delves et al., 2019; McMahon & Kennedy, 2019; Meir et al., 2001; Sunderland & Edwards, 2017). Chapter 7 highlighted how the change in competition rules can impact upon the activity profile, with emphasis upon acceleration. The ability to analyse the impact of any rule change can hold direct influence upon training program prescription. Importantly, rule changes can occur frequently depending upon the sport and competition. For example, the NRL have since altered the competition rules since the publication of Chapter 7 by reinstating traditional penalties for defending teams within the opposition's 40m. For practitioners, it is then important to be able to repeat the process of analysing the competition activity profile before and following subsequent rule changes. Establishing a consistent process to do this by way of filtering and data processing can improve or maintain the quality of these comparisons and potentially lend more confidence to any changes in training program prescription as a result. Figure 9-1 shows an example process practitioners could follow to establish a consistent process for athlete wearable tracking data in competition and training.

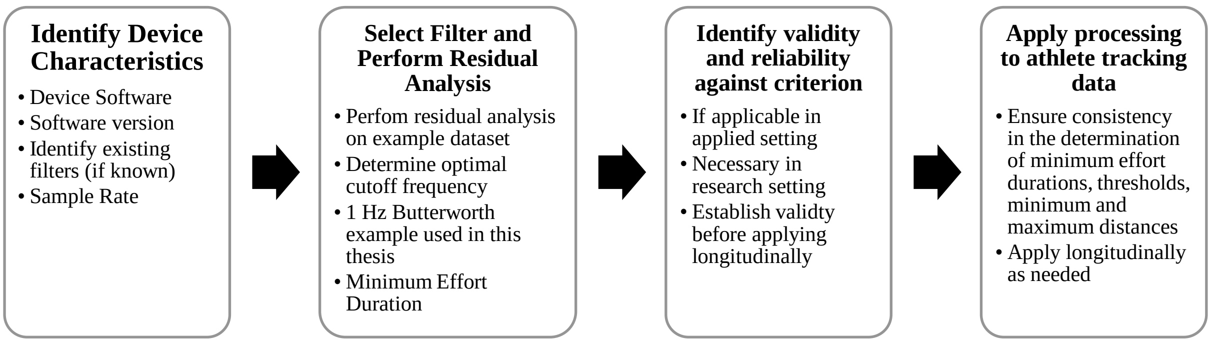

Figure 9-1 Example process in applying a consistent filter process in the applied team sport environment

This thesis focused primarily on the practical application within elite sport science for team sport performance. However, an important component of athlete tracking research is that of establishing the validity and reliability of wearable tracking devices and systems as they are introduced into the market (Aughey, 2011a; Jennings et al., 2010a; Malone et al., 2017; Scott et al., 2016). Governing bodies of sports such as FIFA, have introduced accreditation and preferred provider programmes that endorse different commercial athlete tracking devices and systems that have established validity and reliability (Aughey et al., 2022). It may be that other sporting organisations and governing bodies establish validity and reliability programs for athlete tracking systems in the future. In that case it may be important to evaluate tracking technology from different providers using a similar filtering process to identify the validity and reliability of the technology. Having a consistent method to process tracking data independent of the proprietary software may provide a more appropriate comparison of validity and reliability between providers to then award certification and/or preferred provider status.

Within research, both the individual device models and systems (in the case of LPS and optical) need to be validated by researchers to enable confidence for use at the elite level (Aughey, 2011a; Jennings et al., 2010a; Malone et al., 2017; Scott et al., 2016). However, the majority of validity and reliability research for athlete tracking devices usually compare each individual device model to other devices or criterion measures with an emphasis on the hardware characteristics of the technology (e.g., device sample rate), with limited consideration as to how variables such as speed or acceleration are processed (Scott et al., 2016). As stated previously, researchers may not be aware of how manufacturers may process data, which may also have a direct influence on the validity and reliability for that research (Malone et al., 2017; Varley et al., 2017). For research examining the validity and reliability of acceleration and/or deceleration as measured by wearable technologies, there have been large variations and questionable validity in high intensity deceleration (CV: 56%) (Buchheit, Al Haddad, et al., 2014). Future research may then apply a common filter between devices or systems to compare similar devices more appropriately against a criterion measure. For example, future research may wish to evaluate two 10 Hz GNSS devices from different manufacturers against a three-dimensional motion capture system as a criterion. Hardware between the GNSS devices may be similar, but if the data is processed using the manufacturer's software, researchers may be unaware as to the impact of any filtering imposed on the data (Thornton, Nelson, et al., 2019). Moreover, given the presence of 18 Hz GNSS technology and the comparison of GNSS data compared to higher sampling criterions (i.e., three-dimensional capture systems), up sampling and down sampling of sample rates is common (Beato et al., 2018; Winter, 2009). Again, it may prove inappropriate for practitioners or researchers to try to compare outputs from devices that sample at different rates if the processing of the variable, such as acceleration, is unknown or know to be calculated differently (Buchheit, Al Haddad, et al., 2014). However, if researchers could process the data independently and then apply an experimental or common filter to the tracking devices, they may be able to make more appropriate comparison as to the suitability of the devices in terms of validity and reliability (Figure 9-2).

