Title: Monitoring what matters: A systematic process for selecting training load measures

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ABSTRACT

Purpose: Numerous derivative measures can be calculated from the simple session-Rating of Perceived Exertion (sRPE) tool for monitoring training loads (e.g., acute:chronic workload and cumulative loads). The challenge from a practitioner's perspective is to decide which measures they should calculate and monitor in their athletes for injury prevention purposes. The aim of the current study was to outline a systematic process of data reduction and variable selection for such training load measures. **Methods:** Training loads were collected from 173 professional Rugby Union players during the 2013/14 English Premiership season, using the sRPE method, with injuries reported via an established surveillance system. Ten derivative measures of sRPE training load were identified from existing literature and subjected to principal-component analysis. A representative measure from each component was selected by identifying the variable that explained the largest amount of variance in injury risk from univariate generalised linear mixed-effects models. **Results:** Three principal components were extracted, explaining 57%, 24%, and 9% of the variance, respectively. The training load measures that were highly loaded on component one represented measures of the 'cumulative load' placed on players, component two was associated with measures of 'changes in load', and component three represented a measure of 'acute load'. Four-week cumulative load, acute:chronic workload and daily training load were selected as the representative measures for each component. **Conclusions:** The process outlined in the current study enables practitioners to monitor the most parsimonious set of variables, whilst still retaining the variation and distinct aspects of 'load' within the data.

Key Words: rugby, injury, workload, RPE, team sports

INTRODUCTION

Training load monitoring is currently a prominent issue in elite team sports settings, particularly as a tool to identify those athletes at risk of injury, illness, and non-functional overreaching.[1] The Session-Rating of Perceived Exertion (sRPE) method developed by Foster[2] is amongst the most commonly used measures for quantifying internal workloads in elite team sports.[3] This simple approach involves multiplying the athlete's RPE for a given session (typically using a 1–10 scale) by the duration of the session (in minutes), to derive a training load in arbitrary units (AU). One benefit of this approach is that it can be used to quantify the various training modalities undertaken by team sport athletes, including resistance training[4] and pitch-based conditioning and skills sessions.[5] In addition, the sRPE method has been shown to relate favourably with objective load measures, including heart rate,[6] blood lactate,[6] and match events (e.g., body impacts).[7,8] Thus, the sRPE method represents an inexpensive and highly practical tool for the monitoring of training loads in this setting.

A number of derivative measures of internal training load can be calculated from the daily sRPE values, and investigated with respect to injury risk. For instance, cumulative loads can be calculated by summing a player's sRPE load values over a specified period (e.g., the preceding four weeks),[9,10] whilst changes in load can be assessed by analysing the week-to-week change between the current and previous week's total.[10] More recently, the 'acute-chronic workload ratio' has been used to determine if the comparison of acute (1-week data) to chronic (average weekly load calculated over a rolling 4-week period) load is associated with increased injury risk.[11,12] A number of additional derivative measures from the sRPE method have also been reported in the literature, including training monotony, training strain, and exponentially-weighted moving averages[2,6,13] (see Table 1). The challenge from a practitioner's perspective is to decide which measures they should calculate and monitor in their athletes. With respect to analysing the association between training load measures and injury risk or performance, many of the aforementioned variables are likely to be highly correlated with one another, and so including several of these measures within an analysis may not be advisable for statistical reasons (i.e., multicollinearity).[14] The reduction of these factors to the most parsimonious set of variables, which still convey the underlying dimensions of the data, would be desirable for practitioners. In other words, the ability to objectively identify and monitor the key training load variables from the many derivative measures that can be produced (Table 1), whilst still capturing the unique aspects of 'load', is likely to be beneficial for those involved in training load monitoring. Indeed, the need to simplify practises in elite sport and differentiate the signal from the noise in the measures we monitor was emphasised in a recent editorial.[15] Accordingly, the aim of the current study was to outline a systematic process of data reduction and variable selection for sRPE training load data, which practitioners in team sport settings may use to optimise their athlete monitoring practices.

