Offence vs Defence: Quantifying workload demands in professional Rugby Union.

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Abstract

Title: Offence vs defence: Quantifying workload demands in professional Rugby Union.

Purpose: Rugby Union is a skill-based contact team sport demanding high levels of physical and tactical skill. Ensuring that training matches the physical requirements for match-play demands is, therefore, important for success. Many factors influence the workload demands of match-play, including positional differences and the type of play (offence or defence). This thesis encloses an original and innovative study that compares the locomotive and contact workload demands of offensive and defensive ball-in-play periods for professional rugby union match play.

Methods: Data were collected for 40 professional Rugby Union players across 14 games in the 2021 Super Rugby season. All participants wore GPS units (Apex Pro Pod, STATSport, Newry, NIR). Each match was filmed and coded using the Sportscode video analysis software package (Sportscode 12.4.3, Sportstec, Australia), where contact metrics and type of play (offence and defence) were identified throughout the match. GPS and Sportscode data were combined in a bespoke software package. Data were analysed with the Statistical Analysis System (On-Demand for Academics, version 9.04, SAS Institute Inc., Cary, NC, USA), using a generalised mixed-model procedure (Proc Glimmix) specifying a log link and a Poisson distribution that allowed for overdispersion. The effect magnitudes were assessed for 2 SD changes in predictors.

Results: Most metrics showed small to moderate increases for forwards and backs when offence was compared to defence. Small to large decreases in locomotive metrics, and a very large increase in contacts was observed when comparing forwards to backs, on offence and defence. When the effect of match outcome was examined, small to moderate effects were observed for some metrics for forwards on defence and backs on offence. The effect of fatigue was moderate to very large across most metrics, for forwards and backs in offence and defence.

Conclusion: Offensive periods of play demanded a decisively greater workload than defensive periods of play across most metrics for forwards and backs. Additionally, there was strong evidence that backs performed greater locomotive workload but less contacts compared to forwards in both offence and defence. When winning was compared to losing, there was good evidence that backs achieved greater values for most locomotive metrics on offence, whilst forwards achieved greater values for some metrics during defence. Understanding how workload demands vary between positions and types of play can aid practitioners in effectively replicating match demands, whilst observed differences in workloads between winning and losing can provide insight into outcome-oriented conditioning for each position.

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Table of Contents

List of tables

Abbreviations

BIP: Ball-in-play

BOP: Ball out of play

DSL: Dynamic stress load

GPS: Global positioning unit

HiMet: High-metabolic load distance

HSR: High-speed running

HiVel: High-velocity distance

SpMet: Sprint-metabolic load distance

WCS: Worst-case scenario

Chapter 1. Literature review

1.1 Introduction:

Rugby Union is a skill-based contact team sport that demands high levels of both physical and tactical skill (Duthie, 2006). The game itself consists of two 40-minute halves and is played between two teams, with 15 players on each team (Duthie et al., 2003). There are many physical aspects to the game, both locomotive and contact related, that are measured utilizing very different methodologies, and as such, it can be difficult to quantify overall workload. Being able to understand the workload demands of players throughout a match can help to improve training design and, therefore, game performance. This knowledge could be achieved through more accurate analysis methods and further investigation into the workload that occurs in different periods of the match. In this review, we will summarise the recent literature on such factors to inform us of best research practices and methodologies and help identify potential gaps in the research. Where appropriate, research from similar sporting disciplines (such as rugby league) has been included to increase the depth of information, as in some instances, there is a lack of relevant literature for rugby union itself.

1.2 The locomotive and non-locomotive demands of rugby union:

The workload demands on elite rugby union players continue to increase year by year, highlighting the importance of effective workload quantification and analysis (Owen et al., 2015). These researchers described rugby as an intermittent contact sport, with repeated bouts of low-intensity interspersed with high- and even maximal-intensity periods. The sport is physical in nature, and high-intensity activities can include many acceleration and deceleration events applied in multiple directions, with some of the more intensive decelerations involving contact collisions with opposition players, such as during a tackle or a scrum (Owen et al., 2015). Duthie (2006) stated that speed, strength, power, aerobic capacity, and body composition (muscle mass) are all essential factors that play a role in determining success. The locomotive demands of rugby union have been well described. They include a combination of low-intensity (walking, standing, jogging, and medium-intensity running) and high-intensity (high-intensity running, sprinting) movements (Roberts et al., 2008). Players are also subject to performing multiple accelerations and decelerations throughout the match (Pollard et al., 2018).

Due to the large amount of non-locomotive workload that occurs in a rugby game, the use of locomotive metrics alone cannot realistically quantify the overall workload. There are several events that players will experience during the match that are physically demanding yet do not register a large locomotive load. Rugby union contacts, such as rucks, mauls, tackles, and scrums, contribute significantly to the overall workload that players experience and are considered crucial to the outcome of games (Reardon et al., 2017a).

Forwards, in particular, spend a large proportion of the match during “static exertion” phases, with approximately 15% spent scrummaging and mauling alone (Duthie et al., 2003). These events are essential to quantify when it comes to overall workload, as they are often considered to be the most strenuous part of the game. This is highlighted by the finding that forwards, who are involved in significantly more scrums, rucks, mauls, and ball-carry collisions than backs, have shown greater levels of stress-related biomarkers (creatine kinase) when measured post-match (Smart et al., 2008). These authors also found a relationship between the number of scrums in a match and elevated creatine kinase levels in forwards. A similar relationship was observed for the number of hit-ups in the backs. These findings have highlighted the importance of contact activities when it comes to overall workload, as they cause significant muscle damage and are strenuous for the body. According to Duthie et al. (2005), contact events can vary in intensity. For example, players can act in supporting roles during rucks and mauls without exerting maximal effort. These authors suggested that more accurate quantification of contacts in rugby is needed to further develop our understanding of the workload demands of the game.

Due to the limitations of current methodologies, such as time-motion analysis and microtechnology, many studies have simply excluded the quantification of non-locomotive activities in their research. This is often described as a limitation to any findings that report solely on locomotive match-play demands. According to Austin et al. (2011), activities such as tackling are often not considered when assessing high-intensity exercise, rather, there is a significant focus on locomotion metrics (such as high-speed running (HSR)). These authors emphasised that contact events are typically highly taxing and, therefore, should be included in any assessment of workload. In their investigation into maximal running intensities during rugby union match-play, Read et al. (2019) calculated peak running demands that occurred within a rugby match and acknowledged that their failure to quantify collisions limited their findings. Similarly, in their investigation into the running intensities of match-play in rugby league, Delaney et al. (2015) acknowledged that the results of their study were limited due to their failure to quantify the contact and collision demands of the match. Roberts et al. (2008) discussed that using time-motion analysis in rugby union did not allow for the intensity of static exertion to be quantified in their own study. They concluded that whilst measuring static workload is technically challenging to quantify, its prevalence and importance warrant further investigation.

With such varied and intensive workload requirements, rugby is a sport where physical preparation is essential for success, especially for elite and competitive players (Duthie, 2006). Quantifying and understanding both the locomotive and non-locomotive demands of a match is a crucial step in developing effective training methods to prepare players for competition (Duthie, 2006).

1.3 Technologies for analysing workload demands:

1.3.1 Time-motion analysis:

One common method that aids the understanding of movement patterns and workloads in rugby union matches is time-motion analysis. Time-motion analysis has been used to analyse the movements in a range of sports and involves quantifying the time spent in different activities to determine movement patterns, distance covered, average velocities, level of exertion, and work-to-rest ratios (Duthie et al., 2003).

Duthie et al. (2005) conducted a time-motion analysis study on the movements of super-12 rugby players during competition. Each match was videoed for analysis, and movements were broadly classified as either rest (walking, jogging, and standing) or work (sprinting, static exertion, jumping, striding, lifting, and tackling). The total time, number, and duration of each unique activity were calculated, and differences between positional groups were assessed. The main conclusion from their study was that rugby union is characterised by intense and intermittent movement patterns, with significant differences in workload experienced by forwards compared to backs. Specifically, forwards spent more time performing bouts of static exertion, whilst backs performed more sprints than forwards.

Roberts et al. (2008) used a time-motion methodology during their investigation into the physical demands of elite English rugby union. The movements of players were captured by five separate video cameras and then visualised on a two-dimensional reconstruction of a pitch. Movements were categorised as either low-intensity (walking, standing, jogging, and medium-intensity running) or high-intensity (high-intensity running, sprinting, and static exertion). Backs travelled greater distances and spent more time performing high-intensity running than forwards, whilst forwards were more often engaged in high-intensity activity attributed to more time spent in static exertion. The authors acknowledged that in their study and other rugby union time-motion studies, it was not possible to assess the intensity of activities when players performed bouts of static exertion. Instead, it was assumed that all players performed high-intensity activity during all static exertion periods (Roberts et al., 2008).

Despite its usefulness, the validity of time-motion analysis is questionable, as movement patterns are simplified into categories. In reality, actual play involves the dynamic combination of several tasks, along with skill and tactics (Duthie et al., 2003). Even multiple-camera time-motion analysis systems utilising sophisticated trigonometric software are currently unable to validly measure locomotion workloads (Reilly & Gilbourne, 2003). Reardon et al. (2017a) summarised the limitations in using time-motion for quantifying contact workload, stating that whilst traditional time-motion analyses can determine collision count, they are labour-intensive and have the potential for human error. They are also currently unable to quantify the intensity of collisions.

1.3.2 Global positioning system:

Global positioning systems (GPS) were first made commercially available for field sports in 2003. Since then, there has been a rapid increase in its commonality of use and range of applications (Aughey, 2011). Modern GPS units are lightweight and low-profile, making them ideal for use in a field sport such as rugby. The use of GPS and associated microtechnology is a common method to quantify workload metrics in training and match-play.

GPS systems work by recording the latitude and longitude position of a unit at exact time intervals, which provides a change in distance associated with the change in time. With this raw data, several metrics can be calculated, such as path taken, distance, speed, and timing, which in turn can help evaluate locomotive workload (Kurzawa, 2008). Cummins et al. (2013) acknowledged that GPS have allowed a better understanding of the positional and physiological demands of team sports and can be a useful tool to help prepare athletes for competition. As such, they are now a widely used tool for the analysis of locomotive workload across an extensive range of sports.

The advancement of GPS technology has enabled the analysis of varying speed zones, impact characteristics, and other previously unobtainable metrics of workload and intensity (Cummins et al., 2013). West et al. (2019) pointed out that a wide range of GPS metrics have been collected across organisations, with varying names and definitions. They stated that the most common metrics were distance in speed zones (particularly high-speed running) and total distance. Other common metrics for analysis of workload demands in rugby union included counts of sprints, accelerations, decelerations, sprint distance, peak velocity, high-metabolic power, dynamic stress score, and tackle count (West et al., 2019). Understanding and including a diverse number of metrics has facilitated precise performance comparisons between players, teams, competition levels, and seasons. Furthermore, dividing GPS data into multiple metric categories has provided a more detailed understanding of the physical stressors experienced by players (Cummins et al., 2013). However, Cummins et al. (2013) also pointed out that early published research on rugby union workloads focused primarily on distance travelled as opposed to sprint distance, time spent in different speed zones, and other metrics.

Another challenge is the lack of common naming conventions for GPS metrics between GPS providers. Sometimes, a metric with the same name may measure something different or have different threshold zones. Teams using the same GPS device sometimes change the threshold zones of specific metrics for various reasons, making longitudinal comparisons or comparisons between teams for the affected metric/s impossible (West et al., 2019). For example, HSR is sometimes distance >5.5m.s^{-1}, or it can be distance >5m.s^{-1}, whilst the threshold for the acceleration metric may vary from >1.5m.s^{-2} to >2.5m.s^{-2}.

Young et al. (2019) pointed out that the advancement in GPS technology has enabled the analysis of locomotive workload demands in sports ranging from walking to sprinting, and most studies have presented these demands as distances covered in different speed zones using speed-based thresholds. However, the start-stop nature of a sport may mean that the locomotive workload is not accurately reflected by distances or time in these speed zones, as the often-large workloads involved in changes in speed, i.e., acceleration and deceleration, are not accounted for (Young et al., 2019). The use of acceleration and deceleration count has become popular in the literature, as accelerating and decelerating, even at low speeds, can still be demanding for the player (Osgnach et al., 2010). However, counts of accelerations and decelerations alone cannot provide an accurate representation of the workload occurring as the exact energy cost of changing speed relies on both the magnitude and duration of the activity (Young et al., 2019). As a result, another common metric type has been developed and used in the literature, the calculation of metabolic power and metabolic loading. One example is high-metabolic load distance, calculated as the distance covered at a speed of >5.5m.s^{-1} or while accelerating or decelerating at ≥2m.s^{-2} (Clemente et al., 2020).

