**Title:** The Use of Accelerometers to Quantify Collisions and Running Demands of Rugby Union Match-Play.

**Running Title:** Player Load$^{TM}$ in rugby union.

**Key Words:** Micro-technology, contact sport, impact, validity

**Authors:**

Gregory Roe[a,b], Matthew Halkier[b] Clive Beggs, Kevin Till[a,b] , Ben Jones[a,b].

[a]Institute for Sport, Physical Activity and Leisure, Leeds Beckett University, Leeds, West Yorkshire, United Kingdom

[b]Yorkshire Carnegie Rugby Club, Headingley Carnegie Stadium, St. Michael's Lane, Leeds, West Yorkshire, United Kingdom.

**Corresponding Author and Address:**

Gregory Roe

Room G07, Cavendish,

Institute for Sport, Physical Activity and Leisure

Centre for Sports Performance

Headingley Campus, Leeds Beckett University

West Yorkshire, LS6 3QS

Phone: 07413280008

Email: g.roe@leedsbeckett.ac.uk

## ABSTRACT

***This study examined the relationship between accelerometer metrics and both collisions and running demands during rugby union match-play. Twelve under-18 forwards and 14 under-18 backs were recruited from a professional rugby union club. Six competitive matches were filmed during which players wore micro-technological units (Optimeye S5, Catapult Innovations, Melbourne, Australia). Video footage was analysed for total collisions, while GPS data was analysed for total distance. Accelerometer metrics analysed were Player load$^{TM}$ (PL), Player Load$^{TM}$ 2D (PL2D), and Player Load$^{TM}$ slow (PLslow). A total of 81 player observations were included in the final analysis. Data were analysed using ordinary least squares regression. A 10-fold cross validation analysis was used to validate the findings. All PL variables demonstrated very large relationships with collisions in the forwards, while PLslow demonstrated the largest relationship (large) with collisions in the backs. Therefore, based on the strong relationship in both forwards and backs, PLslow may provide the most useful metric for measuring collision-based activity in both positional groups during match-play. Additionally, nearly perfect and very large relationships were observed between PL and total distance for forwards and backs respectively, suggesting that PL can be successfully used to quantify running demands when other methods are unavailable, for example during indoor training.***

## INTRODUCTION

Micro-technology devices worn by athletes during training and competition provide practitioners with valuable information regarding external load (Gallo et al., 2015). Global positioning systems (GPS) built into these devices provide information regarding how far an athlete has travelled during a training session or match and the speeds at which this distance was achieved (Cummins et al., 2013). Tri-axial accelerometers, housed within these devices, are used to measure accelerations and decelerations. The accelerometer calculates G-forces (G) by dividing the rate of acceleration and deceleration on each axis by gravity (9.8 $m/s^2$). This information can then be used to rate the level of impacts in collision-based sports. The further inclusion of gyroscopes and magnetometers allows the assessment of orientation and rotation during acceleration and deceleration events (Gastin et al., 2014).

The primary focus of team-sport research involving micro-technology has been on the quantification of training and match-demands using GPS (Cummins et al., 2013). However, during collision-sport training and match-play, many collision and impact activities such as tackling, blocking, rucking and mauling involve minimal horizontal displacement and thus is difficult to quantify using this form of micro-technology. Therefore relying solely on GPS metrics to quantify activity demands in these sports may lead to an underestimation of the external load experienced by players (Boyd et al., 2013). In order to fully understand the stress placed on players and accurately estimate external load, valid measurements of activities involving collisions and impacts must be developed. Tackle detection algorithms are available within the micro-technology software, and have been successfully used for detecting and quantifying hit-ups and tackles in rugby league (Gabbett et al., 2010). However, rugby union also involves other types of collisions (e.g., rucks, mauls), which contribute to a large portion of the total collisions during match-play, particularly in the forwards (Smart et al., 2008). Providing accurate information regarding such collisions requires the time-consuming process of aligning raw accelerometer data with video (Gastin et al., 2014), or sophisticated modelling (Kelly et al., 2012), which may not be feasible for many practitioners. To date, there has yet to be a measure devised and validated for quantifying the collision aspect of training and match-play in rugby union. Such information has implications for recovery, injury risk and muscle damage (Gastin et al., 2014) following training and match-play. Furthermore, it can be used to manipulate training load (Gastin et al., 2014) and improve the specificity of training to more accurately replicate the demands of competition (Boyd et al., 2013),

