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The relative contribution of training intensity and duration to daily measures of training load in professional rugby league and union.

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Abstract

This study examined the relative contribution of exercise duration and intensity to team-sport athlete's training load. Male, professional rugby league (n = 10) and union (n = 22) players were monitored over 6- and 52-week training periods, respectively. Whole-session (load) and per-minute (intensity) metrics were monitored (league: session rating of perceived exertion training load [sRPE-TL], individualised training impulse, total distance, BodyLoad™; union: sRPE-TL, total distance, high-speed running distance, PlayerLoad™). Separate principal component analyses were conducted on the load and intensity measures to consolidate raw data into principal components (PC, $k = 4$). The first load PC captured 70% and 74% of the total variance in the rugby league and rugby union datasets, respectively.. Multiple linear regression subsequently revealed that session duration explained 73% and 57% of the variance in first load PC, respectively, while the four intensity PCs explained an additional 24% and 34%, respectively. Across two professional rugby training programmes, the majority of the variability in training load measures was explained by session duration (~60–70%), while a smaller proportion was explained by session intensity (~30%). When modelling the training load, training intensity and duration should be disaggregated to better account for their between-session variability.

Introduction

Measuring the training load of an athlete provides coaches and sports scientists with a quantitative representation of two theoretical constructs: the intensity and duration of the stimulus prescribed to an athlete (i.e. the external load) and their response across psycho-physiological and biomechanical pathways (i.e. the internal load) (Vanrenterghem et al., 2017). It can be measured by a variety of sources (e.g. Global Positioning Systems [GPS], heart-rate-monitors, perceptual-based) (Akubat et al., 2012; Weaving et al., 2014; McLaren et al., 2017). Irrespective of the measurement method, it is common practice to mathematically represent this construct for each individual training session by multiplying a measure of intensity with the duration of the activity completed to amalgamate into a single value (i.e. training load). For example, a 60 min training session spent at a Borg category-10 ratio scale of 5 would yield a session RPE training load (sRPE-TL) value of 300 arbitrary units (AU) (i.e. 5 x 60) (Foster et al., 2001). Similarly, moving at a mean speed of 1.5 $m \cdot s^{-1}$ for 60 minutes would yield a total-distance of 5400 m for the whole session (Lovell et al., 2013; Weaving et al., 2014). Repeated measures of daily training load are then collated within time-series analyses to represent how the previously defined constructs of training load accumulate and decay over time (e.g. across a training programme) such as week-to-week summations (e.g. 17000 m) (Akubat et al., 2012; Taylor et al., 2018) moving-averages or exponentially-weighted-moving-averages (Hulin et al., 2015; Williams et al., 2016; Cummins et al., 2018).

Given the lack of a gold-standard criterion, valid measurements of training load and their representation in time series analyses are thought to be those that can show a dose-response relationship with the outcomes of a training period such as changes in fatigue response, training induced adaptation, injury status or performance (Akubat et al., 2012; Sanders et al. 2017; Fox et al., 2018; Taylor et al., 2018). Recent investigations question the ability of current training load methods variables to accurately predict future training outcomes, such as injury, even when sophisticated analysis techniques are used (Carey et al., 2017; Fanchini et al., 2018). Methodological issues have been reported to contribute to these findings, including the discretisation of continuous training load data (Carey et al., 2018), mathematical coupling (Lolli et al., 2018) and inappropriate use of ratios (Lolli et al., 2018). Although these are important, an unconsidered area is how training load is mathematically represented for an individual training session.

