Title: Locomotor and collision characteristics by phases of play during the 2017 Rugby League World Cup.

Submission Type: Original Investigation.

Author(s): Gordon Rennie[1,2], Nicholas Dalton-Barron[1,2,3], Shaun J. McLaren[1,3], Dan Weaving[1,4], Richard Hunwicks[1,5], Chris Barnes[2,6], Stacey Emmonds[1], Barry Frost[3], Ben Jones[1,3,4,7,8,9].

Affiliations:

[1] Carnegie Applied Rugby Research (CARR) Centre, Institute for Sport, Physical Activity and Leisure, Leeds Beckett University, Leeds, United Kingdom

[2] Catapult Sports, Melbourne, Australia

[3] England Performance Unit, Rugby Football League, Leeds, United Kingdom

[4] Leeds Rhinos Rugby League Club, Leeds, United Kingdom

[5] Catalans Dragons, Perpignan, France

[6] CB Sports Performance Ltd, Rugeley, United Kingdom

[7] Yorkshire Carnegie Rugby Union Club, Leeds, United Kingdom

[8] School of Science and Technology, University of New England, Armidale, NSW, Australia

[9] Division of Exercise Science and Sports Medicine, Department of Human Biology, Faculty of Health Sciences, the University of Cape Town and the Sports Science Institute of South Africa, Cape Town, South Africa

Corresponding author, email address, and ORCiD: Gordon Rennie, g.rennie@leedsbeckett.ac.uk, and https://orcid.org/0000-0002-6529-9694.

Abstract word count: 249

Word count: 3946

Table(s): 5

Abstract

Purpose: Understanding differences in locomotor and collision characteristics between phases of play can help rugby league coaches develop training prescription. There are no data currently available describing these differences at the elite international level. The aim of our study was to determine the differences in average speed ($m \cdot min^{-1}$), high-speed running (> 5.5 $m \cdot s^{-1}$) per minute and collision frequencies per minute ($n \cdot min^{-1}$) between attack and defence during the 2017 Rugby League World Cup (RLWC). **Methods:** Microtechnology data were collected from 24 male professional rugby league players from the same international squad across six matches of the RLWC. Data were then subject to an exclusion criteria and stratified into forwards (n = 9) and backs (n = 7) before being analysed with linear mixed-effects models. **Results:** When comparing attack with defence, forwards and backs had substantially slower average speeds (effect size [ES]; ±90% confidence limits: -2.31; ±0.31 and -1.17; ±0.25) and substantially greater high-speed distance per minute (1.61; ±0.59 and 4.41; ±1.19). Forwards completed substantially more collisions per minute when defending (2.75; ±0.32) whilst backs completed substantially more when attacking (0.63; ±0.70). **Conclusions:** There was greater within- and between-player variability for collision frequency (coefficient of variation [CV] range; 25–28%) and high-speed distance (18–33%) per minute when compared to average speed (6–12%). There are distinct differences in locomotor and collision characteristics when attacking and defending during international rugby league match-play, yet the variability of high-speed running and collisions per minute are large. These data may be useful to plan or evaluate training practices.

Keywords: performance analysis, rugby league, global positioning systems, attacking, defending

Introduction

Domestically, rugby league is played professionally in the European Super League (ESL) and Australasian National Rugby League (NRL). Internationally, teams compete for the Rugby League World Cup (RLWC) every four years after the completion of the domestic season. Other international tournaments are held more frequently (e.g., Four Nations, European Championship, Pacific Cup), although the RLWC is the pinnacle of international rugby league competition. Rugby league is characterised by intermittent and high-intensity locomotor and collision activity, separated by periods of low-intensity activity (Weaving et al., 2019). Players are typically classified into specific playing positions and positional groups; forwards (i.e. props, hooker, second rows and loose forward) and backs (i.e. halves, centres, wings and fullback) (Johnston et al., 2014).

The continued development in microtechnologies (Malone et al., 2017) and their associated algorithms (Hulin et al., 2017) has enabled practitioners to better understand the locomotor and collision characteristics of rugby league competition (Johnston et al., 2014; Delaney et al., 2015; Weaving et al., 2019; Johnston et al., 2019). The characteristics of a whole match, peak characteristics per units of time (Whitehead et al., 2018; 2019), or specific phases of competition (e.g., attack, defence and transition) (Read et al., 2018) can provide practitioners with information to inform their technical–tactical prescription during training. This is important given the large proportion of time rugby league teams spend undertaking 'game-specific' activities during field-based training (Weaving et al., 2014; 2017). In addition, quantifying the variability in locomotor and collision characteristics between different matches is important to understand meaningful changes and inform planning of the training process (Kempton et al., 2014; McLaren et al., 2016).