Recent research in Australian rules football has demonstrated the potential for different accelerometer metrics to assess specific activities during training and match-play. Player Load$^{TM}$ (PL), an accumulation of data from all axes of a tri-axial accelerometer (Catapult Innovations, Melbourne, Australia), has demonstrated a nearly perfect ($r$=0.94) relationship with distance covered (Aughey, 2011). Additionally, Player Load$^{TM}$ Slow (PLslow, PL accumulated during activities when running speed is $<2 m.s^{-1}$ (Catapult Innovations, Melbourne, Australia), has been shown to accumulate to a greater extent during contact, than non-contact small-sided games (Boyd et al., 2010), suggesting that this accelerometer metric is capable of quantifying the collision aspect of match-play. However, the relationship between collisions and PLslow was not assessed, and thus still requires investigation. Furthermore, the use of such accelerometer metrics has yet to be validated in rugby union. Therefore the primary aim of the current study was to investigate the relationship between accelerometer metrics, and running and collision demands of rugby union match-play in forwards and backs. A secondary aim was to investigate if accelerometer metrics differed between forwards and backs. Recent research in senior players has demonstrated large differences in both collisions sustained during match-play (Smart et al., 2008) and in PLslow (McLaren et al., 2015) between forwards and backs. However, no current study has investigated this phenomenon in a single study.

## METHODS

### Experimental Approach to the Problem

In order to assess the relationship between match demands and accelerometer metrics during match-play, accelerometer and GPS data were collected from 6 competitive matches during a single season. Each match was also filmed to quantify the type and amount of collisions sustained by each player.

### Subjects

A total of 26 elite under-18 players including 12 forwards (age 17.4±0.6 years; height 187.3±6.7 cm; body mass 95.7±8.1 kg) and 14 backs (age 17.9±0.6 years; height 180.2±5.1 cm; body mass 83.4±10.2 kg) were recruited from a professional rugby union academy. A total of 81 player observations were used for analysis, 43 for the forwards and 38 for the backs. Each player was involved in a minimum of 75% of the total game time (McLellan and Lovell, 2012). Ethical approval was granted by the University ethics committee and written informed consent was acquired from participants along with parental consent.

### Procedures

During 6 competitive matches, each player wore a specialised vest to house and position a micro-technological unit (Optimeye S5, Catapult Innovations, Melbourne, Australia) in the upper-back region between the shoulder blades. Each unit contained a GPS system sampling at 10Hz, which collected data regarding the locomotive demands of match-play. The units also contained tri-axial accelerometers sampling at 100Hz, which provided information regarding impact acceleration in three planes of movement. The units were turned on prior to the warm-up and turned off following the match. Accelerometer and GPS data were downloaded to a laptop and analysed using Catapult Sprint software (Catapult Innovations, Melbourne, Australia).

Three accelerometer metrics were made available in the Catapult Sprint software (Catapult Innovations, Melbourne, Australia) and analysed from each match; the accumulated PL, Player Load$^{TM}$ 2D (PL2D) and PLslow.

Player Load$^{TM}$ is an accumulation of data collected from all axes (anteroposterior, mediolateral and craniocaudal) and has previously been shown to be reliable in collision-based team sports (Boyd et al., 2011).