The distinction between absolute and relative metric thresholds is also important to consider when assessing workload demands. Absolute threshold zones are set at the same value for everyone in the team, e.g., high-speed running is set at distance > 5.5m.s^{-1} for all players. Relative thresholds are those where zones are individualised for each player, e.g., high-velocity is set at distance > 85% of each individual player's peak velocity. Cummins et al. (2013) pointed out that players are subject to different positional demands and have varied physiological capabilities (for example, forwards have a slower maximum speed than backs on average). This poses an issue for the accuracy of arbitrary (absolute) speed zones for the depiction of workload, as some players require more effort than others to reach specific velocities. However, although setting individualised zones for each player presents a logical solution, it can be logistically problematic for practitioners to do so (Cummins et al., 2013).

Another important consideration is whether metrics are collected as absolute or relative values to time. Cummins et al. (2013) suggested that absolute total distance or total metric values may not be useful for comparison as they are most often correlated to, and therefore reflective of, time on the field, and they do not accurately represent match intensity. The use of metrics per unit of time has enabled accurate quantification of values not only between but within sports, as metrics are adjusted for the amount of time that players spend on the field. Therefore, the use of metric per unit time (e.g., distance per minute, HSR per minute, acceleration per minute, etc.) is recommended, as it presents a more accurate depiction of intensity (Cummins et al., 2013).

In terms of accuracy, there are some issues when it comes to the use of GPS units for quantifying workload in sports. Firstly, GPS units have varied positional accuracies, which typically range from 2.5m to 10m (Schipperijn et al., 2014). Aughey (2011) examined the validity of a 1Hz or 5Hz GPS for measuring human locomotion. They found that GPS sample rate, duration of the task, relative velocity, and type of task can all influence the reliability of GPS. They also noted that GPS accuracy decreased with increased velocity and change of direction. These are important factors to consider when GPS is used for a dynamic game such as rugby, where high-velocity activity and change of direction are both essential characteristics of match-play. Akenhead et al. (2014) conducted a similar evaluation of the reliability and validity of a 10Hz GPS unit. They found that the accuracy of the measurement of instantaneous velocity was inversely related to acceleration, particularly when acceleration exceeded $4m.s^{-2}$. This is an important finding, as much of what we consider to be high-locomotive workload in rugby is related to periods of intensive accelerations (Owen et al., 2015). Despite the limitations to their accuracy in certain circumstances, GPS have provided scope for a better understanding of the physiological and positional demands of team sport, adding value for practitioners when it comes to optimally preparing players for match demands (Cummins et al., 2013).

Although team sports GPS units are constantly evolving and becoming more accurate, they currently still have some accuracy limitations. Despite this, they are considered a useful tool for the evaluation of locomotive workload in rugby and have enabled the analysis of a wide range of locomotive measures that were previously unobtainable for practitioners.

1.3.3 Accelerometer technology:

To quantify additional workload to locomotion, some GPS units may also include accelerometer technology, which enables the recording of impact data. Accelerometers measure acceleration in three separate axes, the sum of which provides a vector magnitude force that can be used to quantify the intensity of a collision (Paul et al., 2022). This is particularly interesting in contact-heavy sports such as rugby, although the accuracy of such data is relatively poor (Cummins et al., 2013). Despite recent studies demonstrating that microtechnology can detect up to 97% of collisions during a rugby league game (Hulin et al., 2017), they are unable to distinguish between the type of contact, a very important factor when analysing game-specific situations (Cummins et al., 2013). Different contact situations have varied demands and exertion on the player, so grouping them all into a single category can misrepresent the relative workload. Naughton et al. (2020) completed a meta-analysis on the collision dose in rugby league. They explained that a more detailed analysis of the differences between collision type is currently not possible, as microtechnology does not differentiate between tackles and ball carries. There is also a lack of research into the validity of automated tackle detection systems and their subsequent effectiveness in quantifying the frequency of collisions (Naughton et al., 2020).

Additionally, not all non-running workloads can be described as a collision. Traditional collision detection systems rely on accelerometer data to quantify the impact (Naughton et al., 2020). However, there are some situations where this is ineffective. For example, Jones et al. (2015) pointed out that many significant contact events involve prolonged static exertion that may not be detected by accelerometers. For example, the forces exerted during a scrum are largely isometric in nature, with lower velocity and longer duration. Additionally, some non-contact acceleratory events during match-play may produce a vector with an adequate magnitude to result in a false positive contact recording (Reardon et al., 2017a). These authors concluded that despite the advances in sensor technology, which may help the characterisation of movement patterns in rugby union, further research is needed to accurately quantify the physiological demands of performance (Jones et al., 2015).

The acceleration-based impact measures of accelerometers are currently not accurate enough to measure contact workloads, highlighting the need for additional tools to be developed and used when attempting to quantify total workload, particularly when assessing non-locomotive events (i.e., contact workload). Ideally, future researchers should look to establish measures that capture not only the occurrence of collisions but their intensity as well (Naughton et al., 2020). This suggestion was reiterated by (Reardon et al., 2017b), who stated that being able to measure collision intensity is essential to improving our understanding of average and single-bout workload demands in rugby union. They concluded that future research should focus on establishing a more valid method of measuring collision and acceleration forces. The ability to combine such an analysis with the existing techniques for quantifying locomotive measures would allow for a more accurate depiction of overall workload demands in rugby union.

Whilst there are certainly limitations to the accurate quantification of contact workload, it is an important consideration when assessing match-play demands. Due to the limitations of GPS accelerometers, complete analysis of workload still requires the pairing of GPS data and manual coding of contact events (Cummins et al., 2013).

1.4 Methods of match analytics:

The sampling methodology used when collecting data throughout a match is of great importance, as different methods can generate drastically different results. Sampling duration is an important consideration when evaluating match-play demands in rugby union, as the game itself is intermittent in nature and is comprised of many ball-in-play (BIP) periods (the duration within the match where live play is occurring) of varying durations where workload demands typically differ. It is important to consider that within the match, there may be periods of work, rest, high-intensity, medium-intensity, and low-intensity, which do not follow a consistent pattern or order between games. To quantify match workload demands, researchers have typically employed two methods: a fixed-time epoch (interval) or a rolling-epoch method, which are described below.

1.4.1 Fixed-time vs rolling epochs:

The fixed-time methodology involves segmenting the match into set epochs, such as eight 10-minute epochs within an 80-minute match (Jones et al., 2015). These authors examined the temporal and positional movement patterns of rugby union players by using a fixed-time methodology, taking averages across each epoch. Matches were separated into 10-minute epochs, and time played past 40 minutes in each half was excluded. This methodology did not exclude periods where the ball was out of play (BOP time), as each of these 10-minute epochs were determined by the running clock-time. Therefore, data for the collected metrics were largely inclusive of rest periods and not representative of actual match intensity. Excluding periods of play that occured after 40 minutes in each half was also a limitation. Although this allowed for even 10-minute epochs to be analysed, it effectively excluded data from the analysis. Arguably, the data collected towards the end of each half is of great importance and may contain important insight into workload demands, such as the effects of fatigue towards the half-time break. This period is essential to include for the validity of metric averages.

A rolling methodology involves taking data from a set block of time (e.g., five minutes), similar to a fixed-time methodology. However, the start of each block occurs at a set interval (e.g. every second) as opposed to starting when the previous block ends (Varley et al., 2012). Some studies, such as Cunningham et al. (2018), have investigated the use of a rolling average methodology to calculate workload metrics from the game. The rolling average methodology was described as having become more prevalent due to sampling resolution concerns when data were analysed in fixed-time periods. In this study, the researchers employed the use of both rolling and fixed-time analysis. They aimed to compare the two techniques to see if there was a significant difference in output metrics based solely on the collection method. They found that movement demands were almost always underestimated when a fixed-time epoch was used compared to rolling due to a loss of sampling resolution with such large timeframes (Cunningham et al., 2018). This finding was consistent irrespective of the epoch length, which was analysed in intervals from 60 to 300 seconds. Despite this, the authors discussed that the use of rolling and shorter fixed-time epochs both resulted in much higher metric values than traditional fixed-time methodologies, such as whole-match, half-match, and even 10-minute epochs. These findings suggested that due to relative sampling resolution, values reported for fixed time epochs such as 5 to 10 minutes and even the use of a shorter-duration fixed-time epoch underrepresented the most intense periods of play that occurred during a match when compared to a rolling methodology (Cunningham et al., 2018).

With their investigation into maximum running intensities in rugby, Read et al. (2019) utilised a rolling average methodology with a 0.1-second rolling mean for several epoch durations (5 and 30 seconds, and 1, 2, 2.5, 3, 4, 5, and 10 minutes). Their findings showed that running intensity decreased as the duration of the epoch lengthened, with all comparisons between each consecutive epoch duration resulting in clear differences. The authors acknowledged that this relationship most likely occurred as shorter timeframes reflected higher intensities due to the relative ball-in-play time. According to the authors, using a rolling mean highlighted greater positional workload differences than previous whole-match and phase-of-play analyses. Their findings suggested that the rolling method can more accurately establish match-play demands and help to develop effective position-specific training protocols (Read et al., 2019).

A similar study by Delaney et al. (2015), investigated the running intensities from match-play in rugby league. They also utilised numerous rolling-average epochs, with 1-,2-,3-,4-,5-,6-,7-,8-,9-, and 10-minute durations. The resulting analysis showed large differences between each consecutive epoch duration, with the greatest being between 1-minute and 2-minute rolling averages. Using a rolling average methodology, the authors concluded that rugby league match-play required considerably more intense periods of play than previously reported (by fixed-time methodologies).

The limitations discussed summarise the importance of considering ball-in-play time as a key determinant of metric outcomes, something that fixed-time methodologies fail to account for. If a fixed-time methodology is used, observed changes in performance may simply be due to correlations between absolute metric values and ball-in-play time. This also explains why data collected in a fixed-time epoch will typically underreport the intensity of metrics, as outputs are inclusive of rest periods in addition to work periods. Delaney et al. (2015) discussed the limitations of the fixed-time methodology, stating that the most intense period of a match does not necessarily fall entirely within a single fixed-time epoch. Therefore, this methodology may underestimate the peak demands of competition. They concluded that whilst a fixed-time methodology may be suitable for describing whole-match intensities or comparing periods within a match, it cannot effectively quantify demands over short and intense periods of play (Delaney, 2017). This consideration is particularly important for workload analysis in rugby, as periods of play will always vary in length, density, and intensity.

Due to the intermittent nature of rugby, using a fixed-time analysis has limitations as a method of quantifying match-play demands, as rugby players are subjected to ball-in-play periods with a wide range of durations and intensity levels. Due to higher sampling frequency and its greater relevance to the nature of the game, the rolling average has become a more popular method to determine the workload demands that players may experience in a match. The use of the rolling average methodology has resulted in the reporting of higher match-play demands than those described initially by studies that utilised a fixed-time analysis. While fixed-epoch and rolling-epoch analyses have provided better insights into the intermittent nature of rugby workload than whole-match averages, arguably, both methods lack accuracy as they utilise fixed-time intervals when the actual durations of the various intermittent work (and rest) intervals can vary greatly.

1.4.2 Ball-in-play methodology:

While the rolling methodology has been shown to more accurately report workload demands than the fixed-time methodology (Cunningham et al., 2018), it is still an artificial representation of the actual varying intermittent interval durations that occur in rugby and is, therefore, susceptible to misrepresenting the true nature of the workload in rugby. Logically, the best method of accurately determining the intermittent workloads during rugby is to analyse the workload during the various intervals when the ball is in play. Ball-in-play (BIP) was described by Pollard et al. (2018) as "*the duration which play is ongoing prior to the ball exiting the pitch or the referee stopping play*" (p.1091). Ball out of play (BOP) refers to the remaining match time where play is not occurring. Although a rugby match is designed to last for 80 minutes in total, players are typically subjected to only around 30 minutes of BIP. The remaining 50 or so minutes are comprised of BOP, injury time, penalty shots, and conversions (Duthie et al., 2003).

Pollard et al. (2018) utilised a BIP analysis, where data were analysed solely in periods of play to determine the workload demands during the 30-40% of the match when play occurred. This method removed the BOP data from the workload analysis, which improved the understanding of the actual output required of players during BIP periods, particularly the peak demands. When compared to whole-match analysis, all metrics showed significantly greater intensities when data was collected from BIP periods. The authors concluded that utilising a BIP analysis more accurately portrayed the movement and collision demands than previous techniques.

In a systematic review of the use of microtechnology to quantify peak demands in football, Whitehead et al. (2018) discussed the impact of sampling duration on intensity, identifying that longer time durations lead to lessened intensity. The authors proposed that this relationship may not be solely due to physiological performance decrement, instead suggesting that the main reason for this decline was a contextual consequence of the technical and tactical demands of the match. The authors stated that longer periods were more likely to encounter a stoppage in play due to an error being made, referee stoppage, the ball going out of play, or a score occurring. Such a stoppage reduced the need for players to maintain a given intensity across that timeframe (Whitehead et al., 2018). Such insights emphasise the usefulness of a BIP analysis, as using this methodology removes the (BOP) periods of the match that would otherwise lower mean intensity values.