To date, there are many studies quantifying the average speed (e.g., total distance / duration) of locomotor activity within domestic rugby league (Hausler et al., 2016), for teams competing in the ESL (Waldron et al., 2011; Twist et al., 2014) and the NRL (Kempton & Coutts, 2016; Gabbett, 2015). These studies have focused on quantifying locomotor characteristics completed either across the whole match, or by first- and second-halves (Twist et al., 2014; Johnston et al., 2014). However, the use of 'whole match' average speed is limited, as these values are inclusive of the time the ball is out of play. As such, the average speed is likely to be substantially greater during prolonged durations (e.g., > 5-minutes) of competition (Whitehead et al., 2018; Cunningham et al., 2018). The effects of ball in play data segmentation have been investigated at semi-professional level within rugby league with average speed shown to be significantly higher when the ball was in play in comparison to whole match demands (whole match 86.7 ± 9.8 *vs.* BIP 125.1 ± 16.1 m.min-1; ES 2.88) (Gabbett, 2015). Therefore, by quantifying the maximal average speed over specific time windows, practitioners can determine the peak running demands during the match and compare these to speeds reached during prescribed technical–tactical training (Whitehead et al., 2018).

Although determining the peak average speeds for different durations is important, such methods fail to determine the differences in locomotor and collision characteristics between specific phases of play (i.e., attack *vs.* defence) (Read et al., 2018); which is often a coaching focus during training sessions (e.g., attacking and defensive drills). For example, in NRL competition, Gabbett et al., (2014) reported that average speed was greater during defence than attack (109 ± 16 *vs.* 82 ± 12 m·min^{-1}) for forwards. Again, such quantification is an important addition to allow technical–tactical coaches to evaluate the movement characteristics of training drills that are specific to the contextual aspects of match-play, but this is yet to be reported relative to elite senior international rugby league competition. Whitehead et al., (2019) compared whole match, match halves, and peak running demands of club and international under-16 rugby league competition. Forwards had higher first-half average speeds during international competition (International 96.2 ± 8.0 *vs.* Club 85.6 ± 10.4 $m{\cdot}min^{-1}$), yet higher second-half average speed during club matches (Club 89.5 ± 9.8 *vs.* International 86.7 ± 8.9 $m{\cdot}min^{-1}$). Furthermore, backs had a lower whole match average speed during international matches (International 83.4 ± 9.3 *vs.* Club 89.9 ± 7.3 $m{\cdot}min^{-1}$) and a lower second-half average speed than club matches (International 77.8 ± 10.3 *vs.* Club 90.3 ± 8.9 $m{\cdot}min^{-1}$). Whilst these between-half locomotor differences have been demonstrated in under-16 international rugby league competition, similar characteristics are yet to be determined at senior elite level.

Rugby league also comprises frequent collision activity, which imposes significant physiological and biomechanical load onto players (Vanrenterghem et al., 2017), thereby increasing perception of effort (Johnston & Gabbett, 2011; Johnston et al., 2014) and energy expenditure (Costello et al., 2019). The majority of research quantifying the characteristics of rugby league competition have failed to account for the interaction between locomotor and collision activity within their analyses, largely due to the requirement for laborious manual coding of collision events via notational analysis (Johnston et al., 2014). Recently, a valid collision detection algorithm for rugby league competition (Hulin et al., 2017) has enabled practitioners and researchers to more easily quantify the collision frequency of competition over longitudinal periods (Weaving et al., 2019) and thus warrants inclusion when evaluating the characteristics of rugby league match-play.

To date, the locomotor and collision characteristics of international rugby league match-play have yet to be reported. As such, National Governing Bodies responsible for the recruitment and physical preparation of players before the tournament have limited international data on which to base preparatory strategies. The availability of such data will serve as a reference point for both developing nations, and also nations competing for the RLWC. Therefore, the aim of our study was to determine the differences in locomotor and collision characteristics (i.e. activity rates) between match halves and phases of play (i.e. attack, defence, transition, ball-in-play and ball-out-play) during the 2017 RLWC. A secondary aim was to describe the within- and between-player variability of these variables and their peak characteristics for different time durations.