METHODS

Subjects

This was a prospective cohort study of professional Rugby Union players registered in the first team squad of four teams competing at the highest level of Rugby Union in England (English Premiership). Training load data were collected for 173 players (team A = 43 players, team B = 41 players, team C = 46 players and team D = 43 players) over one season (2013/14). The study was approved by the Research Ethics Approval Committee for Health at the University of Bath and written informed consent was obtained from each participant.

Methodology

The intensity of all training sessions (i.e., including strength and conditioning and other non-rugby sessions) was estimated using the modified Borg CR-10 RPE (rating of perceived exertion) scale,[16] with ratings obtained from each individual player within 30 minutes after the end of each training session.[17] Each club was briefed on the scale and were given the same scale to use during the season. Each player had the scale explained to them by their strength and conditioning coach and players were asked to report their RPE for each session confidentially to the strength and conditioning coach without knowledge of other players' ratings. Session RPE in arbitrary units (AU) for each player was then derived by multiplying RPE by session duration (min).

From the daily training load values described above, a number of derivative training load measures were calculated (Table 1). The training load measures were identified from previous investigations of the relationship between training load and injury risk. Where multiple training sessions were undertaken on a single day, the sRPE loads from those sessions were summed to give the daily load. All calculated variables were included in a principal-component analysis (PCA) to determine their key underlying components (Table 1).

Time-loss injuries were recorded by the medical personnel at each team using the Rugby Squad medical database (The Sports Office, Wigan, UK). Reported time-loss injuries were included in the study if they occurred in training or 1^{st} or 2^{nd} team competitive matches and if they met the 24-hour time-loss definition.[18] A small number of injuries (n = 24) and match exposure (200 h) during the preseason period in this study produced unstable estimates (i.e., large standard errors); thus, only in-season load and injury data were included in the analyses.

>>>>>>>>>>>>>>>>>>>Table 1<<<<<<<<<<<<<<<<<<

Statistical Analysis

A PCA was undertaken to identify logical combinations of the ten training load measures. PCA is a statistical procedure used to reduce the dimensionality of a given data set that consists of a number of highly correlated variables, whilst retaining as much of the variation in the data set as possible.[19] A similar data reduction process has recently been undertaken to identify key performance variables in an elite sport setting.[20] Variables within a given principal component are correlated with each other, whilst the principal components themselves do not correlate and so explain distinct information.[21] The PCA was performed using IBM SPSS Statistics for Windows (Version 20.0, Armonk, New York, USA). All data were centered and scaled (using within-individual data) before conducting the PCA. The Kaiser-Meyer-Olkin measure was used to verify the sampling adequacy of the data, with a value of 0.5 used as a threshold for acceptability.[22] Bartlett's test of sphericity was also used to determine the suitability of the data for PCA, with significance accepted at an α level of $P \leq 0.05$. Orthogonal rotation (varimax) was used to improve the identification and interpretation of factors.[14] The optimal number of factors to be extracted was determined by examining the scree plot, Eigenvalues and the 'percentage of variance explained' parameters, alongside a conceptual interpretation of the data structure; this multi-faceted approach was recommended by Hair et al.[14] Factor loadings exceeding $\pm$ 0.70 were considered indicative of a well-defined structure.[14]

Once variables had been assembled into components via the PCA procedure, generalised linear mixed-effects models

(GLMM) were used to select the measure (variable) within each principal component that had the largest association with injury risk, and would therefore be selected as the representative measure for that component. The GLMM model was selected for its ability to account for repeated measurements within the data, and was implemented using the *lme4* package[23] with R (version 3.2.4, R Foundation for Statistical Computing, Vienna, Austria). Each training load measure was independently modelled as a fixed effects predictor variable, both by itself (linear model) and with a squared term included to investigate possible non-linear effects (non-linear model).[11,24] Random effects were athlete identity nested within their team, and the residual. The models were offset for players' individual match exposure. The *MuMIn* package[25] was used to calculate a conditional R^2 value (R^2_{GLMM}) for each model, to determine which model explained the greatest amount of variance in injury risk. The R^2_{GLMM} statistic measures the variance explained by both fixed and random factors (i.e. the entire model).[25] The training load measure with the highest R^2 value within each component was selected as the representative measure for that component.