Analyses that utilise BIP time are helpful as they more accurately represent the potential workloads that players may experience within a match. Metric values recorded using a BIP analysis are not artificially decreased by stoppages and rest time, so they more accurately reflect the peak demands that players are likely to encounter during match-play (Pollard et al., 2018). However, it is important to consider that BIP times will vary between matches which could be a limiting factor when using this data to inform training.

1.4.3 Worst-case scenario:

According to Haakma (2021), analysing the workload demands of peak gameplay periods is essential to create a better understanding of the "worst-case scenario" (WCS) that players may experience during a game. This can allow coaches to adequately devise training and prepare for the most intensive periods of match-play that may occur.

Reardon et al. (2017b) investigated the locomotor and collision demands of the longest periods of play in rugby union. They considered the longest period of play that occurred within a match to be the worst-case scenario. The author's reasoned that the single longest period of continuous BIP time would likely involve more high-intensity efforts than previously reported mean data would suggest. They discussed the importance of assessing WCS, stating that understanding the workload demands of longer bouts of play is important to accurately determine outcomes at the highest level of competition (Reardon et al., 2017b). They also discussed the usefulness of WCS to the practitioner, as the demands of training can be monitored, and strategies can be devised to help monitor load and replicate training demands to that of the WCS in match-play. One limitation of this study was that authors defined WCS as being the longest bout of play. According to Pollard et al. (2018), longer plays do not result in the highest running demands. In fact, a review of the use of microtechnology to quantify peak demands in football by Whitehead et al. (2018) concluded that the longer the duration of play, the lower the running intensity due to the physiological, contextual, and technical-tactical demands of the sport. The authors explained that players were unable to maintain intensity as the duration of the play increased due to the shift in the energy continuum.

A study by Delaney (2017) found that substantially higher intensities (metric per-minute values) were observed in shorter periods of play when compared to longer periods of play. This author suggested that prescribing training based on match intensity needs to include the WCS peak metric intensities that occur in match-play, as using the whole match "average" values will not prepare players adequately for the shorter duration, very high intensities that they may experience in competition.

In their investigation into maximum running intensities in rugby, Read et al. (2019) reported the mean and range in order to determine the "maximum" values that players would encounter for each time duration and position. The researcher's reasoned that by understanding these maximum values, or WCS, coaches can prepare players for the most intense periods of play, as opposed to basing the target intensity of mean data. They regarded the exclusion of maximal values as a limitation to much of the literature previously published on rugby match-play demands.

Using a worst-case scenario analysis has useful implications when preparing for match-play. If coaches can simulate peak match intensities during training, players should be well prepared when critical situations arise in game scenarios. It is interesting to note that the worst-case scenario is often based solely on the longest period of play. However, this will not necessarily always be the most intensive and demanding time during a match. True WCS would more accurately be represented by the WCS value for metrics or metric intensities (metric per-minute). Additionally, it is worth considering that the true WCS is often an outlier in the data, so care should be taken when analysing maximum values for the match. The use of a ball-in-play methodology is one effective way to examine the WCS for match play demands, as it provides useful insight into actual intensities when play is occurring. Skill execution, decision-making, and physical capabilities will more likely translate into performance during match-play if training is aligned with WCS demands (Pollard et al., 2018).

1.4.4 Positional differences

One important factor to consider is that the workload demands of rugby vary between positions (Owen et al., 2015). The differences in match demands between forwards and backs have been well documented in the previous literature. According to Duthie et al. (2003), the total work over the duration of the game was lower in backs compared to forwards, as forwards were more often engaged closely with the opposition team. Forwards performed more frequent work activities of longer duration, whilst backs were more often standing, walking, or jogging in support play. However, backs typically covered more distance and engaged in more high-speed running, as the work done by forwards was often during competition for the ball (low-speed movement) (Duthie et al., 2003). These findings were reinforced by those of Roberts et al. (2008), who showed that backs travelled greater distances and spent more time performing high-intensity running than forwards, whilst forwards were more often engaged in high-intensity activity attributed to more time spent in static exertion. Takamori et al. (2022) reported similar findings, stating that it was most likely for backs to perform more high-speed running, striding, and sprinting than forwards, whilst forwards had a higher collision load when compared to backs. According to Duthie (2006), rugby union demanded a moderate amount of static exertion for both the forwards and backs, with 10% and 2% of the match involving these periods for each position, respectively. This equated to roughly 70% of the total work performed by forwards and 25% of the total work performed by backs during competition.

According to Duthie et al. (2005), backs also had longer rest periods than forwards, as additional rest occurred while forwards competed for the ball. Backs spent more time sprinting than forwards due to a greater number of sprint efforts and a longer duration of individual sprints. Shorter sprint durations and sprint distances for the forwards were consistent with their proximity to the opposition, whilst backs were more frequently able to reach maximal velocities due to their positioning further away from the opposing team. Forwards spent significantly more time in static exertion than backs due to a higher occurrence and longer duration of static exertion efforts and performed considerably more jumping and lifting efforts than backs due to their involvement in the lineout.

Similarly, Owen et al. (2015) found that forwards sustained more impacts than backs across all intensity (G-force) zones. They pointed out that forwards were closer to the ball and spent more time in competition with the opposition, resulting in a higher number of tackles and ball carries. Backs were more likely to be farther from the ball, where a large proportion of their contribution required intense running, such as support play, running decoy lines, and covering in defence. Backs also completed more accelerations in zones 2 (6.00-6.49 g) and 3 (6.50-6.99 g), and more decelerations in zone 2, whilst the observed acceleration and deceleration differences in zone 1 (5.00-5.99 g) were trivial.

Pollard et al. (2018) showed that both high-metabolic load distance and high-speed running were significantly higher for backs when compared to forwards across mean whole-match and mean max ball-in-play periods. However, they also found that BIP meters per minute showed no significant difference, suggesting that backs covered the same distance as forwards but at higher intensities. The authors suggested that the role of backs was to utilise the space, where they had more opportunity to generate high velocities, whereas forwards spent more time in competition for the ball. Therefore, acceleration capacity was likely a more important factor for forwards. This reasoning was reinforced in their results, which showed no differences between forwards and backs for mean or max accelerations

The differences in workload between forwards and backs have been well documented and appear to be the direct result of the strategic roles of each position. These differences are worth considering when preparing players for match demands, as players should be conditioned appropriately for the relative workload demands of their position.

1.4.5 Offence vs defence:

One of the important aspects of rugby union is breaking the game up into types of play, specifically, offensive periods and defensive periods. According to Rennie et al. (2020), being able to understand the differences in locomotive and collision workload between types of play can help coaches to develop more accurate training protocols. The common match analysis methods of fixed-time and rolling epochs described earlier don't allow an analysis of offensive versus defensive workloads (as, by nature, these epochs do not distinguish between types of play as they rely on continuous timeframes), resulting in only a few studies on this topic for rugby union (Read et al., 2019).

Read et al. (2018) conducted a study to quantify the workload demands between types of play during academy-level rugby union. They made positional comparisons for each type of play (offence, defence, and BOP). Forwards covered higher relative distances during defensive stages compared to backs, whilst relative distance in offensive periods was similar between positions. Conversely, they found that backs covered more distance when the ball was out of play than forwards. Additionally, the authors reported a trivial difference in relative distance and player-load per minute for forwards when offence was compared to defence. For backs, however, there was a likely greater difference in relative distance and player-load per minute in offence when compared to defence. The authors acknowledged that the sole use of relative distance was a limitation and including high-speed running would have provided additional insight into workload demands. Their research highlighted the notion that different types of play require different physiological demands on players, and there is potential to specify training on this basis to optimally prepare players for match demands.

One study by (Ungureanu et al., 2019) compared game outcomes to technical and tactical aspects of professional rugby union teams during competition. They found that in close games, winners tended to spend more time defending and had less total possession throughout the game. Such findings have demonstrated the importance of understanding the differences between types of play for training specificity. Further breaking down and analysing these types of play could potentially increase match success, highlighted as an example by Ungureanu et al. (2019) with the recommendation that coaches of elite northern hemisphere rugby union teams be aware that successful game outcomes largely occurred when the winning team had strong defence, tackling, and scrumming, alongside high occurrences of defensive line breaking and accumulation of possession when attacking.

Understanding the different types of play during a rugby match has important implications on training design and match outcomes. According to Cummins et al. (2013), measurement of offensive- and defensive-specific contact events would allow for the quantification of loads experienced during individual tackles, cumulative load throughout the game, training, or season, and the relative forces that occur during injury. Detailed workload requirements (using GPS and contact metrics) of different game periods have been documented for sports such as rugby league and academy-level rugby union. However, to our knowledge, they have not yet been thoroughly investigated for professional rugby union. There is an evident lack of research in this area, despite its potential applications for further training specification to replicate match demands.

1.5 Conclusion:

Rugby union is a dynamic sport that demands high levels of physical and tactical skill. Players are subject to high movement workloads, largely consisting of intermittent sprints interspersed with low-intensity bouts. Accelerations, decelerations, and a range of contact scenarios are also highly prevalent in the game. The use of GPS can be beneficial for quantifying workload, especially regarding player locomotion. However, they do not work well in providing analysis of other workload metrics, such as different types of contact and stationary work. Combining multiple GPS metrics with the development of other non-locomotive tools may be the best way to quantify the complete and overall workload in the sport. Analysis of gameplay demands is most accurate when a ball-in-play methodology is used, instead of fixed-time or rolling averages, due to the intermittent nature of the game. A ball-in-play methodology may provide insight into the worst-case-scenario workload demands of match-play, reflecting peak values that players may encounter. To further assist in training specificity, games can be broken into specific types of play, and players categorised into positional groups, all of which demand different workload requirements. These workload requirements and how they differ when combined (e.g., forwards in offence, backs in defence, etc.) are not yet fully understood in detail for professional rugby union. This could be of great use for aiding training design and replicating specific match-play demands.

Chapter 2. Offence vs defence: Quantifying workload demands in professional Rugby Union.

2.1 Introduction:

The physical characteristics of match play in rugby union is an area of research that is growing rapidly. Rugby union is a skill-based contact team sport that demands high levels of physical and tactical skill (Duthie, 2006). Owen et al. (2015) explained that over time, the match play demands of rugby union have increased, and as such, these demands must be quantified to provide a basis for training workloads. The sport is physical in nature, and high-intensity activities can include many acceleration and deceleration events applied in multiple directions, with some of the more intensive decelerations involving contact collisions with opposition players, such as during a tackle or a scrum (Owen et al., 2015). With such a varied and intensive workload required, rugby is a sport where physical preparation is essential for success, especially for elite and competitive players (Duthie, 2006). Movement and contact data can be useful for analysis, allowing coaches greater insight into demands that players face during a game. This information can be used to specify training sessions for increased performance (Duthie et al., 2005). To do this effectively, previous literature has sought to identify how and when workload occurs throughout a rugby union match. However, there is still much to improve on when it comes to accurately defining workload demands.

Many previous studies have utilised time-motion analysis to quantify workload demands in rugby union. The validity of time-motion analysis is questionable, as movement patterns are simplified into categories. In reality, actual play involves the dynamic combination of several tasks, along with skill and tactics (Duthie et al., 2003). Recently, several studies examining match play demands in rugby union have utilised global positioning systems (GPS) to quantify workload. Although GPS units are a very useful tool for the evaluation of workload in rugby and can provide accurate insight into locomotive measures (Aughey, 2011), it is important to understand their limitations when it comes to situational accuracy, such as during change of direction or rapid accelerations and decelerations (Akenhead et al., 2014).

Due to the large amount of non-locomotive workload that occurs in a rugby game, the use of GPS/locomotive metrics alone cannot realistically quantify the overall workload. There are several events that players will experience during the match that are physically demanding yet do not register a large locomotive load. Recent studies have shown that microtechnology accelerometers can detect up to 97% of collisions during a rugby (league) game (Hulin et al., 2017). However, they are unable to distinguish between type and force of contact, two critical factors when analysing game-specific situations (Cummins et al., 2013). Different contact situations can have varied demands and levels of exertion on the player, so grouping them all into a single category can misrepresent relative workload. For this reason, many studies choose only to focus on the locomotive aspect of GPS data collected, and activities such as tackling are not considered when high-intensity exercise is being assessed, despite their obvious physical demands on players (Austin et al., 2011). Due to the limitations of GPS accelerometers, complete analysis of workload still requires the pairing of GPS data and manual coding of contact events (Cummins et al., 2013).

Previous literature has sought to increase the accuracy of measured workloads by better defining how match play is segmented for analysis. Although a rugby match is designed to last for 80 minutes in total, players are typically subjected to only around 30 minutes of actual play (referred to as ball in play (BIP)). The remaining 50 or so minutes are comprised of the ball being out of play (BOP), injury time, penalty shots, and conversions (Duthie et al., 2003). For this reason, many studies are now completing workload analysis on BIP periods only, as if this technique is not employed, roughly 60-70% of data would be collected during periods of the game where the ball is out of play (and thus little to no work is occurring)

(Pollard et al., 2018). BIP analysis has increased the accuracy of reporting workload demands compared to other methods, such as the fixed-time methodology employed by Jones et al. (2015) or the rolling average method by Cunningham et al. (2018). The use of fixed-time or rolling averages can result in a misleading understanding of the actual output required of players during BIP periods, as both methods utilise fixed-time intervals when the actual durations of the various intermittent work (and rest) intervals can vary greatly. Studies such as those by Haakma (2021) and Pollard et al. (2018) split the match into BIP periods and BOP periods for analysis to create a better understanding of the peak (worst-case scenario) demands that players may experience during a game.