Methods

Participants

Data were initially collected from 24 male professional rugby league players (forwards, n = 12; backs, n = 12) from the same international squad during the 2017 RLWC. Following strict data inclusion criteria (number of connected satellites ≥ 10; horizontal dilution of precision (HDOP) ≤ 1; velocity ≤ 10 $m \cdot s^{-1}$; acceleration ≤ ±6 $m \cdot s^{-2}$; Malone et al., 2017; Weston et al., 2015), 72 total observations were included in our study which included multiple data files from 9 forwards (observations = 43; age: 28 ± 4 years; stature: 186.5 ± 5.6 cm; body mass: 99.8 ± 10.4 kg) and 7 backs (observations = 29; age: 28 ± 4 years; stature: 187 ± 6 cm; body mass: 99.8 ± 10.4 kg). Written informed consent was provided by the National Governing Body to analyse anonymised data prior to the commencement of the study, and ethics approval was granted by the Leeds Beckett University institutional ethics committee.

Design

We used a cross-sectional study to determine the locomotor and collision characteristics for whole match, first- and second-half, phase of play (attack, defence, transition, ball-in-play and ball-out-play), and peak characteristics. Data were collected across 6 matches from the 2017

RLWC (wins = 4, losses = 2, points scored [mean ± SD] = 21 ± 16, points conceded = 11 ± 6). The matches included 3 pool matches, a quarter final, semi-final, and final.

Methodology

Each player was fitted with a Global Navigation Satellite System (GNSS) enabled microelectrical mechanical system (MEMS) device (Optimeye S5, Catapult Sports, Melbourne, Australia). The GNSS provides geospatial positioning with global coverage, encompassing both GPS (Global Positioning System) and GLONASS (Global Navigation Satellite System) satellites (Whitehead et al., 2018), sampling at 10 Hz. The GNSS also contains a tri-axial accelerometer, gyroscope and magnetometer sampling at 100 Hz. The test-retest reliability of Catapult Sports Optimeye S5 devices to measure instantaneous speed across a range of starting velocities has been reported to be acceptable (coefficient of variation [CV] = 2.0 to 5.3%) (Varley et al., 2012). The devices were worn in a customised pouch sewn into the players match fitted jersey located between the scapulae. To reduce inter-unit error, each player wore the same device throughout the tournament (Buchheit and Simpson, 2016).

The devices were switched on outside in accordance with manufacturer recommendations to ensure full satellite connection pre-match. Data were downloaded from the MEMS device using the proprietary software (OpenField^{TM}, software version 1.17.0, Build #30874, Catapult Sports, Melbourne, Australia) and 10 Hz GPS data exported to R Studio (version 3.3.1, R Foundation for Statistical Computing, Vienna, Austria) for analysis. Files were then subsequently cut according to a timeline of half-times, attack, defence, transition, ball-in-play and ball-out-play events generated by Opta (Leeds, UK). Time synchronisation between raw GPS files and Opta data was ensured via a 10-digit Unix timestamp at kick-off, provided by Opta. Attacking and defensive phases were defined according to Opta, whilst transition phases were defined in our study as the duration between a zero tackle or a kick in play, and the start of the subsequent tackle count.

Velocity data within each raw file were excluded if the sampling point did not meet the following criteria: number of connected satellites ≥ 10, horizontal dilution of precision (HDOP) ≤ 1, velocity < 10 $m \cdot s^{-1}$, acceleration ≤ ±6 $m \cdot s^{-2}$. These criteria are considered acceptable for GPS data collection (Malone et al., 2017; Weston et al., 2015). Missing velocity data points within the 10 Hz signal were linearly interpolated if the duration of the window for missing data was <10s (or 60 data points). A duration of 10s was chosen, as anything above this was found to result in an unrealistic representation of human locomotion. The interpolation was implemented using the *na.approx* function within the *zoo* package in R. Observations were then excluded if: (1) > 10% of the overall file was missing after interpolation, (2) an individual player had less than 2 observations, and (3) the player participated in less than 1 half of a match (observations excluded = 28). The mean ± SD number of satellites connected during data collection was 11.4 ± 0.3, whilst the HDOP was 0.9 ± 0.1.