1)

$$\sum_{t=0}^{t=n} \sqrt{(fwd_{t=i+l} - fwd_{t=i})^2 + (side_{t=i+l} - side_{t=i})^2 + (up_{t=i+l} - up_{t=i})^2}$$

for $t$ = 0, 0.01, 0.02, 0.03….$n$

Player Load$^{TM}$ 2D is an accumulation of data from the anterioposterior and mediolateral axes only.

2)

$$\sum_{t=0}^{t=n} \sqrt{(fwd_{t=i+l} - fwd_{t=i})^2 + (side_{t=i+l} - side_{t=i})^2}$$

for $t$ = 0, 0.01, 0.02, 0.03….$n$

Player Load Slow is an accumulation of accelerometer data from all 3 axes when GPS velocity is < 0.2 m.min$^{-1}$.

3)

$$\sum_{t=0}^{t=n} \sqrt{(fwd_{t=i+l} - fwd_{t=i})^2 + (side_{t=i+l} - side_{t=i})^2 + (up_{t=i+l} - up_{t=i})^2}$$

for $t$ = 0, 0.01, 0.02, 0.03….$n$ (*values are omitted for velocities* $\geq 2m.s^{-1}$)

(Where *fwd* = forward acceleration, *side* = sideways acceleration, *up* = upwards acceleration, *t* = time; Sprint Help for v5.1, 2013)

The primary locomotive demand analysed from the GPS data was total distance, which has previously been proven reliable (Johnston et al., 2014).

In addition to GPS and accelerometer analysis, the matches were filmed by an expert analyst with a SONY HVR-HD1000 for close views and a SONY Handycam HDR-CX6 for wide-views. Collisions and impacts during match-play were coded by an expert analyst using the same criteria as Smart et al (2008). The specific collisions coded were tackles made, hit-ups, being one of the first three to an attacking breakdown (first three attack), being one of the first three to a defending breakdown (first three defence), total collisions (sum of all collisions sustained during the match) and scrums using Sportscode (Sportec, NSW).

## STATISTICS

Ordinary least squares regression analysis of the data was performed using in-house algorithms written in 'R' (open source statistical software). In order to assess the general applicability of the regression models produced, 10-fold cross-validation was performed, with the root mean square error (RMSE) and the normalized root mean square error (NRMSE) (expressed as a percentage) calculated for the respective measured and cross-validation datasets. For each regression model produced, the difference between the measured and cross-validated NRMSE values was used to quantify the validity of the model. Analysis was performed on the forwards and backs separately. In addition, for the forwards, regression analysis was performed on collision data, with and without the inclusion of scrums. The correlation coefficient was ranked as *trivial* (<0.1), *small* (0.1-0.29), *moderate* (0.3-0.49), *large* (0.5-0.69), *very large* (0.7-0.89) and *nearly perfect* (0.9-0.99) (Hopkins et al., 2009).

Differences in match statistics between forwards and backs were analysed for practical significance using magnitude-based inferences (Batterham and Hopkins, 2006). The threshold to be considered the smallest practically important difference was set at 0.2 x pooled standard deviations (SD), based on Cohen's *d* effect size (ES) principle (Hopkins et al., 2009). The probability that the magnitude of difference was greater than the practically important threshold was rated as <0.5%, *almost certainly not*; 0.5-5%, *very unlikely*; 5-25%, *unlikely*; 25-75%, *possibly*; 75-95%, *likely*; 95-99.5%, *very likely*; >99.5%, *almost certainly* (Hopkins et al., 2009). Those that were less (ES≤0.2) were described as trivial (Batterham and Hopkins, 2006). Where the 90% Confidence Interval (CI) crossed both the upper and lower boundaries of the practically important threshold (ES±0.2), the magnitude of change was described as unclear (Batterham and Hopkins, 2006).