The differences in workload between forwards and backs have been well documented and appear to be the direct result of the strategic roles of each position. Previous literature has shown that backs are more often involved in intense running, whilst forwards typically engage in more contact and static exertion (Duthie et al., 2003, 2005; Duthie, 2006; Jones et al., 2015; Owen et al., 2015; Pollard et al., 2018; Takamori et al., 2022). These differences are worth considering when preparing players for match demands, as players should be conditioned appropriately for their position.

Although BIP analysis is a useful and accurate methodology to quantify workload demands, there is potential to further breakdown match periods to develop an even greater understanding of the situational workload occurrences throughout the match. The most obvious distinction that can be made is splitting BIP further into offensive and defensive periods, as coaches often train for these two scenarios separately (Read et al., 2018). Insight into the demands that occur in each of these scenarios would therefore be useful to specify training appropriately to match relevant situational game demands. To our knowledge, the research in this area is limited for professional rugby union. Read et al. (2018) examined the workload differences between the offensive and defensive phases of rugby union, utilising

GPS and accelerometer data. Their findings suggested that offence was more demanding than defence for backs, whereas demands were similar between types of play for forwards. However, players included in the study were under the age of 18 so their findings may not be suitable for informing professional-level interventions.

Further research is required to develop a greater understanding of the workloads during different types of play in professional rugby union. We believe that the use of defined Sportscode metrics (categorising contact instances into separate events and ranking their intensities) will enable a much more accurate analysis of contact demands than accelerometer data, which is important as such events are extremely taxing and should more often be included in the assessment of workload (Austin et al., 2011). Combining this with GPS locomotive data will result in a comprehensive tool to quantify the overall workload in the sport. We also believe that there is still a gap in the research when it comes to defining the workload differences between offensive and defensive periods of the game for professional rugby union. To further assist in training specificity, games can be broken into specific types of play, and players categorised into positional groups, all of which demand different workload requirements. These workload requirements and how they differ when combined with one another (e.g., forwards in offence, backs in defence, etc.) are not yet fully understood in detail for professional rugby union. However, such an analysis would contribute to the field by quantifying the overall demands that occur in these distinctive periods of the game, aiding training specificity and situational preparation.

Therefore, the aim of the current study is to compare workload demands of offensive and defensive ball-in-play periods of professional rugby union match-play by evaluating selected GPS locomotive measures and quantifying Sportscode (contact) metrics.

2.2 Methods:

2.2.1 Participants:

GPS and Sportscode data were collected from 40 professional male rugby union players from one professional New Zealand Super Rugby team (age: 25 yrs ± 3.2; Height 187.7 cm ± 6.6, body mass 107.8 kg ± 12.4). Participants were provided with information outlining the rationale, procedures, and potential applications of the study. Informed consent forms were signed by all participants before the commencement of this study. Throughout this study, all participants were in full-time training and were deemed healthy and injury-free. All participants were familiarised with the data collection procedures prior to commencement and were not required to make changes to their regular competition and training for the duration of our study. Participants were grouped into the following positions: Forwards (props, hooker, second row, loose forwards) and backs (midfield backs, inside backs, and outside backs).

2.2.2 Procedures:

Data collection took place during 14 in-season games of the 2021 Super Rugby season. All participants wore GPS units (Apex Pro Pod, STATSport, Newry, NIR) which collected data at a sampling frequency of 10 Hz. Before the pre-match warm-up, GPS units were switched on and activated as per the manufacturer's guidelines ~30-60 min before kick-off. Devices were then placed in a tightly fitting vest with a custom-made pocket situated between the scapulae. Vests are designed to fit the GPS units as close as possible to the participant's body to minimise the chance of accidental unit movement and are worn underneath the playing shirts. To minimise inter-unit variability, each participant wore the same GPS unit for each match. After the match, GPS units were switched off and gathered in a 16-point charging case which simultaneously downloaded the GPS data files for each participant onto a computer using STATSports Sonra software (STATSports Sonra, Newry, NIR).

Each match was filmed using cameras from various angles. The footage was obtained from the television provider for the match. After the match, the footage was downloaded into the Sportscode video analysis software package (Sportscode 12.4.3, Sportstec, Australia). Timestamps were then created for the start and end of specified events, these being Ball out of play (BOP) offensive ball-in-play periods (OFF), and defensive ball-in-play periods (DEF). These events were manually coded using criteria set in appendix A. Another event was created spanning the entire match, from the exact start of the match (aligned with the beginning of the first OFF or DEF instance) to the exact end of the match (aligned with the end of the last OFF or DEF instance). This event was then exported as a single video file. The full-match video file was imported into STATSports Sonra software alongside the corresponding GPS data for each given match. The video was aligned to the GPS data by adjusting the start time upon import until visual cues (accelerations, decelerations, change of direction, etc.) corresponded with velocity values in the GPS data.

The Sportscode timeline with OFF, DEF, and BOP events was then exported from Sportscode as an XML file and imported into the STATSports Sonra software as tags. These events automatically aligned with the start of the video upon import, so they were automatically synced with the GPS data. The OFF and DEF tags were then used to create drills, where the start and end times of each drill corresponded exactly to the imported tag. Drills were labelled in sequence (OFF01, OFF02, and DEF01, DEF02, etc.) for the entire match. GPS data was then exported as a CSV file, showing key metrics for the time periods designated by each drill.

The GPS metrics chosen for analysis were based on common locomotion metrics previously examined in the literature for rugby union. Metrics chosen included the following: Total distance (distance), high speed running (HSR), sprint distance (Sprint), high-metabolic load distance (HiMet), acceleration count (accelerations), deceleration count (decelerations), high-velocity distance (HiVel), sprint-metabolic load distance (SpMet), and dynamic stress load (DSL), The metric zone classifications were: HSR >5.5m.s^{-1}, sprint >7.5m.s^{-1}, HiMet >25.5w/kg, accelerations >2m.s^{-2}, decelerations>-2m.s^{-2}, HiVel >85% maximal speed, SpMet >50w/kg, which were calculated as per the methods used in the STATSports Sonra software (STATSports Sonra, Newry, NIR). The dynamic-stress load metric was calculated automatically from impact data using a custom algorithm included in the STATSports GPS software. The impact data is the magnitude sum of the data from the tri-axial accelerometer in the STATSports GPS unit calculated over 1-second intervals. The algorithm generated a weighted total of impacts above 2G, with the weightings based on a convex curve of the G-Force ratings.

Contact events were manually coded in the Sportscode software as per the criteria set in appendix A. All collision instances were categorised into the following: Hit ups, offence order of arrival, lineout offence, maul offence, scrum offence, tackle, defence order of arrival, lineout defence, maul defence, and scrum defence. Each instance was also categorised into one of three weighted efforts, either minimal, hard, or maximal, corresponding to a weighting value of 1, 3, and 5, respectively, based on the criteria set in appendix A. These weightings were selected as derivatives of the Borg CR10 RPE scale weightings and descriptors (Williams, 2017). The resulting events in Sportscode were a combination of the type of contact and the contact weighting (e.g. tackle, hard), recorded as a weighted count. The contact instances were coded as a 2-second event, with the start time being aligned with the occurrence of the corresponding contact instance. The contact event timeline was then exported as an XML file.

To combine the GPS and contact data, we used a bespoke software called Sportyweb. The GPS CSV file was imported and labelled according to the week and opponent. The contact

XML file was imported separately into Sportyweb and labelled in the same way as the CSV file (the software used this unique label to pair the files upon import).

The start and end time of each OFF and DEF drill were determined by the GPS CSV. Sportyweb would then allocate the contact events into the correct drill based on the time they occurred. It is important to note that the contact XML categorised instances using the game time (where the start of the game = 00:00). Each contact event, therefore, had a game time value for the start and end of the instance. To assign each contact event into the correct drill, Sportyweb added the game time of each instance (in this case, the start time of the event was used as this is what was aligned with the contact instance) to the clock time of the beginning of the first OFF or DEF drill (the start of the match). The resulting clock time of each contact event was then assigned to the appropriate OFF or DEF drill, depending on where it fell in relation to the start time and end time of each drill.

It is important to note that the XML game time (00:00) value began at the start of the original video file (upon import into Sportscode). This video file always started a few seconds before kick-off. As we considered the beginning of game time to be at the start of the first OFF or DEF instance, the XML file had to be aligned appropriately and this “dead time” removed. To align the contact XML to the GPS CSV, the start time of the first OFF or DEF instance in the XML was subtracted from the clock time of the CSV file. The resulting clock time value was the true game start time of the XML file. This value was entered upon importing the XML file and used to align both data sets.

It is also important to note that each GPS drill was rounded to the nearest second in Statsports. This means that contact events that occurred very close to the start or end of an OFF or DEF drill were sometimes excluded, as they fell outside the drill timeframe due to rounding. Of a total 12,811 contacts, Sportyweb correctly accounted for 12,405, with an overall accuracy of 96.8%.

Once the data sets were aligned, a summary CSV file was exported from Sportyweb, with the OFF drills, DEF drills, and corresponding GPS and contact metrics for each player and each drill. Additional information, such as game outcome and opposition rank, was manually added to this summary CSV file.

2.2.3 Data analysis:

All data were analysed with the Statistical Analysis System (On-Demand for Academics, version 9.04, SAS Institute Inc., Cary, NC, USA). Player metrics were either counts (accelerations and decelerations), counts weighted by distance (high-velocity distance, high-metabolic load distance, high-speed running distance, sprint-metabolic load distance, sprint distance, and total distance), or counts weighted by other factors (Contacts and dynamic stress load) in each match and were therefore analysed with a generalised linear mixed model procedure (Proc Glimmix) specifying a log link and a Poisson distribution that allowed for overdispersion. Each player metric was analysed separately with the same mixed model. The fixed effects in the model were: player position (nominal: Backs, Forwards); type of play (nominal: Defence, Offence); the interaction of player position and type of play; match outcome (nominal: loss, win); the interaction of match outcome, player position, and type of play; end-of-season opposition ranking (linear numeric); round of the match (linear numeric); and the log of ball-in-play time (linear numeric) interacted with player position and type of play. The predicted means for the different levels of the nominal predictors were adjusted to mean opposition rank, the middle round of the season, and the grand mean of time spent in each type of play across all matches and players.

The linearity of each numeric predictor was assessed by visual inspection of plots of standardised residuals vs the predictor for any non-uniformity. The random effects in the model were: player identity (nominal), to estimate differences between player means; the interaction of player identity with log of ball-in-play time, to estimate individual differences in the effect of time; match identity (nominal), to estimate differences between match means; the interaction between player identity and match identity, to estimate each player's mean change of defence and offence between matches; and the residual, specified as a Poisson variance allowing for over- or under-dispersion (particularly important for measures representing running distances). The covariance matrix for player identity and its interaction with time was set to unstructured to allow the solutions for these random effects to be correlated (a random-intercepts and -slopes model). For some dependent variables, the mixed model did not converge unless the random effects for athlete identity and time within athletes were set to uncorrelated.

The following outcomes derived from the fixed effects were expressed as factors with 90% factor confidence limits: the difference between means of player positions; the change between the means of defence and offence; the changes between the means for losing and winning; the change between the means when playing the weakest vs the strongest opposition team; the changes between the means for the first and last match of the season; and the relationship between player metrics and player time on offence or defence expressed as the slope (coefficient, in %/% units) of ball-in-play time. A measure of fatigue was also calculated from the coefficient for ball-in-play time as the factor difference between the mean value predicted for the mean time on the field vs the predicted mean for a 1:1 linear relationship between the metric and time on field (for forwards and backs in offence and defence). The standard deviations representing differences between player means (from the random effect for player identity) and individual differences in fatigue (from the interaction of player identity with ball-in-play time) were also expressed as factors with 90% confidence limits (and in %/% units for fatigue) and assessed for magnitude.