One unconsidered area is the hierarchical level in which training load variables are aggregated (e.g. seconds, min, hourly, daily, weekly, monthly or yearly) (Anthanasopoulous et al., 2017). For example, the highest hierarchical level of data aggregation within a training load context might be a macrocycle (i.e. yearly [e.g. 270,000 m]) then mesocycle (i.e. monthly [e.g. 41,000 m]) then microcycle (i.e. weekly [e.g. 14,500 m]) down to the lowest currently reported level of daily training load (e.g. 3,000 m). However, there has been little evaluation of the validity of amalgamating the intensity and duration of an individual/daily training session into a single variable. This is important to evaluate as most methods used to quantify training load (e.g., heart rate or GPS) sample at much higher frequencies (e.g. heart beat-to-beat, 10 Hz GPS speed sampling frequency). In other disciplines, time-series data represented at higher frequencies (e.g. min *vs.* daily) have been shown to provide different information to aggregated data at higher hierarchical levels, and by combining the information provided between the different levels of the temporal hierarchy (e.g. min by min, daily, weekly, monthly) forecasting accuracy has been shown to improve (Anthanasopoulous et al., 2017). Considering this, given the perceived importance of training load monitoring (Akenhead & Nassis, 2015) it is necessary to evaluate the validity of current mathematical representations of training load, including the amalgamation of training session intensity and duration into a single value. However, the issue of time-series aggregation in respect to the monitoring of training load has been largely ignored.

Conceptually, this is important to consider as historically, there has been much theoretical and experimental debate as to whether it is the volume or intensity of training that is most efficacious and/or effective to drive training-induced adaptations or other outcomes of training such as injury (Hawley, 2008; Seiler, 2010; Seiler et al., 2013). Although the representation of training volume is often accepted as the duration of the session (time [s or min]), the most appropriate method to represent the intensity of a training session is disputed (Banister, 1975; Akubat & Abt, 2011; Akubat et al., 2012). For example, in team sports, using the mean intensity (e.g. either mean speed, rating of perceived exertion or heart rate) of a session leads to a loss of information by not taking into account the exponential physiological response to increasing exercise intensity during intermittent exercise (Akubat & Abt, 2011). This has led to methods of individualising the numerical representation of training intensity. The individualised training impulse (iTRIMP) was developed (Manzi et al., 2009) to alleviate this issue, by weighting the exercise intensity using each individual's heart-rate–blood-lactate relationship established during incremental exercise. From this, the current iTRIMP method is to calculate an iTRIMP value for each heart beat and then sum to aggregate into a single value for that daily training session.

Considering this theoretical debate concerning the importance of session duration and intensity, it would seem counterintuitive to amalgamate intensity and duration into a single value. This is because, even when adopting a sophisticated individualisation of training intensity (e.g. iTRIMP), the mathematical method of aggregating volume and intensity into a single value for each daily training session means there is a subsequent loss of information regarding training intensity when collecting repeated measurements of daily training load across a training programme. This is because the between-session variability in intensity is also concurrently bound to the between-session variability in training duration. For example, two different daily training sessions (e.g. long duration, low intensity; low duration, high intensity) can provide the same daily training load value despite clear differences in the intensity and durations of the sessions. Therefore, when collecting repeated measures within a time-series representation (e.g. daily training load over a two-year period of time), the two daily training sessions are numerically represented as being the same and subsequently inferred to elicit the same type and magnitude of training adaptation or outcome over time, despite clear differences in the intensity and volume of the exercise prescription. Despite the widespread use of these practices in professional team sports, little is known regarding the extent to which the variability in multiple aggregated daily training session values (e.g., sRPE-TL = 420 AU; iTRIMP = 212 AU) over a period of training are affected by the variability in the duration or intensity of the training sessions. Specifically, further examination of how much of the variability in training load measures is captured by both duration and intensity across a period of training is needed.

Therefore, the aim of the current study was to investigate the relationship between session duration, intensity and load represented by many common measures in professional rugby league and rugby union players across a period of training. In particular, in order to better represent the total training-load- and intensity-related information, principal component analysis (PCA) was used to construct orthogonal (i.e. uncorrelated) linear-weighted composite variables (principal components, PCs) from training intensity and load variables collected across both professional rugby union and rugby league training programmes. Consolidating raw data into principal components as such eliminates redundancy and collinearity in the measured variables and thus identifies more clearly the key relationships between constructs of training intensity, duration, and load.