**RESULTS**

Table 1. Results of linear regression analysis with cross-validation for the Forwards for: (i) number of collisions; (ii) number of collisions plus scrums; and (iii) distance travelled

| | **Independent Variables** | **Measured r value, inference and ($r^2$)** | **Measured RMSE (NRMSE)** | **Cross-validated r value, inference and ($r^2$)** | **Cross-validated RMSE (NRMSE)** | ***Difference in model accuracy** |
|---|---|---|---|---|---|---|
| **No. of collisions** | PL | 0.727 *very large* (0.528) | 6.260 (13.61%) | 0.666 *large* (0.444) | 6.818 (14.82%) | 1.21% |
| | PL2D | 0.758 *very large* (0.575) | 5.939 (12.91%) | 0.701 *very large* (0.492) | 6.522 (14.18%) | 1.27% |
| | PLslow | 0.701 *very large* (0.492) | 6.494 (14.12%) | 0.643 *large* (0.414) | 7.001 (15.22%) | 1.10% |
| **No. of collisions plus scrums** | PL | 0.785 *very large* (0.616) | 6.444 (13.43%) | 0.761 *very large* (0.579) | 6.749 (14.06%) | 0.64% |
| | PL2D | 0.817 *very large* (0.667) | 5.996 (12.49%) | 0.796 *very large* (0.633) | 6.299 (13.12%) | 0.63% |
| | Plslow | 0.799 *very large* (0.638) | 6.252 (13.03%) | 0.778 *very large* (0.605) | 6.540 (13.62%) | 0.60% |
| **Distance** | PL | 0.943 *nearly perfect* (0.890) | 328.621 (9.05%) | 0.937 *nearly perfect* (0.878) | 346.550 (9.54%) | 0.49% |
| | PL2D | 0.924 *nearly perfect* (0.853) | 379.982 (10.46%) | 0.915 *nearly perfect* (0.837) | 400.816 (11.03%) | 0.57% |

| | | | | | | |
|---|---|---|---|---|---|---|
| | Plslow | 0.899 *very large* (0.809) | 432.907 (11.92%) | 0.886 *very large* (0.785) | 459.447 (12.65%) | 0.73% |

The relationships between accelerometer metrics, total collisions (with and without scrums) and distance for the forwards are presented in Table 1. All accelerometer metrics demonstrated *very large* relationships with collisions, although the r and $r^2$ values increased slightly when scrums were included. Both PL and PL2D demonstrated almost perfect relationships with total distance, while the relationship between total distance and PLslow was *very large*. The difference in model accuracy between the measured and validated datasets was small for all variables (0.49 to 1.27%).

Table 2. Results of linear regression analysis with cross-validation for the Backs for: (i) number of collisions; and (ii) distance travelled.

| | **Independent Variables** | **Measured r value, inference and ($r^2$)** | **Measured RMSE (NRMSE)** | **Cross-validated r value, inference and ($r^2$)** | **Cross-validated RMSE (NRMSE)** | ***Difference in model accuracy** |
|---|---|---|---|---|---|---|
| | PL | 0.477 *moderate* (0.228) | 5.607 (23.36 %) | 0.362 *moderate* (0.131) | 6.059 (25.25 %) | 1.89 % |
| **No. of collisions** | PL2D | 0.530 *large* (0.281) | 5.410 (22.54 %) | 0.439 *moderate* (0.193) | 5.796 (24.15 %) | 1.61 % |
| | PLslow | 0.613 *large* (0.376) | 5.041 (21.00 %) | 0.551 *large* (0.304) | 5.354 (22.31 %) | 1.30 % |
| **Distance** | PL | 0.898 *very large* | 352.472 (9.80 %) | 0.881 *very large* | 378.162 (10.52 %) | 0.71 % |

| | | | | | | |
|---|---|---|---|---|---|---|
| | | (0.806) | | (0.776) | | |
| | PL2D | 0.880 | 380.263 | 0.853 | 416.953 | 1.02 % |
| | | *very large* | (10.57 %) | *very large* | (11.59 %) | |
| | | (0.774) | | (0.728) | | |
| | Plslow | 0.819 | 458.538 | 0.790 | 491.160 | 0.91 % |
| | | *very large* | (12.75 %) | *very large* | (13.66 %) | |
| | | (0.671) | | (0.624) | | |

The relationships between accelerometer metrics, total collisions and distance are presented for backs are presented in Table 2. PLslow demonstrated the largest relationship with total collisions, while PL demonstrated the largest relationship with total distance. The difference in model accuracy between the measured and validated datasets was small for all variables (0.71 to 1.89%).