Locomotor metrics included average speed and high-speed running distance (>5.5 $m \cdot s^{-1}$) per minute. Collision frequencies were determined by the OpenField™ automatic collision detection algorithm, which has previously demonstrated a strong and positive correlation (r = 0.96) with notational analysis (specificity 91.7 ± 2.5%, accuracy 92.7 ± 1.3%), after collisions were excluded when PlayerLoad™ < 1 AU and duration < 1 s (Hulin et al., 2017). Maximum locomotor and collision characteristics were calculated using the rolling average method (Delaney et al., 2017), over a range of windows (1- to 10-minutes).

Statistical Analyses

All statistical analyses were performed in R Studio. Since the aims of our study were to understand differences in match characteristics (i.e. activity rates), all data were expressed per minute and treated as continuous variables. The data were visually inspected for normality using histograms and *Q*–*Q* plots. Data did not always follow an approximate normal distribution and is therefore summarised as the median and quartile range (lower quartile [25%] to upper quartile [75%]). Therefore, to reduce error arising from non-uniform residuals, all outcome measures were log-transformed prior to analysis, and subsequently back-transformed post-analysis (representing effects as accurate percentages, Hopkins et al., 2009).

Our design located units of analysis (match characteristics) nested in clusters of units (player). We therefore used separate linear mixed-effects models (via the *lme4* package) to compare average speed, high-speed distance per minute and collision frequency per minute between phases of play (attack and defence) and match period (first- and second-half). We opted not to compare the transition phase with attack or defence, or compare ball-in- versus out-of-play, because the practical applications of such differences are limited. Subsequently, data were split by positional group and modelled with a random intercept (variance component) to estimate the within- and between-player variability (expressed as a coefficient of variation [CV]). Datasets were then combined before phases of play and positional group were entered as separate categorical fixed effects to compare differences between levels.

To describe the peak locomotor and collision characteristics as a function of time (i.e. duration of the moving average window), we adopted a power law approach similar to that recently described by Delaney et al., (2017). Here, we used general linear models (via the *glm2* package), with player ID entered as a categorical fixed effect and time entered as a continuous covariate, to derive the intercept and slope of the within-player log–log relationships. The strength and fit of each model was expressed using Pearson's product moment correlation coefficient (*r*) and the coefficient of determination (R^2).

Uncertainty in all outcome measures and ranges of values compatible with our data and statistical models were expressed as 90% confidence intervals (CI; Greenland, 2019). We then used non-clinical magnitude-based inferences (Batterham & Hopkins, 2006) to provide an interpretation of these ranges in relation to standardized effect thresholds. Observed SDs (pooled within- and between-player) were multiplied by thresholds of 0.2, 0.6, 1.2, and 2.0 to anchor small, moderate, large, and very large differences, respectively (Batterham & Hopkins, 2006). Subsequently, the chance of a difference being the observed magnitude (e.g., small, moderate) or trivial was calculated by converting the *t*-statistic for the effect relative to the threshold (difference – threshold/ standard error of the difference) into a continuous probability via the one-tailed *t*-distribution. Quantitative probabilities were then assigned to the following qualitative probabilistic terms: possibly, < 0.5%, most unlikely; 0.5–4.9%, very unlikely; 5–24.9%, unlikely; 25.0–74.9%, possibly; 75.0–94.9%, likely; 95.0– 99.5%, very likely; > 99.5%, most likely (Batterham & Hopkins, 2006). The effect was declared unclear if the chance of being both substantially positive and negative was ≥ 5%.

Results

Table 1 shows the median and quartile range for duration, average speed, high-speed distance per minute and collisions per minute during whole match, first- and second-half and phases (i.e. attack, defence and transition; and ball-in and ball-out of play) and peak 1-, 5- and 10-minute periods.

*** INSERT TABLE 1 ***

Table 2 shows the differences and their associated inferences between phases of play (i.e. attack *vs.* defence). Table 3 shows the differences and their associated inferences between first- *vs.* second-half periods of play.

*** INSERT TABLE 2 ***

*** INSERT TABLE 3 ***

Table 4 shows whole match data represented as mean and variability (within- and between-player).