Methods

Participants

Ten male professional rugby league players from the same European Super League club (mean [standard deviation; SD]): age: 25 [3] y; stature 185 [6] cm; mass 94.0 [8.3] kg) and twenty-two male professional rugby union players from the same Championship club (mean [SD]: age: 27 [4] y; stature 187 [7] cm; mass 102.2 [13.1] kg) took part in the investigation. Written informed consent was provided by all players prior to participation in the study. Institutional ethics approval was granted prior to commencement of the study, which conformed to the Declaration of Helsinki.

Design

Observational research designs were conducted across a 6-week pre-season (rugby league) and 52-week complete season (rugby union). Subject to player availability (e.g. injury, selection to match-day squad), training load, intensity and volume were monitored in every field-based training session or match (rugby league; n = 24 sessions; rugby union; n = 179 sessions). Rugby league and rugby union players provided a mean (SD) of 19 (4) and 103 (36) sessions, respectively (total individual observations; rugby league: n = 197; rugby union: n = 2266).

In the rugby league dataset, measures of session training load collected were sRPE-TL (AU), iTRIMP (AU), total-distance (m) and BodyLoad™ (AU). Session intensity was calculated by normalising each training load measure by the session duration. Measures of session intensity were sRPE (AU), iTRIMP per min ($AU \cdot min^{-1}$), $m \cdot min^{-1}$, and BodyLoad per min ($AU \cdot min^{-1}$).

In the rugby union dataset, measures of session training load collected were sRPE-TL (AU), PlayerLoad™ (AU), total- and individualised-high-speed-distance (m). Measures of session intensity were sRPE (AU), PlayerLoad per min ($AU \cdot min^{-1}$), meters per min ($m \cdot min^{-1}$), and individualised-high-speed-distance per min ($m \cdot min^{-1}$).

In both datasets, session duration (min) was the sole measure of session volume.

Methodology

Training load variables were collected using either GPS, tri-axial accelerometer, heart rate or category-ratio scaling methods during or following each session or match. Prior to the commencement of the study, all players were familiarised with these methods of data collection as per the club's usual practices. The content of the training programmes was prescribed by the respective coaching staff with no input from the research team.

Whole-session training load measurements

Rugby league dataset

Total-distance was measured during each training session using the GPS component of the microtechnology device (SPI Pro XII, GPSports, Canberra, Australia) which attains a 15 Hz sampling rate through linear interpolation of the 5 Hz GPS chip (Weaving et al., 2014). These specific devices have been reported to provide an acceptable degree of validity and reliability during a high-intensity, intermittent, team-sport specific circuit (Johnston et al., 2014). Throughout the data collection period, the mean (SD) number of satellites and horizontal dilution of precision was 9 (1) and 0.97 (0.32), respectively suggesting suitable accuracy of the data (Malone et al., 2017). A 100 Hz tri-axial accelerometer also housed within the SPI Pro XII was used to collect BodyLoad™, which is a vector magnitude measure that aims to account for the total external load resulting from accelerations, decelerations, changes of direction and impacts and was collected as per previous methods (Lovell et al., 2013; Weaving et al., 2014). The tri-axial accelerometer used to quantify BodyLoad™ has previously demonstrated acceptable validity and reliability to quantify accelerations (Kelly et al., 2015). Both total-distance and BodyLoad™ were calculated and exported from the manufacturer's proprietary software (TeamAMS Version 16.1, GPSports, Canberra, Australia).

iTRIMP was calculated by modelling each player's heart rate-blood lactate response established during an incremental treadmill test (5 x 4 min stages commencing at 7 $km \cdot h^{-1}$ and incrementing by 2 $km \cdot h^{-1}$) and from that determining a weighting factor that was then applied to each heart rate measured during training and matches as per previous methods (Akubat et al., 2012; Manzi et al., 2013; Weaving et al., 2014; Taylor et al., 2017). Heart rate was collected during each training session (every 5 s) using Polar heart rate straps (T14, Polar, Oy, Finland) which transmitted continuously to the microtechnology device (SPI Pro XII, GPSports, Canberra, Australia). To determine the total iTRIMP value for each session, each 5 s heart rate during the session was weighted according to the individuals own established weighting factors and summed. Raw heart rate data for every training session were exported from the GPS manufacturer software (TeamAMS Version 16.1, GPSports, Canberra, Australia) into dedicated software to determine individual session iTRIMP values (iTRIMP Software, Training Impulse LTD, UK).