Match statistics derived from performance analysis, accelerometer and GPS are presented in Table 3. Forwards were *almost certainly* involved in a greater number of collisions than backs, but *likely* covered less distance.

Table 3: Summary of match statistics derived from performance analysis, accelerometer and global positioning system data.

| | **Forwards** | **Backs** | **Standardised Difference (ES±90%CI)** | **Chances for greater/similar/lower values and inference** |
|---|---|---|---|---|
| Game time (mins) | 66±13 | 70±11 | -0.32±0.37 | 71/28/1 – possibly lower |
| Hit-ups | 4±3 | 4±2 | 0.11±0.37 | 8/57/35 – unclear |
| First 3 (attack) | 11±6 | 4±3 | 1.43±0.38 | 0/0/100 – almost certainly greater |
| First 3 (defence) | 2±2 | 1±1 | 0.40±0.54 | 4/23/73 – possibly greater |
| Tackles | 9±5 | 6±3 | 0.64±0.37 | 0/2/98 – very likely greater |
| Total collisions | 26±9 | 14±6 | 1.32±0.37 | 0/0/100 – almost certainly greater |
| Scrums | 14±5 | | | |
| Player Load | 483±113 | 479±102 | 0.01±0.37 | 17/63/20 – unclear |
| Player Load 2D | 312±75 | 286±58 | 0.30±0.37 | 1/31/68 – possibly greater |
| Player Load slow | 219±52 | 190±41 | 0.51±0.37 | 0/8/92 – likely greater |
| Distance (m) | 4747±1002 | 5201±810 | -0.48±0.36 | 90/10/0 – likely lower |

Data presented as mean ± standard deviation, Cohen's *d* effect size ± 90% CI, probabilities and inferences.

**DISCUSSION**

This study aimed to investigate the relationship between accelerometer metrics, and running and collision demands of rugby union match-play in forwards and backs and compare the accelerometer metrics between forwards and backs. The results indicate that PL variables may be useful for quantifying collision-based activity during rugby union match-play. For both measured and cross-validated data sets, all PL variables demonstrated *very large* relationships with collisions in the forwards, while PLslow demonstrated the largest relationship (*large*) with collisions in the backs. Therefore, based on the strong relationship in both forwards and backs, PLslow may provide the most useful metric for measuring collision-based activity in both positional groups. Additionally, PL exhibited *nearly perfect* and *very large* relationships with total distance in forwards and backs respectively for both measured and cross-validated data sets, and thus can be successfully used to quantify the running demands of rugby union match-play.

At present, a validated metric for quantifying collision-based activity in rugby union match-play has not been reported. However, the results from the present study suggest that accelerometer metrics may provide practitioners with useful information regarding the load accumulated as a result of collision-based activity. For forwards, all PL variables showed *very large* relationships with total collisions, while in backs PLslow demonstrated the greatest relationship (*large*) with total collisions, for both the measured and cross-validated data sets. The difference in the magnitude of relationships between the two positions may be to due to the greater collision activity experienced by the forwards during match-play (Table 3). Findings in professional rugby league players indicate that stronger relationships exist between PL variables and collision activity in playing positions that are exposed to a higher amount of collisions during competition (Gabbett, 2015). Nevertheless, given that PLslow had a relationship with collisions of similar magnitude to other PL variables (PL and PL2D; *very large*) in forwards, and the largest relationship (*large*) with collisions in backs for both the measured and cross-validated data sets, this PL metric may provide the most useful measure of collision activity in all rugby union players. Understanding the collision activity rugby players are exposed to can help inform recovery strategies for players post-match (Roe et al., 2016a, Roe et al., 2016b), and improve the specificity of training (Boyd et al., 2010). An interesting finding of the present study was the increase in strength of relationship between PL variables and collisions when scrums were included in both the measured and cross-validated data sets (Table 1). This finding suggests that scrums may contribute to the overall load sustained by forwards during match-play and therefore unlike in previous research (e.g. Smart et al (2008)), should be considered as part of the over-all collision count when assessing collision activity in this positional group.