*** INSERT TABLE 4 ***

The within-player log–log relationships of peak locomotor and collision characteristics with time are shown in Table 5. Relationship strength was very large to near perfect (r = 0.88–0.92). For each variable, the peak intensities of competition can be estimated as function of time (t; seconds) using the following equation:

$$\text{Meters or collisions per minute} = \text{intercept} \times t^{\text{slope}})$$

*** INSERT TABLE 5 ***

Discussion

Understanding differences in locomotor and collision characteristics between attacking and defending can help rugby league coaches develop training prescription and evaluation practices, but there are currently no published data describing these differences at the elite international level. The primary aim of our study was to determine the differences in average speed, high-speed distance per minute and collision frequency per minute (i.e. activity rates) during different phases of play throughout the 2017 RLWC. The main finding was that both forwards and backs had substantially slower average speeds but covered substantially greater high-speed distance per minute when attacking compared with defending. Forwards completed substantially more collisions per minute when defending whilst backs completed substantially more when attacking.

Previous research has utilised time motion optical analyses to determine locomotor and collision characteristics using professional ESL and NRL players. Sykes et al. (2009) demonstrated that outside backs, pivots, and back rows completed greater percentage of high intensity running in attack when compared to defence. These findings support our results; albeit the method of data capture differed from the wearable used within our investigation. The findings of our study demonstrate the distinct positional locomotor and collision characteristics of attacking and defending during the highest level of rugby league match-play and may be useful for the planning of specific technical-tactical training modalities (e.g., goal line attack *vs.* goal line defence drills) in international teams.

This is the first study, to our knowledge, across any professional rugby league competition to detail locomotor and collision characteristics when attacking and defending for backs. Our findings demonstrate that backs are likely to experience large increases in high-speed (10.2 *vs.* 3.6 $m \cdot min^{-1}$) and moderate increases in collision frequency when attacking (0.5 *vs.* 0.4 $n \cdot min^{-}$

^{1}). For forwards, the average speeds and collision frequencies during attack and defence (Table 2) are generally in agreement with previous research (Gabbett et al., 2014), where forwards completed greater average speeds (defence = 109 *vs.* attack = 82 $m \cdot min^{-1}$) and collision frequencies (defence = 1.9 *vs.* attack = 0.8 $n \cdot min^{-1}$) when defending. However, Gabbett et al., (2014) also reported greater high-speed distance per minute (> 5.0 $m \cdot s^{-1}$; 5.3 *vs.* 3.9 $m \cdot min^{-1}$) when defending. The differences between our work and Gabbett et al., (2014) could be due to the differences in high-speed thresholds (> 5.5 *vs.* > 5 $m \cdot s^{-1}$) or the large match-to-match variability of high-speed running (Table 4) (Kempton et al., 2014) which was not considered as a random effect within the statistical analyses of previous research (Gabbett et al., 2014). Players have previously been shown to demonstrate greater neuromuscular fatigue post-match when exposed to a higher number of collisions (Oxendale et al., 2016) due to associated oedema, inflammation, and physiological damage at a cellular level which is suggested to attenuate force generation capacity thus delay the recovery process (Naughton et al., 2018). Collectively, current study findings demonstrate the positional independence in locomotor and collision activity which has implications for the planning or evaluation of technical–tactical training, and possibly recovery intervention. For example, if training has a predominately attacking focus, then coaches might expect an increase in high-speed locomotor activity per minute for both positional groups, with backs also experiencing large increases in collision frequency.

The findings of our study show a lower between- and within-player variability between matches for average speed (CV range = 5 to 20%) than high-speed (range = 9 to 60%) or collisions (range = 12 to 49%), similar to previous work (Kempton et al., 2014; McLaren et al., 2016). Our estimates of whole match locomotor within-player variability appear higher than those reported in the NRL (total distance = 4%, high-speed [> 15 km·h-1] distance = 15%, very-high-speed [> 21 km·h-1] distance = 37%; Kempton et al., 2014), although we acknowledge key methodological differences between our study and Kempton et al., (2014), such as the greater sample of matches and players, differences in opposition standard, high-speed thresholds and metrics (i.e. intensity *vs.* load), and data exclusion criteria. Nonetheless, this is the first study to report the variability of locomotor characteristics during a World Cup tournament and also the first to report the variability of collision characteristics in rugby league. The large CVs for both within- and between-players suggest that weekly exposure to collisions are unlikely to be consistent. Knowledge of this can have specific implications for the planning of the training and recovery process, given the increased energetic demands of collision activity (Costello et al., 2019) and its subsequent relationships with the time course of recovery (McLellan et al., 2011; Twist et al., 2012; Oxendale et al., 2016). Therefore, careful monitoring of the between-match changes in collision activity could be a useful strategy for practitioners to inform modifications to the prescription of training and recovery modalities. With this in mind, however, our data further indicate inherent difficulty when attempting to evaluate the systematic effects of a training or recovery intervention when using an individual's change in match characteristics during an international tournament since these changes would need to be unrealistically large to say with any confidence that they're not simply noise or normal variation (McLaren et al., 2016).