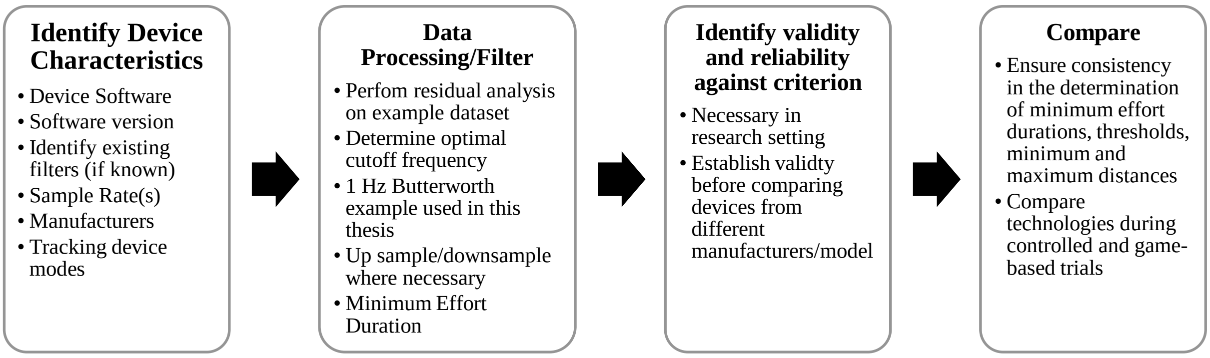

Figure 9-2 Example process in applying a consistent filter process in the research environment

9.3 Summary

This thesis examined the use of a common filter in the processing of athlete acceleration from GNSS technology in team sports. Chapter 3 examined how acceleration had been quantified across team sport activity profiles, which identified a lack of information surrounding how acceleration had been processed by wearable tracking manufacturers. The thesis then attempted to identify how acceleration had been processed by wearable tracking manufacturers via an anonymous survey (Chapter 4). However, a lack of survey responses, which may be due to the intellectual property and commercial risk facing manufacturers, limited the scope of the survey. As a countermeasure, the thesis then examined the use of applying a common processing method between two different GNSS/GPS devices during rugby league training sessions (Chapter 5). The experimental filter showed no substantial difference in acceleration between both devices. The experimental filter was then validated against a three-dimensional motion capture system during team sport movements and small-sided games to assess wider, longitudinal applications in the forthcoming chapters (Chapter 6). To assess the suitability of the 1 Hz Butterworth filter, the processing methodology was applied across three rugby league seasons to assess the impact of a rule change that was hypothesised to directly impact upon acceleration (Chapter 7). Chapter 7 allowed for longitudinal use of the experimental filter across numerous seasons, which was identified as a common applied scenario for practitioners. Further, the experimental filter was used again during an in-season analysis looking at the distribution of the training activity profile in elite rugby league with different microcycle lengths during the season (Chapter 8). The experimental filter allowed for comparison between training weeks, but also allowed for more appropriate comparison between training and competition volume and intensity, with respect to acceleration-based metrics. The rationale for Chapter 8 again highlighted the practical significance of being able to apply consistent filtering processes in the calculation of acceleration in team sport conditions. As the notion of applying a consistent filtering process in the handling of athlete acceleration is largely unexplored, future application should analyse the impact of common processing when interchanging tracking systems and for use when establishing or comparing the validity and reliability of introduced tracking devices and systems. Given the experimental filter was used in the validation against a three-dimensional motion system during team sport movements, generalisation of this technique to other team sports would be expected, provided researchers and practitioners established the validity of the processing and handling methodology, in similar fashion to the methodology used in this thesis.

9.4 Practical Applications

The practical applications of this thesis are:

1. Researchers and practitioners may elect to process athlete GNSS data independently of the GNSS proprietary software in order to enable more appropriate comparisons of variables such as acceleration across longitudinal periods.

2. This experimental methodology (1 Hz, fourth order Butterworth filter) or another validated methodology could be used by team sport practitioners and researchers if they wish to process their athlete tracking data independently of the GNSS proprietary software, and if appropriate for their athletes and datasets.

3. To identify their own custom data-handling process, researchers and practitioners may elect to incorporate a residual analysis or other method to identify appropriate cutoff frequencies for their athlete tracking data sets in conjunction with the selection of a filter.

4. Researchers and practitioners should attempt to validate their choice of filter/cutoff frequency against a criterion measure before applying custom processing to their athlete GNSS data.

5. The use of a consistent process to handle athlete GNSS data may allow for better comparison between athlete wearable tracking devices and systems when assessing device validity and reliability.

6. With the use of a consistent process, longitudinal analysis of athlete tracking data over several seasons or years may be possible. The consistent processing of data may help improve the accuracy of the data and minimise the impact of software or device firmware updates that inevitably occur over a longitudinal period.

9.5 Conclusions

The conclusions of this thesis are:

1. There is a lack of knowledge within research as to how EPTS manufacturers filter and process GNSS data which may have an impact upon the consistency in the calculation of acceleration. However, it is clear from the results in this thesis that EPTS manufacturers process GNSS data differently which has implications for acceleration outputs which will differ between systems for the same activity.

2. The use of a common filter and cutoff frequency reduced the difference in acceleration outputs between two GNSS devices from different manufacturers.

3. This thesis developed a common filtering process for GNSS-based acceleration using a 1 Hz, fourth order Butterworth filter that was subsequently validated against a criterion measure for applied use.

4. Through longitudinal analysis with a common filter, the introduction of the six-again rule changed the activity profile of NRL competition, with an increase in acceleration intensity across all positions.

5. Through longitudinal analysis with a common filter, speed intensity during NRL training weeks in-season were manipulated to facilitate performance when fewer training sessions were completed in shorter microcycles. The intensity of impulse was maintained regardless of the recovery between matches.

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