Rugby union dataset

Each player wore a microtechnology device (Optimeye X4, Catapult Innovations, Melbourne, Australia; firmware version: 7.17) containing 10 Hz GPS, 100 Hz tri-axial accelerometer, gyroscope and magnetometer. GPS-based measures of total-distance and individualised high-speed-distance were downloaded to, and then exported from, proprietary Catapult Openfield Software (version 1.12.0). High-speed-distance thresholds were individualised for each player as a percentage (> 61%) of the maximal velocity achieved during a 40 m maximal sprint which was assessed using the microtechnology device at regular intervals during the data collection period (Roe et al., 2016).

PlayerLoad™ was derived from the 100 Hz tri-axial accelerometer as per previous methods (Boyd et al., 2011). Throughout the data collection period, the mean (SD) number of satellites and horizontal dilution of precision was 12 (1) and 0.72 (0.27), respectively suggesting suitable accuracy of the data (Malone et al., 2017).

For both the rugby league and rugby union datasets, each player provided their sRPE with limited third-party observation ~30 minutes after the completion of each training session and match, using a modified Borg category ratio-10 scale (Foster et al., 2001). This rating was then multiplied by training session duration to give sRPE-TL (Foster et al., 2001).

Statistical Analysis

All analyses were performed separately on the rugby league and rugby union datasets. In both datasets, PCA was conducted twice using a custom-built algorithm in R (R v1.1.3, R Foundation for Statistical Computing, Vienna, Austria)—first, on the training load variables and then secondly on the intensity variables. In each case, PCA involved mean-adjusting and standardising the data to unit variance, and constructing a n by m matrix, X, containing m measured variables, each comprising n observations representing the individual training sessions. From these, the respective covariance matrices, X^TX, were computed and eigen-decomposition performed to generate the eigenvalues and eigenvectors for each covariance matrix. The original (mean adjusted and standardized) data were then projected into the eigenspace of the covariance matrix, to construct a pair of n by m matrices containing the PC 'scores' for the respective training load and intensity data sets. Having done this the proportion of variance attributable to each constructed PC was determined from the respective eigenvalues.

Subsequently, multiple linear regression analysis was used with a simultaneous enter method to examine the contribution of duration (first independent variable) and intensity (second to fifth independent variables, represented by four PCs) on each of the four training load PCs (dependent variables). The strength of each bivariate association was calculated using Pearson's r, with 95% confidence intervals (CI) used to represent uncertainty in the estimates. To determine how much of the variance in each training load PC could be explained by volume (session duration) and intensity, the coefficient of determination (R^2) was calculated for each stage of all models in both the rugby league and rugby union datasets. Variable inflation factors for the rugby league (duration = 1.16; 1st intensity PC = 1.00; 2nd intensity PC = 1.05; 3rd intensity PC = 1.07; 4th intensity PC = 1.03) and rugby union (duration = 1.19; 1st intensity PC = 1.08; 2nd intensity PC = 1.05; 3rd intensity PC = 1.06; 4th intensity PC = 1.00) demonstrated minimal levels of multicollinearity within the regression models.

Results

Whole-session training load and intensity

Table 1 describes the mean and standard deviations of the observed training load and intensity variables for the rugby league and rugby union datasets.

Table 2 describes the results of the principal component analysis (% of variance explained by each principal component and associated eigenvectors) for 1.) the measured training load variables and 2.) the measured training intensity variables for both the rugby league and rugby union datasets.

Session duration and regression analyses

For the rugby league and union datasets, the mean (SD) session durations were 44 (16) and 75 (30) min, respectively.

Figure 1 displays the scatterplots and r value (95% confidence interval) for the relationship between the 1st (Fig 1A), 2nd (Fig 1B), 3rd (Fig 1C) and 4th (Figure 1D) training load PCs with session duration for the rugby league dataset.