Whilst knowledge of the locomotor and collision characteristics completed across a whole match are useful, describing their peak values of competition are important to provide valid comparisons with training during technical–tactical sessions. The mean peak average speed completed over a 5-minute window during the RLWC (forward = 121 m·min^{-1} and back = 119 m·min^{-1}) appear slightly higher than that previously reported in the ESL (forwards = ~110 m·min^{-1}; backs = ~113 m·min^{-1}) (Weaving et al., 2019) and NRL (forwards = ~113; backs =

~113 m·min^{-1}) (Johnston et al., 2019). This could be explained by the lower number of match observations and inclusion of a large proportion of knock-out fixtures during the RLWC (*vs.* domestic season) or differences in the microtechnology used to determine the mean peak average speeds (Thornton et al., 2019).

As the RLWC is a quadrennial event that is contested following the completion of the domestic (i.e. NRL or ESL) season, international coaches need to consider how much time to allocate within training to ensure players are appropriately prepared for the physical demands of the tournament. To support practitioners to plan training targets for technical–tactical drills when the aim is to equal or exceed the peak average speeds of matches, Delaney et al., (2017) proposed quantifying the power law relationship between the peak average speeds completed across a range of durations during matches. By quantifying the slope (i.e. rate of decline of peak running intensity) and intercept values of the relationship between the change in peak average speed with the change in duration, practitioners can estimate the likely peak average speed for a given drill for each individual player. Our present study is the first to replicate this method using a within-player approach, using both locomotor and collision data collected during international rugby league matches. Based on the intercept and slope results of our study detailed within Table 5, should a practitioner wish to prescribe a small sided game (e.g., 2-minutes in duration) for the forwards that equals the mean peak average speed during 2017 RLWC matches, a target intensity of approx. 148 m·min^{-1} (2-minute peak m·min^{-1} = 404.6 × 120$^{-0.21}$) would be suggested. This example could assist practitioners to plan the locomotor characteristics of technical-tactical training.

We acknowledge that limitations of our study is the case study design. Although case studies can serve as a powerful tool to bridge the science-practice gap (Halperin, 2018), these reports can lack generalizability to the wider population or sport. Our results therefore represent a specific cross-sectional example of a finals reaching team that is likely to differ for other teams of different nationalities and between successive RLWCs, due to the evolution of the sport itself and rule changes. Our sample size is therefore restricted, which indeed limited further analysis of interest requiring more degrees of freedom (e.g., examining for systematic change in intensity throughout competition, or more granular positional stratification). In efforts to advance our knowledge of international rugby league match characteristics, we recommend that multiple nations participating within elite competition should where possible look to collaborate on larger scale projects. Furthermore, considering data from additional international competitions (e.g., 4 Nations) could prove to be a useful exercise, as the differences between types of international competition is yet to be established. Nonetheless, practitioners and researchers might use our methodology as framework to evaluate their own contexts.

Conclusions

There are distinct locomotor and collision characteristics of attacking and defending phases during professional rugby league match-play. Both forwards and backs have a greater average speed in defence, and greater high speeds per minute in attack during international tournament match-play. For collisions, forwards are exposed to more in defence, while backs have more in attack. There is larger variation between matches for high-speed running and collisions, suggesting the need to consider this when interpreting changes in these characteristics of match-play between different matches.

Disclosure statement

We report no potential conflict of interest.