Locomotive demands of match-play also demonstrated strong relationships with accelerometer data. *Nearly perfect* and *very large* relationships were observed for forwards and backs respectively between PL and total distance for both the measured and cross-validated data sets, supporting previous findings in elite Australian rules football players (Aughey, 2011). These findings suggest that PL may be an effective alternative to measure locomotive load when other methods of analysis (e.g. GPS) are unavailable (Boyd et al., 2013).

A secondary aim of the present study was to examine the differences in common match statistics between elite academy forwards and backs. *Almost certainly* greater differences between forwards and backs were seen for total collisions, similar to findings in elite senior rugby union players (Smart et al., 2008, Jones et al., 2014).

However, this finding was not fully reflected in the accelerometer data derived from the two groups. The standardized difference between forwards and backs for total collisions was much greater than the difference between PLslow (ES=-1.32 versus -0.51 respectively). The discrepancy may be due to the fact that much of the locomotive activity of rugby union players takes place at low speeds (Cahill et al., 2013). Therefore, as forwards *likely* cover less distance than backs (Table 1), the accumulation of PLslow during match-play in the backs may result from greater distances covered at slow speeds and thus reduce the difference when compared to the forwards.

Locomotive demands of match-play were also different between the forwards and backs, although not to the same extent as has been observed in senior players (Cahill et al., 2013, Jones et al., 2014). *Likely* small differences (ES=0.2-0.6) were observed between the two playing positions for total distance. Similar differences were also observed between the two groups for PL, further supporting the use of this accelerometer metric to quantify the running demands of rugby union match-play.

In summary, this study demonstrated the usefulness of accelerometers for quantifying the demands of rugby union match-play. PLslow demonstrated *very large* and *large* relationships with total collisions in forwards and backs respectively, and therefore represent a useful measure for quantifying rugby union collision-based activity for both forwards and backs. Furthermore, PL exhibited *nearly perfect* and *very large* relationships with total distance in backs and forwards respectively and thus can be successfully used to quantify the running demands of rugby union match-play.

## PRACTICAL APPLICATIONS

Practitioners may confidently use accelerometer metrics to quantify different aspects of match-play in rugby union players. In particular, PLslow provides a useful measure of the load sustained by both forwards and backs during collision activity of match-play. Such information may be used to tailor post-match recovery practices in those who have accumulated a greater total amount during a match. Furthermore, the ability to quantify collision and impact-based activity may also be used to improve the specificity of training to more closely replicate the demands of match-play. Additionally, PL can provide useful information regarding the locomotive demands of rugby union during periods where GPS and time-motion analysis are not available, for example during indoor training or loss of GPS satellite.


## ACKNOWLEDGEMENTS

The authors would like to thank Andrew Rock (Academy director) and all the players who were involved in the project. This research was part funded by Leeds Rugby as part of the Carnegie Adolescent Rugby Research (CARR) project

## REFERENCES


Aughey, R. J. 2011. Applications of GPS technologies to field sports. Int J Sports Physiol Perform, 6, 295-310.

Batterham, A. M. & Hopkins, W. G. 2006. Making meaningful inferences about magnitudes. Int J Sports Physiol Perform, 1, 50-7.