The magnitudes of outcomes derived from fixed effects were assessed with thresholds set at 0.2, 0.6, 1.2, 2.0, and 4.0 of the log-transformed observed between-player standard deviation (Hopkins et al., 2009), corresponding to small, moderate, large, very large, and extremely large qualitative effect sizes, respectively (Supplementary Table 1); the magnitude thresholds for the standard deviations were half these values (Smith & Hopkins, 2011) (Supplementary Table 2). Sampling uncertainty in the estimates of effects is presented as 90% compatibility limits. Decisions about magnitudes accounting for the uncertainty were based on one-sided interval hypothesis tests, according to which a hypothesis of a given magnitude (substantial, non-substantial) is rejected if the 90% compatibility interval falls outside that magnitude (Hopkins, 2020, 2022). P-values for the tests were, therefore, the areas of the sampling distribution of the effect (t for means, z for variances) falling within the hypothesized magnitude, with the distribution centred on the observed effect. Hypotheses of inferiority (substantial-decrease) and superiority (substantial-increase) were rejected if their respective p-values ($p_{\downarrow}$ and $p_{\uparrow}$) were <0.05; rejection of both hypotheses represents a decisively trivial effect in equivalence testing. When only one hypothesis was rejected, the p-value for the other hypothesis, when >0.25, was interpreted as the posterior probability of a substantial true magnitude of the effect in a Bayesian analysis with a minimally informative prior (Hopkins, 2019) using the following scale: >0.25, possibly; >0.75, likely; >0.95, very likely; and >0.995, most likely (Hopkins et al., 2009). The probability of a trivial true magnitude ($1 - p_{\downarrow} - p_{\uparrow}$) was also interpreted when >0.25, with the same scale. The probabilities are shown in tables with superscripted symbols (* for substantial effects, ^{0} for trivial effects). Probabilities were not interpreted for effects with inadequate precision at the 90% level, defined by the failure to reject both hypotheses ($p_{\downarrow} > 0.05$ and $p_{\uparrow} > 0.05$). Effects with adequate precision at the 99% level ($p_{\downarrow} < 0.005$ or $p_{\uparrow} < 0.005$) are shown in bold since these have a lower probability (<0.005) for the effect having the opposite substantial magnitude; for the mean effects of fatigue, these also represent effects that have a conservatively low risk of harm (most unlikely to impair performance), if implemented. The hypothesis of non-inferiority (non-substantial-negative) or non-superiority (non-substantial-positive) was rejected if its p-value ($p_{N\downarrow} = 1 - p_{\downarrow}$ or $p_{N\uparrow} = 1 - p_{\uparrow}$) was <0.05, representing a decisively substantial effect in minimal-effects testing: very likely or most likely substantial.

2.3 Results:

The order of the metrics in the tables was determined by the correlations between the metrics, with the expectation that highly correlated metrics will have similar effects. Correlations and clustering of metrics are presented in Supplementary Table 3, where clusters of metrics have been identified as those with high correlations (>0.60) between metrics within clusters and low correlations (<0.60) between metrics between clusters.

Metric mean values for each combination of position and type of play and metric standard deviations are reported in Table 1. The means and SDs are all derived from the mixed-model and therefore represent values after adjustment for the fixed and random effects in the model. The player observed between SD is the typical difference between players in a given position and type of play in a typical match; it is the combination of the within-match player SD (the residual in the model, the Poisson variability), the pure between-player SD (the typical difference between player means over the season), and the player match-to-match SD (the typical change in the mean of a player's offence and defence values between matches). The pure between-player SD has a practical application and is shown in greater detail below in Table 2. The match SD is a pure representation of the typical difference between the match means. The differences between means apparent in Table 1 are detailed in Table 3. For most measures, the observed between-player SD arises mainly from the random Poisson variation, and, with one exception, there is no contribution from consistent match-to-match variation (player match-to-match factor SD of 1.00). The values for match SD in the table show that there are real differences between match means for most metrics, but these are much less than the observed differences between players.

Typical differences between the season-mean player values represented by the true between-player standard deviation are represented in Table 2. The majority of metrics showed moderate to large differences between players, with sufficient precision for the true magnitudes to be very likely or most likely.

The factor effects comparing each position and type of play for each metric are presented in Table 3. Small to moderate increases were observed for the majority of metrics between offence and defence, for both forwards and backs. Most of these effects had adequate precision at the 99% level for true magnitudes to be very likely or most likely substantial. When comparing forwards to backs, most metrics, particularly those of a locomotive nature, showed a large decrease between forwards and backs across both offence and defence, with sufficient precision at the 99% level for the true magnitudes to be most likely substantial. Conversely, a very large increase in contacts was observed between forwards and backs for both offensive and defensive periods of play.

The observed metric changes between winning and losing shown in Table 4 were mostly trivial but lacked adequate precision for forwards on offence and for backs on defence. Small effects were observed for some metrics for forwards on defence, typically tending to increase when the match outcome was winning compared to losing; some of these changes had adequate precision at the 99% level, but at most, they were only likely substantial. The effects with the most likelihood of being substantial were for backs on offence, with small to moderate increases or decreases observed for most metrics.

The effect on each metric of player time on the field is expressed in Table 5 as %/% units, and as a factor effect, with values below 1.00 representing fatigue. Fatigue effects are equivalent to a decrease in metric value per minute. The between-player standard deviation for each metric is also shown, representing the individual differences between players in fatigue. For the majority of the metrics, the magnitude of fatigue was large or very large for forwards on both offence and defence, and for backs on defence, with sufficient precision at the 99% level for true magnitudes to be most likely substantial. Fatigue was somewhat less clear for backs on offence, with most magnitudes of fatigue being moderate or large, with some effects having adequate precision only at the 90% level and with one effect being unclear. The individual differences in fatigue ranged from trivial to very large, but there was adequate precision only for contacts and only at the 90% level.

Data are not shown in tables for the effects of opposition ranking and season trend. The majority of observed effects for opposition ranking were trivial, several with inadequate precision. Many showed a possibility of a small increase when playing the weakest vs the strongest team (rank 10 vs 2), but only two had adequate precision at the 99% level: a small, possibly substantial, possibly trivial increase for accelerations; and a trivial, possibly substantial increase for sprint-metabolic load distance. Season trend showed a number of small effects, the majority with adequate precision at the 99% level; there were increases for contacts (possibly), accelerations (likely), and decelerations (likely), whilst there were decreases for high-metabolic load distance and sprint-metabolic load distance (possibly), sprint distance and high-velocity distance (likely), and high-speed running (most likely).

2.4 Discussion:

The aim of this study was to compare the workload demands of offensive and defensive periods of professional rugby union match play. For most metrics, there was a decisively greater workload on offence compared to defence, with small to moderate differences observed across most metrics for forwards and backs. One potential reason for these differences is that during defence, a large amount of time is spent moving backwards whilst facing the opposition. Jogging and running backwards restrict the capacity to achieve high velocities. Although running backwards and sideways occurs at a lower speed, the energetics of these alternative modes of locomotion can contribute to the physiological demands of the player (Reilly, 1997). These demands may therefore be underestimated for defence, as current measures of workload rely largely on velocity and speed zones alone. This could be considered a limitation of our findings. Researchers in future should aim to quantify the time spent performing different locomotive movements, such as sideways and backwards walking and running, as well as their relevant workload requirements. Current GPS data does not allow for this distinction.

Haakma (2021) found no distinct patterns for when the worst-case scenario GPS demands may occur throughout the ball-in-play periods of a match, suggesting that players need to be optimally conditioned for peak demands to occur at any point during the game. When compared to the results of the current study, this finding highlights the importance of distinguishing between offensive and defensive periods of play. Read et al. (2018) presented the only research directly comparable to the current study, with positional workload examined for offence and defence. They reported no substantial difference in distance per minute and player-load per minute for forwards on offence compared to defence. For backs, there was a likely greater difference in distance per minute and player-load per minute on offence when compared to defence. Similar results were reported in rugby league by Rennie et al. (2020). They showed that forwards and backs had slower average speeds on offence but covered substantially greater high-speed distance when compared to defence. However, a substantially higher collision count was observed for forwards on offence and backs on defence, indicating that defence was more demanding for forwards when it comes to collisions but less demanding when it comes to intense running, whilst offence was more demanding for both locomotive and collision workload for backs. It is worth noting that differences in these results when compared to the current study may be due to the different strategic and physiological demands of rugby league when compared to rugby union, highlighting that the two games require a different approach to conditioning. The results of the current study are largely consistent with those of Read et al. (2018) and Rennie et al. (2020), particularly for backs, as almost all metrics were decisively greater on offence when compared to defence.

The results of the current study indicate decisive differences in most metrics between forwards and backs in offence and defence. In particular, backs experienced decisively more locomotive workload than the forwards on offence and defence, while forwards had a decisively greater contact load than backs. Similar effects have been observed in numerous previous studies: backs have been involved more often in intense running than forwards, whilst forwards have engaged in more contact and static exertion (Duthie et al., 2003, 2005; Duthie, 2006; Jones et al., 2015; Owen et al., 2015; Pollard et al., 2018; Takamori et al., 2022). Cunningham et al. (2018) showed that backs perform more locomotive workload than forwards, but did not include an assessment of contact workload in their analysis.

Whilst most differences for locomotive metrics were most likely large, the difference in total distance between forwards and backs was likely small on offence and possibly small on defence, showing that backs covered a similar distance to forwards but at higher intensities. It has been suggested in the previous literature this is due to forwards being in close proximity to the opposition, whilst backs have more space to achieve greater running velocities (Duthie et al., 2005; Owen et al., 2015; Pollard et al., 2018). Pollard et al. (2018) have shown that both high-metabolic load distance and high-speed running were significantly higher for backs when compared to forwards across the whole match and across the maximum of ball-in-play periods, but there was no significant difference between positions for ball-in-play meters per minute. These results are similar to those of the current study.

Some differences between backs and forwards in the current study showed minor deviations from those in other studies. Read et al. (2018) found that the difference in relative distance between forwards and backs was unclear on offence but likely greater in forwards on defence. This study was conducted on academy-level players, so it may not provide a direct comparison to professional rugby union. Pollard et al. (2018) reported trivial differences in acceleration and deceleration metrics between forwards and backs, explaining that forwards, despite not having space to achieve high velocities, were still required to perform multiple short accelerations and decelerations. This explanation may apply to our own study, where the differences for these metrics were likely small at most, whilst most other locomotive metrics showed decisively large or very large effects.

When winning was compared to losing, there was very good evidence that backs achieved greater high-speed-running distance on offence and modest or good evidence for greater values of other locomotive metrics. The differences between winning and losing lacked adequate precision for most metrics for backs on defence. When paired with the decisively greater workload requirements of backs on offence compared with defence, these effects are perhaps indicative of the importance (for winning) of greater involvement of backs during offensive periods, particularly when it comes to measures of running intensity. There was very good evidence that backs experienced fewer contacts, accelerations, and decelerations on offence when winning was compared to losing. One possible explanation is that the backs of a winning team evade contacts on offence and thereby achieve more successful advances against the opposition. In our experience, accelerations above $2 m.s^{-2}$ are easier to achieve from a stationary position; therefore, lower counts of accelerations and decelerations on offence could indicate fewer "stop/start" periods because the opposition is making fewer tackles and not halting the advancing play (resulting in a successful offence). When winning was compared to losing, some metrics showed possibly, or likely small increases for forwards on defence, whilst differences for forwards on offence were mostly unclear or trivial. In contrast to the backs, forwards required greater workloads during defence when the match outcome resulted in a win, despite decisive evidence that forwards performed greater workloads with most metrics during offence when compared to defence.

Unsurprisingly, there was decisive evidence for player fatigue with most metrics for forwards and backs in offence and defence, as the longer a player is on the field, the more the metrics would be expected to decline due to the demands of the match. Our results align with other observations of fatigue, such as those by Pollard et al. (2018), who found that, as the length of play increased, the relative metric intensity decreased. However, our results are a measure of match fatigue, whereas theirs are indicative of fatigue within each period of play. Interestingly, the fatigue effects for backs tended to have greater magnitudes for defence than offence, even though backs experienced an increased workload across most metrics when offence was compared to defence. Backs were less involved physically in defensive than offensive plays and perhaps were consequently able to take more time to rest during defensive periods as the match progressed and players fatigued. Such a strategy could allow for greater intensities to be achieved during offensive plays, when the backs' involvement appeared to be more prominent (in terms of workload) and more important (in terms of winning). The magnitudes of fatigue for forwards were similar between offensive and defensive periods, even though the intensities on offence were generally decisively greater on offence.

A limitation of the current study is that only a single team and season were analysed. Results are, therefore, inclined to reflect the strategic and conditioning practices of this team and season. Researchers in future should examine similar effects in multiple seasons and multiple teams. We also acknowledge the limitations in the accuracy of GPS metrics at higher velocities and during changes of direction, as discussed by Aughey (2011) and (Akenhead et al., 2014), although the random nature of this error was overcome by adequate sample size, resulting in trustworthy outcomes. Additionally, research on the relationships between our measure of weighted contact load and players' perception of contact load or against performance and injury outcomes is yet to be completed in detail. The contact events that were unaccounted for (3.4%) due to timeframes being rounded in the Sportyweb software had no meaningful effect on results due to their random nature and relatively small quantity. Researchers in future should look to validate and improve the accuracy of weighted counts as a measure of contact load in rugby union.