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Table 1. Median (lower quartile–upper quartile) for whole match; first- and second-half; attack, defence, transition; ball-in-play, ball-out-play; and peak locomotor and collision intensities during the 2017 Rugby League World Cup

Variable	Duration (min)		Average speed ($m \cdot min^{-1}$)		High speed distance per minute ($m \cdot min^{-1}$)		Collisions per minute ($n \cdot min^{-1}$)	
	Forward	Back	Forward	Back	Forward	Back	Forward	Back
Whole match	58 (28 - 93)	90 (60 - 93)	84 (53 - 97)	78 (60 - 96)	4.7 (1.6 - 8.3)	6.2 (3.7 - 10.2)	0.7 (0.4 - 1.4)	0.3 (0.2 - 0.7)
First-Half	32 (10 - 49)	46 (33 - 49)	84 (51 - 103)	85 (65 - 100)	4.4 (1.4 - 9.6)	5.9 (3.2 - 10.2)	0.8 (0.4 - 1.4)	0.3 (0.2 - 0.9)
Second-Half	28 (11 - 47)	44 (27 - 47)	82 (37 - 95)	77 (44 - 97)	4.9 (1.2 - 8.2)	5.7 (1.8 - 10.2)	0.7 (0.3 - 1.9)	0.3 (0.1 - 0.7)
Attack	18 (7 - 32)	29 (20 - 32)	91 (64 - 121)	88 (68 - 116)	6.7 (2.1 - 17.0)	9.5 (5.5 - 19.0)	0.7 (0.3 - 1.7)	0.5 (0.2 - 1.1)
Defence	16 (7 - 31)	24 (15 - 31)	120 (72 - 135)	106 (76 - 128)	3.8 (0.3 - 13.2)	3.8 (0.5 - 20.7)	1.6 (1.0 - 2.9)	0.5 (0.1 - 1.4)
Transition	3 (1 - 7)	5 (3 - 7)	111 (75 - 146)	118 (89 - 171)	7.8 (0.2 - 33.6)	10.2 (0.2 - 44.6)	0.9 (0.2 - 2.5)	0.7 (0.1 - 2.3)
Ball-in-play	37 (18 - 67)	58 (38 - 67)	105 (69 - 124)	98 (73 - 118)	5.5 (1.2 - 11.1)	8.6 (4.9 - 15.4)	1.1 (0.7 - 2.1)	0.5 (0.2 - 0.9)
Ball-out-play	21	34	40	42	10.6	16.1	0.1	0.0

	(5 - 41)	(22 - 41)	(21 - 52)	(23 - 59)	(2.3 - 27.0)	(7.1 - 28.2)	(0.0 - 0.2)	(0.0 - 0.1)
Peak 1-min			171	170	40.5	55.8	4.0	3.0
			(150 - 217)	(145 - 199)	(20.2 - 90.1)	(27.3 - 79.4)	(3.0 - 7.0)	(2.0 - 5.0)
Peak 5-min			121	119	13.8	19.6	1.8	1.0
			(96 - 135)	(93 - 136)	(5.1 - 30.0)	(10.6 - 27.4)	(1.2 - 3.0)	(0.6 - 2.2)
Peak 10-min			104	104	9.3	13.0	1.3	0.7
			(81 - 125)	(86 - 124)	(4.0 - 19.4)	(7.6 - 20.5)	(0.8 - 2.5)	(0.3 - 1.3)

Table 2. Comparison of locomotor and collision characteristics between match phases of play during the 2017 Rugby League World Cup

Variable	Position	Grand mean		Attack *vs.* Defence difference		Inference*
		Attack	Defence	% (90% CI)	Effect size (90% CI)	
Average speed	Forwards	89	117	-24.2	-2.31	Very likely very large (95%)[a]
($m \cdot min^{-1}$)				(-27.4 to -21.0)	(-2.62 to -2.01)	
	Backs	91	105	-13.5	-1.17	Most likely moderate (> 99.9%)[a]
				(-16.3 to -10.7)	(-1.41 to -0.92)	
High speed distance per	Forwards	6.4	3.4	90.4	1.61	Likely large (87%)[a]
minute				(57.3 to 123.6)	(1.02 to 2.19)	
($m \cdot min^{-1}$)	Backs	10.2	3.6	183.5	4.41	Most likely large (> 99.9%)[a]
				(140.2 to 226.7)	(3.37 to 5.45)	

Collisions per minute ($n \cdot min^{-1}$)	Forwards	0.7	1.6	-59.9 (-66.8 to -53.0)	-2.75 (-3.07 to -2.43)	Most likely large (> 99.9%)[a]
	Backs	0.5	0.4	24.0 (-2.8 to 50.9)	0.63 (-0.07 to 1.33)	Likely small/ unlikely trivial (84/13/3)

Numbers are the probability (percentage chance) of the difference (attack vs defence) being the observed magnitude (small/ moderate/ large/ very large). Small effects are presented with the probabilities of being substantially higher in attack/ practically equivalent [trivial]/ substantially higher defence. All other effects are presented with the percent chance of being the observed magnitude (when $P_{small} \geq 95\%$), where the probability of being trivial is most unlikely (< 0.5%; [a]).