Boyd, L., Gallaher, E., Ball, K., Stepto, N., Aughey, R. & Varley, M. 2010. Practical application of accelerometers in Australian football. Journal of Science and Medicine in Sport, 13, e14-e15.

Boyd, L. J., Ball, K. & Aughey, R. J. 2011. The reliability of MinimaxX accelerometers for measuring physical activity in Australian football. Int J Sports Physiol Perform, 6, 311-21.

Boyd, L. J., Ball, K. & Aughey, R. J. 2013. Quantifying external load in Australian football matches and training using accelerometers. Int J Sports Physiol Perform, 8, 44-51.

Cahill, N., Lamb, K., Worsfold, P., Headey, R. & Murray, S. 2013. The movement characteristics of English Premiership rugby union players. J Sports Sci, 31, 229-37.

Cummins, C., Orr, R., O'Connor, H. & West, C. 2013. Global positioning systems (GPS) and microtechnology sensors in team sports: a systematic review. Sports Med, 43, 1025-42.

Gabbett, T., Jenkins, D. & Abernethy, B. 2010. Physical collisions and injury during professional rugby league skills training. J Sci Med Sport, 13, 578-83.

Gabbett, T. J. 2015. Relationship Between Accelerometer Load, Collisions, and Repeated High-Intensity Effort Activity in Rugby League Players. J Strength Cond Res, 29, 3424-31.

Gallo, T., Cormack, S., Gabbett, T., Williams, M. & Lorenzen, C. 2015. Characteristics impacting on session rating of perceived exertion training load in Australian footballers. J Sports Sci, 33, 467-75.

Gastin, P. B., Mclean, O. C., Breed, R. V. & Spittle, M. 2014. Tackle and impact detection in elite Australian football using wearable microsensor technology. J Sports Sci, 32, 947-53.

Hopkins, W. G., Marshall, S. W., Batterham, A. M. & Hanin, J. 2009. Progressive statistics for studies in sports medicine and exercise science. Med Sci Sports Exerc, 41, 3-13.

Johnston, R. J., Watsford, M. L., Kelly, S. J., Pine, M. J. & Spurrs, R. W. 2014. Validity and interunit reliability of 10 Hz and 15 Hz GPS units for assessing athlete movement demands. J Strength Cond Res, 28, 1649-55.

Jones, M., West, D., Harrington, B., Cook, C., Bracken, R., Shearer, D. & Kilduff, L. 2014. Match play performance characteristics that predict post-match creatine kinase responses in professional rugby union players. BMC Sports Sci Med Rehabil, 6, 38.

Kelly, D., Coughlan, G., Green, B. & Caulfield, B. 2012. Automatic detection of collisions in elite level rugby union using a wearable sensing device. Sports Eng, 15, 81-92.

McLaren, S. J., Weston, M., Smith, A., Cramb, R. & Portas, M. D. 2015. Variability of physical performance and player match loads in professional rugby union. J Sci Med Sport. (Ahead of Print)

MCLELLAN, C. P. & LOVELL, D. I. 2012. Neuromuscular responses to impact and collision during elite rugby league match play. J Strength Cond Res, 26, 1431-40.
ROE, G., DARRALL-JONES, J., TILL, K. & JONES, B. 2016a. Preseason Changes in Markers of Lower-body Fatigue and Performance in Young Professional Rugby Union Players. Eur J Sport Sci. (In Press)
ROE, G., TILL, K., DARRALL-JONES, J., PHIBBS, P., WEAKLEY, J., READ, D. & JONES, B. 2016b. Changes in Markers of Fatigue Following a Competitive Match in Academy Rugby Union Players. South Afric J Sports Med, (In Press)
SMART, D. J., GILL, N. D., BEAVEN, C. M., COOK, C. J. & BLAZEVICH, A. J. 2008. The relationship between changes in interstitial creatine kinase and game-related impacts in rugby union. Br J Sports Med, 42, 198-201.