Figure 2 displays the scatterplots and r value (95% confidence interval) for the relationship between the 1st (Fig 2A), 2nd (Fig 2B), 3rd (Fig 2C) and 4th (Figure 2D) training load PCs with session duration for the rugby union dataset.

Table 3 and 4 present the results of the linear regression models for the rugby league (Table 3) and rugby union (Table 4) datasets, reporting the magnitude of variance (r^2) in the 1st to 4th training load PCs that was captured by duration and the intensity PCs.

In the rugby league dataset, session duration explained 73% of the variance in the 1^{st} training load PC and the combined intensity PCs explained 24% of the variance (Table 4). The intensity PCs explained more of the variance for the lower ranked training load PCs: 2^{nd} (r^2 = 0.76), 3^{rd} (r^2 = 0.75) and 4^{th} (r^2 = 0.80), with duration explaining 3–15% (Table 3).

In the rugby union dataset, session duration explained 57% of the variance in the 1^{st} training load PC and the combined intensity PCs explained 34% of the variance (Table 4). The intensity PCs explained more of the variance in the lower ranked training load PCs: 2^{nd} (r^2 = 0.84), 3^{rd} (r^2 = 0.82) and 4^{th} (r^2 = 0.71), with duration explaining 0–5% (Table 4).

Figure 1. Rugby league dataset. Scatterplots and r value [95% confidence interval] for the relationship between 1^{st} (Fig 1A), 2^{nd} (Fig 1B), 3^{rd} (Fig 1C) and 4^{th} (Figure 1D) training load PCs and session duration.

Figure 2. Rugby union dataset. Scatterplots and r value [95% confidence interval] for the relationship between 1^{st} (Fig 3A), 2^{nd} (Fig 3B), 3^{rd} (Fig 3C) and 4^{th} (Figure 3D) training load PCs and session duration.

Discussion

The main finding of the current study is that the majority of combined variance captured in the measured training load variables is explained by session duration. This was evidenced as PCA revealed that the 1^{st} PC accounted for 70% and 74% of the total training load variance in the rugby league and union datasets, respectively. Subsequently, session duration was able to account for 73% and 57% of these variances (Table 3 and 4, respectively), suggesting that the majority of the aggregated whole training load metrics provide a greater reflection of session duration. While the majority of the variance in the measured training load appears to be associated with duration, the much weaker relationship between duration and the lower ranked training load PCs in the rugby league (2^{nd}: R^2 = 0.15; 3^{rd}: R^2 = 0.08 and 4^{th} R^2 = 0.03; Table 3) and rugby union datasets (2^{nd}:Rr^2 = 0.05; 3^{rd}: R^2 = 0.01 and 4^{th} R^2 = 0.00; Table 4) show that other factors, such as intensity, have a more auxiliary contribution to measures of training load.

Collectively, the results of this study suggests that session duration reflected the largest portion of the variance shared by the aggregated daily training load variables over the training periods within professional rugby league and union training. As the summation and moving- or exponentially-weighted moving average of these daily training load values are used to relate to important training outcomes such as injury (Hulin et al., 2016) or changes in physiological adaptation (Akubat et al., 2012; Taylor et al., 2017), researchers and practitioners should note that these representations could be predominately representing the inherent variability in the duration of sessions across periods of time. This is logical, as total-distance is the mean speed of the session multiplied by the duration of the session, whereas sRPE-TL is the players' perceived intensity of the session multiplied by the session duration. Therefore, although intensity is reflected by these measures, by aggregating with session duration, it appears that duration becomes the major contributory component to the variability in training load over a period of time.