Table 3. Comparison of locomotor and collision intensities between match periods during the 2017 Rugby League World Cup

Variable	Position	Grand mean		First- *vs.* Second-Half difference		Inference*
		First-Half	Second-Half	% (90% CI)	Effect size (90% CI)	
Average speed ($m \cdot min^{-1}$)	Forwards	84	79	6.7 (1.7 to 11.7)	0.54 (0.14 to 0.94)	Likely small, unlikely trivial (92/8/0)
	Backs	83	78	7.5 (3.5 to 11.4)	0.58 (0.27 to 0.88)	Very likely small, very unlikely trivial (98/2/0)[a]
High speed distance per minute ($m \cdot min^{-1}$)	Forwards	4.3	4.1	5.9 (-9.3 to 21.1)	0.14 (-0.22 to 0.51)	Unclear (40/54/6)
	Backs	6.4	5.4	17.9	0.70	Likely small, unlikely trivial

				(4.9 to 31.0)	(0.19 to 1.21)	(95/5/0)
Collisions per minute ($n \cdot min^{-1}$)	Forwards	0.7	0.7	0.6 (-10.4 to 11.7)	0.02 (-0.31 to 0.35)	Unclear (18/68/14)
	Backs	0.4	0.3	6.3 (-7.5 to 20.1)	0.18 (-0.21 to 0.57)	Unclear (46/48/6)

Numbers are the probability (percentage chance) of the difference (first- *vs.* second-half) being substantially higher in the first-half/ practically equivalent [trivial]/ substantially higher the second-half. All other effects are presented with the percent chance of being the observed magnitude (when $P_{small} \geq 95\%$), where the probability of being trivial is most unlikely (< 0.5%; [a]).

[a]possibly moderate (45%)

Table 4. Average match performance and the associated within- and between-player variability of locomotor and collision intensities during the 2017 Rugby League World Cup

			Variability (CV [%] (90% CI))	
Variable	**Position**	**Grand mean (raw units)**	**Within-player (match-to-match)**	**Between-player**
Average speed ($m \cdot min^{-1}$)	Forwards	81	9.9 (8.1 to 12.3)	7.6 (4.3 to 13.7)

	Backs	81	6.1 (4.8 to 7.9)	11.5 (6.8 to 19.9)
High speed distance per minute ($m \cdot min^{-1}$)	Forwards	4.3	32 (26 to 41)	33.2 (19 to 60)
	Backs	6.0	19 (14 to 24)	18 (9.4 to 35)
Collisions per minute ($n \cdot min^{-1}$)	Forwards	0.7	25 (20 to 31)	28 (16.4 to 49)
	Backs	0.4	29 (22 to 39)	26 (12 to 58)

Table 5: Intercept and slope values for estimating peak match locomotor and collision intensities. Peak intensities can be estimated as function of time (*t*; seconds) using the following equation: meters or collisions per minute = intercept × t^{slope})

Variable	Position	*r* (90% CI)	R^2	Intercept (90% CI)	Slope (90% CI)
Average speed ($m \cdot min^{-1}$)	Forwards	0.92 (0.90 to 0.93)	0.85	404.6 (388.2 to 421.7)	-0.21 (-0.23 to -0.20)
	Backs	0.92 (0.91 to 0.94)	0.85	381.7 (343.8 to 423.7)	-0.20 (-0.23 to -0.18)
High speed distance per minute ($m \cdot min^{-1}$)	Forwards	0.83 (0.80 to 0.85)	0.69	641.2 (523.9 to 784.8)	-0.66 (-0.72 to -0.61)
	Backs	0.92 (0.91 to 0.94)	0.86	542.0 (458.8 to 640.4)	-0.59 (-0.62 to -0.56)
Collisions per minute ($n \cdot min^{-1}$)	Forwards	0.87 (0.85 to 0.89)	0.76	32.0 (26.9 to 38.0)	-0.50 (-0.55 to -0.46)
	Backs	0.88 (0.86 to 0.90)	0.78	39.4 (32.7 to 47.5)	-0.62 (-0.68 to -0.57)