2.5 Conclusion:

This study examined the locomotive and collision workload demands of offensive and defensive periods of professional rugby union match play. More specifically, differences were examined between select GPS (locomotive) and Sportscode (contact) metrics to evaluate the effects of type of play, position, match outcome, fatigue, and their interaction with one another during game-specific scenarios. To our knowledge, this is the first study to examine the ball-in-play workload demands of professional rugby union in such detail. Offensive periods of play demanded a decisively greater workload than defensive periods of play for both forwards and backs across most metrics. There was also strong evidence that backs performed greater locomotive workload but less contacts compared to forwards in both offence and defence. When winning was compared to losing, there was good evidence that backs achieved greater values for most locomotive metrics on offence, whilst forwards achieved greater values for some metrics during defence. Understanding how workload demands vary between position and type of play can aid practitioners in effectively preparing players for match-play by enabling them to accurately replicate these demands during training. Additionally, the observed differences in workload demands between winning and losing can provide insight into outcome-oriented conditioning for each position and type of play. Researchers in future should aim to more accurately quantify locomotive demands by examining the workload requirements of different modes of movement, such as sideways and backwards running. Examining similar effects in multiple seasons and multiple teams would also be worthwhile, as this would increase the depth of understanding of workload demands in rugby union as a whole.

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Tables

Table 1. Player values (means and factor standard deviations) and differences between matches (Match SD) provided by the Poisson-regression analysis for each player metric.

	Player means				Player factor SDs (×/÷)				
	Fwds offence	Fwds defence	Backs offence	Backs defence	Obsvd btwn	Within-match	Pure btwn	Match-match	Match SD (×/÷)
HiVel (m)	257	209	457	360	1.48	1.38	1.24	1.00	1.09
HiMet (m)	239	198	410	332	1.43	1.34	1.22	1.00	1.05
HSR (m)	59	36	188	136	1.93	1.61	1.57	1.00	1.14
SprintMet (m)	49	37	128	104	1.73	1.49	1.45	1.00	1.03
Sprint (m)	3	2	46	27	3.93	2.78	2.49	1.18	1.30
Distance (m)	1039	923	1189	998	1.31	1.30	1.06	1.00	1.01
Contacts	83	58	28	20	1.50	1.49	1.10	1.00	1.03
Accelerations	34	34	39	36	1.40	1.34	1.17	1.00	1.00
Decelerations	30	28	30	30	1.47	1.41	1.18	1.00	1.00
DSL	90	77	91	65	1.64	1.40	1.44	1.00	1.04

SD, standard deviation; Fwds, forwards; Obsvd, observed; btwn, between; HiVel, high-velocity distance; HiMet, high-metabolic load distance; HSR, high-speed running distance; SprintMet, sprint-metabolic load distance; Sprint, sprint distance; Distance, total distance; DSL, dynamic stress load.
Contacts and DSL are weighted counts; Accelerations and Decelerations are counts.

Table 2. Typical differences between the season-mean player values represented by the pure between-player standard deviation in Table 1. Uncertainty in the factor effects is shown as factor (×/÷) 90% compatibility limits.

	Factor effect	Effect size
HiVel	1.24, ×/÷1.06	**Moderate******
HiMet	1.22, ×/÷1.06	**Moderate******
HSR	1.57, ×/÷1.13	**Large******
SprintMet	1.45, ×/÷1.11	**Large******
Sprint	2.49, ×/÷1.34	**Large******
Distance	1.06, ×/÷1.04	Small**
Contacts	1.10, ×/÷1.11	Small
Accelerations	1.17, ×/÷1.06	Moderate***
Decelerations	1.18, ×/÷1.06	**Moderate*****
DSL	1.44, ×/÷1.10	**Large******

HiVel, high-velocity distance; HiMet, high-metabolic load distance; HSR, high-speed running distance; SprintMet, sprint-metabolic load distance; Sprint, sprint distance; Distance, total distance; DSL, dynamic stress load.

Magnitudes were assessed by standardisation using the observed between-player SD (Table 1 and Supplementary Table 2).

Bayesian likelihoods of substantial change: *possibly; **likely; ***very likely; ****most likely. *** and **** indicate rejection of the non-superiority or non-inferiority hypothesis ($p_{N\downarrow}$ or $p_{N\uparrow}$ <0.05 and <0.005 respectively).

Bayesian likelihoods of trivial change: ^{0}possibly; ^{00}likely; ^{000}very likely, ^{0000}most likely.

Likelihoods are not shown for effects with inadequate precision at the 90% level (failure to reject any hypotheses: <0.05). Magnitudes in bold have acceptable precision with 99% compatibility limits.

Table 3. Differences between player means for forwards and backs on offence and defence expressed as factor effects and effect sizes. Uncertainty in the factor effects is shown as factor (×/÷) 90% compatibility limits.

	Factor effect	Effect size
Forwards – offence vs defence		
HiVel	1.23, ×/÷1.08	**Small** ↑***
HiMet	1.21, ×/÷1.07	**Small** ↑****
HSR	1.62, ×/÷1.15	**Moderate** ↑****
SprintMet	1.32, ×/÷1.11	**Small** ↑***
Sprint	1.39, ×/÷1.41	Small ↑*^{o}
Distance	1.13, ×/÷1.06	**Small** ↑***
Contacts	1.44, ×/÷1.07	**Moderate** ↑****
Accelerations	0.99, ×/÷1.07	Trivial^{oo}
Decelerations	1.08, ×/÷1.08	**Trivial** ↑^{o}*
DSL	1.17, ×/÷1.07	**Small** ↑**
Backs – offence vs defence		
HiVel	1.27, ×/÷1.08	**Moderate** ↑****
HiMet	1.24, ×/÷1.08	**Small** ↑****
HSR	1.39, ×/÷1.11	**Small** ↑****
SprintMet	1.22, ×/÷1.10	**Small** ↑**
Sprint	1.75, ×/÷1.18	**Small** ↑***
Distance	1.19, ×/÷1.08	**Moderate** ↑****

Contacts	1.43, ×/÷1.16	**Moderate ↑******
Accelerations	1.07, ×/÷1.09	**Trivial ↑^{0}***
Decelerations	1.00, ×/÷1.10	Trivial
DSL	1.40, ×/÷1.10	**Moderate ↑******
Offence – Forwards vs Backs		
HiVel	0.56, ×/÷1.17	**Large ↓******
HiMet	0.58, ×/÷1.16	**Large ↓******
HSR	0.31, ×/÷1.35	**Large ↓******
SprintMet	0.38, ×/÷1.29	**Large ↓******
Sprint	0.07, ×/÷1.90	**Large ↓******
Distance	0.87, ×/÷1.08	**Small ↓*****
Contacts	2.96, ×/÷1.14	**Very large ↑******
Accelerations	0.87, ×/÷1.14	**small ↓****
Decelerations	1.01, ×/÷1.15	Trivial
DSL	0.99, ×/÷1.28	Trivial
Defence – Forwards vs Backs		
HiVel	0.58, ×/÷1.18	**Large ↓******
HiMet	0.60, ×/÷1.17	**Large ↓******
HSR	0.27, ×/÷1.37	**Large ↓******
SprintMet	0.35, ×/÷1.30	**Large ↓******
Sprint	0.09, ×/ 1.94	**Large ↓******
Distance	0.93, ×/÷1.08	**Small ↓*^{0}**
Contacts	2.92, ×/÷1.16	**Very large ↑******
Accelerations	0.93, ×/÷1.14	Small ↓*^{0}
Decelerations	0.94, ×/÷1.15	Trivial
DSL	1.18, ×/÷1.28	Small ↑*^{0}

HiVel, high-velocity distance; HiMet, high-metabolic load distance; HSR, high-speed running distance; SprintMet, sprint-metabolic load distance; Sprint, sprint distance; Distance, total distance; DSL, dynamic stress load.

Magnitudes were assessed by standardisation using the observed between-player SD (Table 1 and Supplementary Table 1).

Bayesian likelihoods of substantial change: *possibly; **likely; ***very likely; ****most likely. *** and **** indicate rejection of the non-superiority or non-inferiority hypothesis ($p_{N\downarrow}$ or $p_{N\uparrow}$ <0.05 and <0.005 respectively).

↑ and ↓ indicate a substantial positive and negative effect, respectively.

Bayesian likelihoods of trivial change: ^{0}possibly; ^{00}likely; ^{000}very likely, ^{0000}most likely.

Likelihoods are not shown for effects with inadequate precision at the 90% level (failure to reject any hypotheses: <0.05). Magnitudes in bold have acceptable precision with 99% compatibility limits.

Table 4. Differences between player means for winning vs losing, for forwards and backs on offence and defence, expressed as factor effects and effect sizes. Uncertainty in the factor effects is shown as factor (×/÷) 90% compatibility limits.

	Factor effect	Effect size
Forwards Offence – win vs loss		
HiVel	1.10, ×/÷1.16	Small ↑^{*o}
HiMet	1.02, ×/÷1.12	Trivial
HSR	1.11, ×/÷1.25	Trivial ↑^{o*}
SprintMet	1.00, ×/÷1.15	Trivial
Sprint	0.96, ×/÷1.61	Trivial
Distance	0.97, ×/÷1.09	Trivial
Contacts	1.04, ×/÷1.10	Trivial ↑^{o*}
Accelerations	0.91, ×/÷1.10	**Small ↓^{*o}**
Decelerations	0.93, ×/÷1.11	Trivial ↓^{o*}
DSL	0.91, ×/÷1.11	**Trivial ↓^{o*}**
Forwards Defence – win vs loss		
HiVel	1.18, ×/÷1.16	**Small ↑****
HiMet	1.13, ×/÷1.12	**Small ↑****
HSR	0.95, ×/÷1.27	Trivial
SprintMet	1.07, ×/÷1.17	Trivial ↑^{o*}
Sprint	0.65, ×/÷1.64	Small ↓^{*o}
Distance	1.09, ×/÷1.09	**Small ↑^{*o}**
Contacts	1.09, ×/÷1.11	**Small ↑^{*o}**
Accelerations	1.09, ×/÷1.19	**Small ↑^{*o}**
Decelerations	1.07, ×/÷1.11	Trivial ↑^{o*}
DSL	1.04, ×/÷1.12	Trivial^{oo}
Backs Offence – win vs loss		
HiVel	1.10, ×/÷1.15	Small ↑^{*o}
HiMet	1.04, ×/÷1.11	Trivial ↑^{o*}
HSR	1.40, ×/÷1.21	**Small ↑*****
SprintMet	1.08, ×/÷1.12	**Trivial ↑^{o*}**
Sprint	1.59, ×/÷1.42	**Small ↑****
Distance	0.96, ×/÷1.09	Trivial ↓^{o*}

Contacts	0.69, ×/÷1.18	**Moderate ↓******
Accelerations	0.83, ×/÷1.11	**Small ↓*****
Decelerations	0.80, ×/÷1.13	**Small ↓*****
DSL	0.82, ×/÷1.12	**Small ↓****
Backs Defence – win vs loss		
HiVel	1.04, ×/÷1.15	Trivial
HiMet	1.02, ×/÷1.12	Trivial
HSR	0.99, ×/÷1.22	Trivial
SprintMet	0.96, ×/÷1.13	Trivial^{oo}
Sprint	0.78, ×/÷1.45	Trivial ↓^{o*}
Distance	1.06, ×/÷1.10	Small ↑^{*o}
Contacts	0.99, ×/÷1.23	Trivial
Accelerations	0.98, ×/÷1.11	Trivial
Decelerations	0.97, ×/÷1.13	Trivial
DSL	1.04, ×/÷1.14	Trivial^{oo}

HiVel, high-velocity distance; HiMet, high-metabolic load distance; HSR, high-speed running distance; SprintMet, sprint-metabolic load distance; Sprint, sprint distance; Distance, total distance; DSL, dynamic stress load.

Magnitudes were assessed by standardisation using the observed between-player SD (Table 1 and Supplementary Table 1).

Bayesian likelihoods of substantial change: *possibly; **likely; ***very likely; ****most likely. *** and **** indicate rejection of the non-superiority or non-inferiority hypothesis ($p_{N\downarrow}$ or $p_{N\uparrow}$ <0.05 and <0.005 respectively).

↑ and ↓ indicate a substantial positive and negative effect, respectively.

Bayesian likelihoods of trivial change: ^{0}possibly; ^{00}likely; ^{000}very likely, ^{0000}most likely.

Likelihoods are not shown for effects with inadequate precision at the 90% level (failure to reject any hypotheses: <0.05). Magnitudes in bold have acceptable precision with 99% compatibility limits.

Table 5. The effect of player time on the field on each metric expressed as the slope (coefficient) of time in the Poisson-regression model (in %/% units), and as fatigue, calculated at the factor reduction in the given metric from the predicted 1:1 linear value after the mean time on the field of forwards and backs in offence and defence.