To better understand the contribution of intensity to the representation of training load, the training load variables were normalised to session duration (whole session training load divided by session duration) and multiple linear regression performed using the intensity PC scores (Table 3 and 4). Indeed, when the 1^{st} to 4^{th} PC scores of intensity were regressed onto the individual training load PC scores, training intensity had a smaller contribution towards the total explained variance within the first (primary) training load PC (~30%). Interestingly, the combined intensity PCs were much more strongly related to the lower ranking (i.e., capturing less total variance) training load PCs (*rugby league*: 2^{nd} PC: R^2 = 0.76; 3^{rd} PC: R^2 = 0.75; and $4^{th:}$ PC: R^2 = 0.80; *rugby union*: 2^{nd} PC: R^2 = 0.84; 3^{rd} PC: R^2 = 0.82; and $4^{th:}$ PC: R^2 = 0.71) than to the 1^{st} training load PC (*rugby league:* R^2 = 0.24; *rugby union:* R^2 = 0.34). These findings therefore support the lesser, relative contribution of intensity to training load measures, providing additional evidence to suggest that session duration is a primary explanatory variable.

Despite these findings, there is still much debate over whether it is the intensity or duration of the training session that is more important in driving adaptation or training induced responses which is likely dependent on the specific sport (Hawley, 2008). For example, in world class endurance runners, both the total volume of training (r = 0.75 to 0.77) and high-intensity-interval training volume (0.53 to 0.56) completed over 3 to 7 year periods were substantially related to performance in this cohort.

(International Association of Athletics Federations [IAFF] Score) (Casado, Handley, Santos-Concejero, Ruiz-Perez, 2019). Therefore, theoretically, it is currently unclear whether it is duration or intensity that should be given more weighting within the representation of training load and future consensus is needed to establish how much weighting should be given to duration or intensity. However, the findings also suggest that for practitioners who manage large squads of players and do not have the resources to utilise such methods (e.g. community sport settings, youth teams), training duration could be a simple and cost-effective introductory approach to monitoring the training load of their athletes, as it provides adequate surrogate information of commonly used training load measures that have been reported to associate with outcomes such as injury (Hulin et al., 2015; Cummins et al., 2018). For researchers and practitioners working at the elite level in team-sports, the findings suggest that time-series methods that can consider more granular representations of training intensity and duration (i.e. training load) should be explored in an attempt to provide greater sensitivity to explain important training outcomes such as changes in fitness, injury risk and/or performance.

In the first instance, a disaggregation of daily training intensity and duration could be used when modelling training load. For example, rather than multiplying intensity and duration into a single daily variable (i.e. vector), disaggregating the training load into two individual variables of duration and training intensity within the model could be used to alleviate the co-dependence (between intensity and duration) that arises when aggregating into a single daily value. Alternatively, future research should explore the disaggregation of training load data at more granular levels. For example, while sRPE and average speed ($m \cdot min^{-1}$) provide an average session intensity, the iTRIMP provides a measure of intensity every 5s by multiplying with each individuals own weighting factor from the heart-blood lactate relationship during an incremental test (Akubat et al., 2012; Weaving et al., 2014). Therefore, for a 60-min training session, 720 individual iTRIMP values are generated. However, by simply summating/aggregating these multiple iTRIMP values into a single value for the daily training session, it is highly likely that valuable information regarding the within- and between-session fluctuations in session intensity are overlooked (i.e. lower intensity, higher duration session *vs.* higher intensity, lower duration session). This omitted information could potentially provide practitioners and researchers with a more valid and reproducible signal of the true training load prescribed to team sport athletes. While the use of GPS tracking and heart rate is commonplace, much work still remains regarding the development of suitable signal processing approaches that can optimise the available training load data collected. For example, the use of Fourier transforms to analyse the frequency content of time series signals is widely used in other disciplines (Kammler, 2007; Walker, 2017) as is taking into account the combined information provided by all available levels of the temporal hierarchy (e.g. yearly, monthly, weekly, daily, minutes, seconds) when forecasting future outcomes like injury or training induced adaptations (Oliveria & Ramos, 2019). The findings of the current study suggest that such methods warrant future consideration when modelling the training load and responses over time to mitigate the predominant reflection of session duration when representing repeated measurements of training load across a training period.

Finally, the study is not without its limitations. Whilst we have considered a number of different variables to represent the internal and external training load it is likely that the observed relationships might not hold true with the inclusion of other training load variables. In addition, whilst we conducted the analysis on two separate rugby codes, both datasets involved training prescription from a single club meaning the training practices (and the subsequent observed relationships between training intensity, duration and load) employed might not be representative of other sports and different training prescriptions.

Conclusions

The current use of training load measures that aggregate training duration and intensity into single daily values are unlikely to provide much additional information to that provided by the duration of the training session across professional rugby league and rugby union training programmes. Future research needs to establish methods of representing the training load within time series analysis that can appropriately account for variability in training intensity between sessions.

Table 1. Mean ± standard deviation of the observed training load and training intensity variables for the professional rugby league and rugby union datasets.

	Training Load	**Training Intensity**
Rugby League Dataset		
Total Distance	3069 ± 1451 m	70.1 ± 21.8 $m \cdot min^{-1}$
iTRIMP	242 ± 98 AU	7.1 ± 2.2 $AU \cdot min^{-1}$
BodyLoad	63.3 ± 48 AU	1.5 ± 1.0 $AU \cdot min^{-1}$
sRPE-TL	276 ± 151 AU	6.2 ± 1.7 AU
Rugby Union Dataset		

Total Distance	4567 ± 1973 m	63.2 ± 19.1 m·min^{-1}
Individualised High-Speed Distance	201 ± 264 m	2.7 ± 3.0 m·min^{-1}
PlayerLoad	427 ± 191 AU	5.9 ± 1.8 AU·min^{-1}
sRPE-TL	298 ± 178 AU	3.8 ± 1.8 AU

Table 2. Results of the two principal component analyses for the training load and training intensity measures. Including the % of variance explained and eigenvectors (component loadings) for each principal component.

	Load PC1	Load PC2	Load PC3	Load PC4	Intensity PC1	Intensity PC2	Intensity PC3	Intensity PC4
Rugby league								
% of variance explained	69.5	17.1	10.6	2.7	63.0	22.7	8.7	5.4
iTRIMP	0.50	0.22	0.84	0.01	-0.54	0.27	-0.69	0.40
Total-Distance	0.54	-0.06	-0.30	0.78	-0.56	-0.31	-0.13	-0.76
BodyLoad ™	0.46	-0.78	-0.08	0.41	-0.49	-0.56	0.45	0.51
sRPE-TL	0.49	0.58	-0.45	0.47	-0.41	0.72	0.55	-0.08
Rugby union								
% of variance explained	73.8	14.9	11.3	0.0	62.6	20.2	14.5	2.7
Total-Distance	0.51	0.03	-0.29	0.73	0.62	-0.07	-0.30	0.72
High Speed	0.31	-0.91	0.25	-0.10	0.46	-0.30	0.83	-0.08
PlayerLoad™	0.50	0.09	-0.16	0.00	0.62	0.08	-0.37	-0.69
sRPE-TL	0.39	0.37	0.83	0.00	0.14	0.95	0.27	0.08

Table 3. Results of the linear regression models from the rugby league dataset.

Response Variable	**Predictor Variables**		**R^2 Change**	**R^2 Accumulated**
Training Load PC1	Duration		**0.73**	**0.73**
	Duration + Intensity PC1–4		**0.24**	**0.97**
Training Load PC2	Duration		**0.15**	**0.15**
	Duration + Intensity PC1–4		**0.76**	**0.91**
Training Load PC3	Duration		**0.08**	**0.08**
	Duration + Intensity PC1–4		**0.75**	**0.83**
Training Load PC4	Duration		**0.03**	**0.03**
	Duration + Intensity PC1–4		**0.80**	**0.83**

Table 4. Results of the linear regression models from the rugby union dataset.				
Response Variable	**Predictor Variables**		R^2	
			Change	**Accumulated**
Training Load PC1	Duration		**0.57**	**0.57**
	Duration + Intensity PC1–4		**0.34**	**0.91**
Training Load PC2	Duration		**0.05**	**0.05**
	Duration + Intensity PC1–4		**0.84**	**0.89**
Training Load PC3	Duration		**0.01**	**0.01**
	Duration + Intensity PC1–4		**0.82**	**0.83**
Training Load PC4	Duration		**0.00**	**0.00**
	Duration + Intensity PC1–4		**0.71**	**0.71**

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