		Fatigue	
	Slope (%/%)	Factor effect	Effect size
Forwards Offence			
HiVel	0.73, ±0.11	0.57, ×/÷1.24	**Large** ↓****
HiMet	0.67, ±0.11	0.51, ×/÷1.24	**Large** ↓****
HSR	0.84, ±0.17	0.71, ×/÷1.40	Small ↓**
SprintMet	0.58, ±0.16	0.43, ×/÷1.37	**Large** ↓****
Sprint	1.14, ±0.47	1.32, ×/÷2.58	Small ↑
Distance	0.81, ±0.08	0.67, ×/÷1.17	**Large** ↓****
Contacts	0.63, ±0.12	0.47, ×/÷1.28	**Large** ↓****
Accelerations	0.61, ±0.10	0.45, ×/÷1.23	**Very large** ↓****
Decelerations	0.59, ±0.11	0.43, ×/÷1.26	**Very large** ↓****
DSL	0.64, ±0.12	0.48, ×/÷1.26	**Large** ↓****
Forwards Defence			
HiVel	0.75, ±0.11	0.58, ×/÷1.26	**Large** ↓****
HiMet	0.72, ±0.11	0.54, ×/÷1.26	**Large** ↓****
HSR	1.04, ±0.21	1.09, ×/÷1.54	Trivial
SprintMet	0.76, ±0.17	0.59, ×/÷1.44	**Moderate** ↓***
Sprint	1.21, ±0.52	1.53, ×/÷3.01	Small ↑
Distance	0.78, ±0.08	0.62, ×/÷1.17	**Large** ↓****
Contacts	0.66, ±0.13	0.49, ×/÷1.31	**Large** ↓****
Accelerations	0.62, ±0.10	0.44, ×/÷1.24	**Very large** ↓****
Decelerations	0.63, ±0.12	0.46, ×/÷1.28	**Very large** ↓****
DSL	0.60, ±0.12	0.42, ×/÷1.28	**Large** ↓****
Backs Offence			
HiVel	0.83, ±0.10	0.69, ×/÷1.24	**Moderate** ↓***
HiMet	0.80, ±0.11	0.64, ×/÷1.27	**Large** ↓***
HSR	0.81, ±0.13	0.65, ×/÷1.32	**Moderate** ↓***
SprintMet	0.82, ±0.16	0.67, ×/÷1.41	Moderate ↓**
Sprint	0.81, ±0.25	0.65, ×/÷1.71	Small ↓*o
Distance	0.86, ±0.09	0.72, ×/÷1.21	**Moderate** ↓***
Contacts	0.86, ±0.21	0.72, ×/÷1.59	Moderate ↓
Accelerations	0.78, ±0.13	0.60, ×/÷1.32	**Large** ↓***

Decelerations	0.76, ±0.15	0.58, ×/÷1.38	**Large** ↓***
DSL	0.84, ±0.15	0.69, ×/÷1.38	Moderate ↓**
Backs Defence			
HiVel	0.67, ±0.10	0.49, ×/÷1.23	**Large** ↓****
HiMet	0.65, ±0.11	0.47, ×/÷1.26	**Very large** ↓****
HSR	0.46, ±0.13	0.32, ×/÷1.31	**Large** ↓****
SprintMet	0.54, ±0.15	0.38, ×/÷1.38	**Large** ↓****
Sprint	0.31, ±0.24	0.23, ×/÷1.67	**Moderate** ↓***
Distance	0.83, ±0.09	0.57, ×/÷1.20	**Very large** ↓****
Contacts	0.46, ±0.21	0.32, ×/÷1.55	**Very large** ↓****
Accelerations	0.71, ±0.12	0.53, ×/÷1.29	**Large** ↓****
Decelerations	0.69, ±0.14	0.51, ×/÷1.33	**Large** ↓****
DSL	0.70, ±0.15	0.52, ×/÷1.38	**Large** ↓****
Fatigue between-player standard deviation			
HiVel	0.03, ±0.13	1.07, ×/÷1.31	Small
HiMet	0.11, ±0.15	1.25, ×/÷1.38	Large
HSR	0.00	1.00	Trivial
SprintMet	0.18, ±0.22	1.48, ×/÷1.61	Large
Sprint	0.18, ±0.32	1.47, ×/÷2.00	Small
Distance	0.00	1.00	Trivial
Contacts	0.22, ±0.11	1.61, ×/÷1.26	Very large***
Accelerations	0.15, ±0.14	1.37, ×/÷1.35	Large
Decelerations	0.15, ±0.16	1.38, ×/÷1.41	Large
DSL	0.15, ±0.16	1.37, ×/÷1.39	Large

HiVel, high-velocity distance; HiMet, high-metabolic load distance; HSR, high-speed running distance; SprintMet, sprint-metabolic load distance; Sprint, sprint distance; Distance, total distance; DSL, dynamic stress load.

Magnitudes were assessed by standardisation using the observed between-player SD (Table 1 and Supplementary Table 1).

Bayesian likelihoods of substantial change: *possibly; **likely; ***very likely; ****most likely. *** and **** indicate rejection of the non-superiority or non-inferiority hypothesis ($p_{N\downarrow}$ or $p_{N\uparrow}$ <0.05 and <0.005 respectively).

↑ and ↓ indicate a substantial positive and negative effect, respectively.

Bayesian likelihoods of trivial change: ^{0}possibly; ^{00}likely; ^{000}very likely, ^{0000}most likely.

Likelihoods are not shown for effects with inadequate precision at the 90% level (failure to reject any hypotheses: <0.05). Magnitudes in bold have acceptable precision with 99% compatibility limits.

Supplementary Table 1. Magnitude thresholds for a factor increase and decrease in mean effects. Thresholds were derived from the observed between-player standard deviation via log transformation.

	Obsvd btwn	Small	Moderate	Large	Very large	Extremely large
HiVel	1.48	1.08, 0.92	1.27, 0.79	1.60, 0.62	2.19, 0.46	4.80, 0.21
HiMet	1.43	1.07, 0.93	1.24, 0.81	1.54, 0.65	2.04, 0.49	4.18, 0.24
HSR	1.93	1.14, 0.88	1.48, 0.67	2.20, 0.45	3.72, 0.27	13.9, 0.07
SprintMet	1.73	1.12, 0.90	1.39, 0.72	1.93, 0.52	2.99, 0.33	8.96, 0.11
Sprint	3.93	1.31, 0.76	2.27, 0.44	5.17, 0.19	15.4, 0.06	238, 0.00
Distance	1.31	1.06, 0.95	1.18, 0.85	1.38, 0.72	1.72, 0.58	2.94, 0.34
Contacts	1.50	1.08, 0.92	1.28, 0.78	1.63, 0.61	2.25, 0.44	5.06, 0.20
Accelerations	1.40	1.07, 0.93	1.22, 0.82	1.50, 0.67	1.96, 0.51	3.84, 0.26
Decelerations	1.47	1.08, 0.93	1.26, 0.79	1.59, 0.63	2.16, 0.46	4.67, 0.21
DSL	1.64	1.10, 0.91	1.35, 0.74	1.81, 0.55	2.69, 0.37	7.23, 0.14

Obsvd, observed; btwn, between; HiVel, high-velocity distance; HiMet, high-metabolic load distance; HSR, high-speed running distance; SprintMet, sprint-metabolic load distance; Sprint, sprint distance; Distance, total distance; DSL, dynamic stress load.

Supplementary Table 2. Magnitude thresholds for evaluating the pure between-player factor standard deviations. Thresholds were derived from the observed between-player standard deviation via log transformation.

	Obsvd btwn	Small	Moderate	Large	Very large	Extremely large
HiVel	1.48	1.04, 0.96	1.12, 0.89	1.27, 0.79	1.48, 0.68	2.19, 0.46
HiMet	1.43	1.04, 0.96	1.11, 0.90	1.24, 0.81	1.43, 0.70	2.04, 0.49
HSR	1.93	1.07, 0.94	1.22, 0.82	1.48, 0.67	1.93, 0.52	3.72, 0.27
SprintMet	1.73	1.06, 0.95	1.18, 0.85	1.39, 0.72	1.73, 0.58	2.99, 0.33
Sprint	3.93	1.15, 0.87	1.51, 0.66	2.27, 0.44	3.93, 0.25	15.4, 0.06
Distance	1.31	1.03, 0.97	1.08, 0.92	1.18, 0.85	1.31, 0.76	1.72, 0.58
Contacts	1.50	1.04, 0.96	1.13, 0.89	1.28, 0.78	1.50, 0.67	2.25, 0.44
Accelerations	1.40	1.03, 0.97	1.11, 0.90	1.22, 0.82	1.40, 0.71	1.96, 0.51
Decelerations	1.47	1.04, 0.96	1.12, 0.89	1.26, 0.79	1.47, 0.68	2.16, 0.46
DSL	1.64	1.05, 0.95	1.16, 0.86	1.35, 0.74	1.64, 0.61	2.69, 0.37

Obsvd, observed; btwn, between; HiVel, high-velocity distance; HiMet, high-metabolic load distance; HSR, high-speed running distance; SprintMet, sprint-metabolic load distance; Sprint, sprint distance; Distance, total distance; DSL, dynamic stress load.

Supplementary Table 3. Correlations between metrics. The metrics have been ordered and outlined to show clusters with generally higher correlations between metrics within the clusters than between the clusters.

Metric	1	2	3	4	5	6	7	8	9	10	11
1.Time	.	-0.03	-0.07	0.07	0.05	0.22	-0.13	-0.15	-0.23	-0.05	-0.07
2.HiVel/min	-0.03	.	0.95	0.86	0.79	0.60	0.77	-0.46	0.32	0.10	0.33
3.HiMet/min	-0.07	0.95	.	0.86	0.84	0.62	0.75	-0.47	0.43	0.15	0.32
4.HSR/min	0.07	0.86	0.86	.	0.88	0.78	0.52	-0.55	0.11	-0.10	0.12
5.SprintMet/min	0.05	0.79	0.84	0.88	.	0.77	0.46	-0.54	0.25	-0.02	0.07
6.Sprint/min	0.22	0.60	0.62	0.78	0.77	.	0.31	-0.53	-0.07	-0.25	-0.08
7.Distance/min	-0.13	0.77	0.75	0.52	0.46	0.31	.	-0.28	0.45	0.25	0.49
8.Contacts/min	-0.15	-0.46	-0.47	-0.55	-0.54	-0.53	-0.28	.	0.03	0.24	0.20
9.Accelerations/min	-0.23	0.32	0.43	0.11	0.25	-0.07	0.45	0.03	.	0.64	0.39
10.Decelerations/min	-0.05	0.10	0.15	-0.10	-0.02	-0.25	0.25	0.24	0.64	.	0.38
11.DSL/min	-0.07	0.33	0.32	0.12	0.07	-0.08	0.49	0.20	0.39	0.38	.

Min, minute; HiVel, high-velocity distance; HiMet, high-metabolic load distance; HSR, high-speed running distance; SprintMet, sprint-metabolic load distance; Sprint, sprint distance; Distance, total distance; DSL, dynamic stress load.

Appendices

Appendix A: Contact and event coding criteria.

Contact Coding Manual (Chittenden, J. 2021)	
Hit Up	
When the player is carrying the ball into contact. The player will either disrupt the defensive line or travel with intent to engage at the opposition. In offensive play if the player experiences a contact without being in possession of the ball within camera shot, this is classed as a hit up. Any contention for an aerial ball is classed as a hit up. Only judge by contact with other players, not contact with ground. As they score a try, hit ups can be counted.	
Minimal	*Hard*
• Minimal attempt to contact from opposition • One or two hands may touch but not impede travelling speed or create stoppage • Ankle or shank tap • Scrape through a tackle at speed having minimal contact with the opposition.	• Is when players are tackled and end up on the ground. • Loses significant momentum in contact, ending up in a one-on-one wrestle while driving forwards or backwards during the carry • Fends are classed as hard-hit ups • Full body contact from a tackle (knees up)

• Minimal aerial collision with another player • Can be more than one hard hit up or a combination of hit ups in one run (if there are no opposition players within a one-meter radius after the first hit up). • Attempt of a leg tackle with only one arm by the opposition. • Player slips at speed with minimal contact to opposition.	• Full body aerial collision – consider contact with ground • Can be more than one hard hit up or a combination of hit ups in one run (if there are no opposition players within a one-meter radius after the first hit up). • If there is a minimal contact of the legs closely followed by an upper body full wrap tackle, then code it as one hard. • Brought down by a two-handed wrap tackle anywhere on the body if they are grounded • If the offensive player is facing backwards to an incoming hit.
Tackle	
The attacking ball carrier is brought to ground by the opposition. In defensive play if the player experiences a contact without being in possession of the ball within camera shot, this is classed as a tackle. Only judge by contact with other players, not contact with ground.	
Minimal	*Hard*
• Missed tackle • One or two hands only touches the opposition player (does not create a backwards force). • If a leg tackle is made with only one arm. • Shirt tackles are minimal tackles. • Both arms are used but only on one leg/arm.	• Making a tackle and the opposition ends up on the ground. • The attacking player loses significant momentum moving forward and collides harshly with the surrounding players. • Leg tackles (2 legs) are classed as hard if both arms are used. • Full body wrap arounds are hard tackles. • If they end up getting dragged down by a two arm one leg tackle but, made shoulder or torso contact beforehand it is a hard tackle.
Attack OOA	
Order of arrival to the offensive ruck. Ruck occurs after the tackled player has been brought to the ground. Players can arrive at the ruck and position themselves in a way they are about to get contacted but may not experience contact therefore, it will be a minimal ruck arrival. If the player is entering an area where the ball is being played on the ground it is classed as an OOA. Box kick blocking is included Halfbacks are not coded for OOA's unless they make a clear attempt (i.e. do more than just distribute the ball)	
Minimal	*Hard*
• Minimal is making minimal contact while at the ruck.	• Hard is when an attacking player arrives at the ruck and makes

<table>
<tr><td>• A hand may be on the ruck but no clear intent to enter the ruck for a clean out has been made.
• Players can be in impact positions but do not experience any contact (bracing).
• Box kick guards are classified as minimal OOA's
• If a player arrives and it is originally a minimal contact but then a hard contact, the hard contact overrides the minimal
• Halfbacks are not included for minimal OOA arrivals.
• Shirt pulling is minimal contact</td><td>collision or major impact to other players.
• Clean outs
• Makes big impact (disrupts the ruck)
• Can have multiple hard OOA's from the same player in one ruck (e.g., one attempt, two attempt)</td></tr>
<tr><td colspan="2">Defence OOA</td></tr>
<tr><td colspan="2">Order of arrival to the defensive ruck. Ruck occurs after the tackled player has been brought to the ground.
Players can arrive at the ruck and position themselves in a way they are about to get contacted but may not experience contact therefore it will be a minimal ruck arrival.
If they are entering an area where the ball is being played on the ground it is classed as an OOA.</td></tr>
<tr><td>Minimal</td><td>Hard</td></tr>
<tr><td>• Minimal is making minimal contact while at the ruck.
• Players may attempt to engage the ruck but choose to abandon the intention.
• Shirt pulling is minimal contact.
• If the defending player gets pushed away by the opposition or they push them
• Attempt at blocking a box kick
• Contact with ruck but no major force to move players is generated
• Gets caught up standing in the middle of the ruck</td><td>• Hard is when a defending player arrives at the ruck and makes collision or major impact to other players.
• Clean outs
• Makes big impact (disrupts the ruck).
• Can have multiple hard OOA's from the same player in one ruck (e.g., one hit, two hit).</td></tr>
<tr><td colspan="2">Lineout Offence</td></tr>
<tr><td colspan="2">Forwards set up an offensive lineout to retrieve the ball.
Once the ball exits the lineout, no other contacts are coded unless a maul occurs.</td></tr>
<tr><td>Minimal</td><td>Hard</td></tr>
<tr><td>• All attacking players part of the lineout who do not lift or jump are coded with minimal contact.
• The hooker (thrower) is always coded as minimal contact.
• Only forwards are coded in lineouts. No backs.</td><td>• All attacking players who are part of the lineout and are lifters or jumpers are coded with hard contact.
• Only forwards are coded in lineouts. No backs.
• Attacking players who lift and jump to retrieve the ball safely after kickoff. Once they are grounded the jumper does not get coded for a hit</td></tr>
</table>

<table>
<tr><td></td><td>up. However, if the lifters attempt to engage in the ruck once grounded this is coded separately as an Attacking OOA.</td></tr>
<tr><td>Lineout Defence</td><td></td></tr>
<tr><td colspan="2">Forwards set up a defensive lineout to contest the opposition throw and lineout.
Once the ball exits the lineout, no other contacts are coded unless a maul occurs.</td></tr>
<tr><td>Minimal</td><td>Hard</td></tr>
<tr><td>• All defending players part of the lineout who do not lift or jump are coded with minimal contact.
• Only forwards are coded in lineouts. No backs.</td><td>• All defending players who are part of the lineout and are lifters or jumpers are coded with hard contact.
• Only forwards are coded in lineouts. No backs.</td></tr>
<tr><td colspan="2">Maul Offence</td></tr>
<tr><td colspan="2">When a rolling maul occurs
Formation of a maul occurs following a lineout</td></tr>
<tr><td>Hard</td><td>Maximal</td></tr>
<tr><td>• When the defensive players involved in a maul remains in contact for three seconds or less (brief inclusion).
• When a defensive player takes one hit at the maul (like a OOA action but hitting a maul rather than a ruck).
• Once the ball is grounded and is distributed to the next phase a new metric occurs.</td><td>• Maximal is when the defensive players involved in the maul drives forward and remains in contact for three or more seconds.
• If a player re-enters the maul (multiple rejoins).
• Once the ball is grounded and is distributed to the next phase a new metric occurs.</td></tr>
<tr><td colspan="2">Maul Defence</td></tr>
<tr><td colspan="2">When a rolling maul occurs
Formation of a maul occurs following a lineout
When players attempt to hold players up in tackles</td></tr>
<tr><td>Hard</td><td>Maximal</td></tr>
<tr><td>• When the defensive players involved in a maul remains in contact for three seconds or less (brief inclusion).
• When a defensive player takes one hit at the maul (like a OOA action but hitting a maul rather than a ruck).</td><td>• Maximal is when the defensive players involved in the maul drives forward and remains in contact for three or more seconds.
• If a player re-enters the maul (multiple rejoins).</td></tr>
<tr><td colspan="2">Scrum Offence</td></tr>
<tr><td colspan="2">When one scrum pack engages against the opposing scrum pack.
Code backs if included (player numbers down if teams carded)</td></tr>
<tr><td>Hard</td><td>Maximal</td></tr>
<tr><td>• If the ball exits the scrum in under 3 seconds (from when the ref says set) the scrum is classified as hard work.</td><td>• If the ball exits the scrum after 3 seconds (from when the ref says set) the scrum is classified as hard work.</td></tr>
</table>

	• This occurs even if the front row collapses because they are still experiencing contact and forces around them.
Scrum Defence	
When one scrum pack engages against the opposing scrum pack. Code backs if included (player numbers down if teams carded)	
Hard	*Maximal*
• If the ball exits the scrum in under 3 seconds (from when the ref says set) the scrum is classified as hard work.	• If the ball exits the scrum after 3 seconds (from when the ref says set) the scrum is classified as hard work. • This occurs even if the front row collapses because they are still experiencing contact and forces around them.

Ball in Play Criteria	
Kicks	The first BIP of the match is when the ball hits the players boot at kick off. Penalty kicks are excluded from BIP, unless it hits the crossbar and stays in play. BOP starts when the ball hits the players boot for fulltime or halftime kicks
Scrums	If the ball goes into the scrum and it results in a penalty, free kick or successful exit code it as a BIP. If the scrum is reset, it will stay as a BOP (even if the ball goes into the scrum).
Lineouts	The frame where the hooker's elbow has flexion for lineout throws is the start of a BIP lineout. If a lineout throw is not straight or the lines aren't straight, then this will count as a BOP.
Quick Taps	If a quick tap is taken it counts as "play on." Therefore, the BIP continues, and no BOP occurs. If there is an extremely large stoppage in play (>10 sec) before the quick tap there can be a BOP.
BOP	When the ref blows the whistle due to an infringement or stop in play. Sideline official's flag goes up on the sideline after a BIP kick.
OFF	Periods within BIP where the team in question has possession of the ball until possession is legally gained by the opposing team.
DEF	Periods within BIP where the opposing team has possession of the ball until possession is legally gained by the team in question.

Appendix B: Ethics approval.

The University of Waikato
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0800 WAIKATO (924 528)

HECS Human Ethics Committee
Brett Langley
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THE UNIVERSITY OF
WAIKATO
Te Whare Wānanga o Waikato

29 November 2021

Luke Stevens
Brett Smith

Re: HECS Ethics Approval of Application HREC(HECS)2021#34 "Offense vs Defense: Quantifying workload demands in professional Rugby Union."

Dear Luke:

Thank you for submitting your addendum to application HREC(HECS)2021#34 for ethical approval.

We are pleased to provide formal approval for your project, including the following activities:

- Recruit approximately 23 males, aged 18 to 40 years, from [Rugby club]
- Analyse participant's GPS data and Sportscode data, that was collected per normal team protocol during every game over the 2021 season.

This approval letter replaces the prior approval of the same name.

Please contact the committee by email (hecs-ethics@waikato.ac.nz) if you wish to make changes to your project as it unfolds, quoting your application number with your future correspondence. Any minor changes or additions to the approved research activities can be handled outside the monthly application cycle.

We wish you all the best with your research.

Kind regards,

Brett Langley, PhD
Chairperson
HECS Human Ethics Committee
University of Waikato

Appendix C: Information sheet.

The University of Waikato, Te Huataki Waiora School of Health.

Information sheet: [Rugby club] **Rugby Union players**

Research project Title:
Offense vs Defense: Quantifying workload demands in professional Rugby Union.

Researchers:
Luke Stevens
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Approvals:
This research project has been approved by the Human Research Ethics Committee of the University of Waikato under HREC(HECS)2021#34.

Experiment Purpose:
This research project seeks to explore and analyse the difference in locomotive and contact workload metrics between offensive and defensive phases of play in professional rugby union.

Rationale:
Rugby union is a sport that demands high levels of physical and tactical skill. Players are subject to high movement and contact workloads, the understanding of which can enable coaches to better prepare players for optimal performance. Previous literature has examined the notion of worst-case scenario within the match to determine when the most demanding period of play is likely to occur, however no comparison of workload metrics has previously been made between offensive and defensive phases of play for professional Rugby Union.

Procedure:
Player's GPS data and Sportscode data will be collected during every game over the season, as per normal team protocol. If players consent to the use of their data, GPS metrics and Sportscode metrics will be analysed post-season to determine the difference in workload between offensive and defensive phases of the match.

Confidentiality:

Confidentiality and participant anonymity will be strictly maintained. Individual participants will not be named, and neither will the team, however, in some cases, player positions relating to certain findings may be mentioned, and it will be mentioned that the team is a professional squad that compete in the New Zealand/Trans-Tasman Super Rugby competition. It should however be noted that while every effort is made to ensure confidentiality, this cannot be guaranteed.

Likelihood of Discomfort:
The normal matches are rigorous and involve a number of discomforts and some potential risks. The [Rugby club] seek to minimise these discomforts and risks through a comprehensive safety plan, associated monitoring procedures, and employment of specialist medical personnel who are present during every training session and match. This project does not require the players to do anything more or different than what is normally required by the team for training and matches.

Your rights as a participant

- Participation in this study is completely voluntary. You do not have to participate, nor will there be any repercussions for not participating.
- You can withdraw from the study and have all your data withdrawn at any time up until 4 weeks after signing the informed consent form. You do not require a reason for withdrawing. This can be done by contacting and informing either of the researchers.
- You can ask any further questions about the study at any time.
- Any personal data will be kept strictly confidential and destroyed at the completion of the project. All Sportscode and GPS data will be de-identified and retained for five years, as per University of Waikato regulations. Analysed data from your participation in the research project will be included in a master's thesis publication and potentially journal articles and conference papers.
- You can receive a copy of the findings at the completion of the study if you are interested.

Researcher
Luke Stevens (Master's student researcher) can be contacted by email at lukestevens077@gmail.com, or by phone +64212678535 regarding this project.

In addition, Dr Brett Smith (supervisor) can also be contacted by phone 021 628963 or by email brett@waikato.ac.nz regarding this project.

Resolution of any disputes:

If you are unhappy with an aspect of this research, please contact the researcher. If you are not happy with how your issues are dealt with and wish to discuss these issues further or make a complaint to a higher authority, please contact the Chair of the Committee, email hecs-ethics@waikato.ac.nz, postal address, University of Waikato, Te Whare Wananga o Waikato, Private Bag 3105, Hamilton 3240

Results
A Master's thesis will be completed from this research by the end of 2022. A copy of this thesis, generated from this study will be available after this date which can be obtained by contacting the researcher, it will also be sent to the [Rugby club] upon completion.

Appendix D: Research consent form.

The University of Waikato, Te Huataki Waiora School of Health.

Research Consent Form: [Rugby club] Rugby Union players

Research project:
Offence vs Defence: Quantifying workload demands in professional Rugby Union.

Name of researcher: Luke Stevens

Name of supervisor: Brett Smith

By signing below, I acknowledge that I have received an information sheet about this research project or have had the study explained to me by the researcher's supervisor. I have had the chance to ask any questions and discuss my participation with other people. Any questions have been answered to my satisfaction.

Please indicate by ticking the boxes below:

- ☐ I understand that participation in this study is completely voluntary.
- ☐ I understand that I can withdraw from the study without reason, and have all of my data withdrawn, at any time during the study up until 4 weeks after signing this form, by contacting one of the researchers.
- ☐ I understand that I can ask any further questions about the study at any time.
- ☐ I understand that all personal data will be kept strictly confidential and destroyed at the completion of the project, and that all research data will be de-identified and retained for five years, as per University of Waikato regulations.
- ☐ I understand that this research will be included in a Master's thesis publication and potentially journal articles and conference papers.
- ☐ I am interested in receiving a copy of the findings at the completion of the study.

Participant's name: ____

Signature: ____ **Date:** _______________________