RESULTS

A total of 8027 individual training weeks were observed during the study period, with 173 players providing 32 ± 8 training weeks each. Table 2 displays the mean values for each training load measure across the study period. For these 173 players, a total of 465 time-loss injuries (303 match, 162 training; 391 contact, 74 non-contact) were reported during the study period. Mean weekly training loads over the course of the season were 1706 ± 239 AU.

Both the Kaiser-Meyer-Olkin measure of sampling adequacy and Bartlett's test of sphericity indicated that the data were suitable for PCA, with values of 0.74 and $P < 0.001$, respectively. Three principal components were identified (Figure 1); component one explained 57% of the variance, component two explained an additional 24% of variance, and component three explained an additional 9% of total variance Overall, the three components explained 90% of total variance. Table 3 displays the factor loadings after rotation. The training load measures that were highly loaded on component one represented measures of the 'cumulative load' placed on players, component two was associated with measures of 'changes in load', and component three represented a measure of ‘acute load’. The identified dimensions of the training load measures were deemed to have good face validity.

>>>>>>>>>>>>>>>>>>>Table 2 <<<<<<<<<<<<<<<<<<<

>>>>>>>>>>>>>>>>>>>Figure 1 <<<<<<<<<<<<<<<<<<

>>>>>>>>>>>>>>>>>>>Table 3 <<<<<<<<<<<<<<<<<<<

Table 4 displays the results of the variable selection process. From the six measures highly loaded on component one, the non-linear model for 4-week cumulative load displayed the largest association with injury risk (R^2_{GLMM}: 42.67%). From the two measures highly loaded on component two, acute:chronic workload displayed the largest association with injury risk (R^2_{GLMM}: 42.13%), with the non-linear model again providing the highest model fit compared to the linear model. Daily training load was the only variable highly correlated with component three (acute load), and so was automatically selected as the representative variable for this component (R^2_{GLMM}: 36.97%), with the linear model providing a better model fit compared to the non-linear model.

>>>>>>>>>>>>>>>>>>>Table 4 <<<<<<<<<<<<<<<<<<

DISCUSSION

The aim of the current study was to aid practitioners employing athlete load monitoring by outlining a systematic process of data reduction to allow them to select the most relevant measures to monitor for injury risk identification. The PCA characterised three underlying dimensions: cumulative loads, changes in loads, and acute loads. Four-week cumulative load, acute:chronic workload and daily training load were selected as the representative measures for each component, respectively, based on their association with the injury dataset in this Rugby Union population. The variables selected in this instance are likely be unique to the current dataset, but the process outlined here may be used to select and monitor the most parsimonious set of variables (whilst still retaining the variation and unique components within the data) in other settings for both injury risk and performance monitoring.

The three components identified by the PCA each explained a unique dimension of training load. Component one, which explained the largest proportion of variance (57%), was most associated with training load measures describing the cumulative load that players had been subjected to, including 1-

4 week cumulative loads and the exponentially-weighted moving average. Measures of 'cumulative load' have been strongly associated with injury risk in elite Australian footballers[9,10] and Rugby Union.[24] It may be that these cumulative load measures describe the accumulation of fatigue within players, which may result in a reduction in the stress-bearing capacity of tissue,[26] and thus an increased likelihood of injury. Additionally, accumulated fatigue may alter neuromuscular control responses, such that potentially hazardous movement strategies are employed that increase the likelihood of injury.[27] However, recent evidence suggests that cumulative loads that are too low may also augment injury risk,[24,28] perhaps due to associated reductions in players' fitness levels.[29] As such, the cumulative loads accumulated by collision sport athletes should be monitored, to aid the management of these 'fitness' and 'fatigue' effects.

The second component identified by the PCA was highly associated with the two training load measures that describe the absolute and relative changes in a player's load (week-to-week change and acute:chronic workload, respectively). This component described an additional 24% of total variance. Substantial previous-to-current week changes in load were found to significantly increase injury risk in elite Australian footballers[10] and Rugby Union players.[24] These results were deemed to be especially pertinent to players returning from injuries; a more conservative approach to the increase in week-to-week training loads for previously injured players was therefore advocated. Elsewhere, the acute:chronic workload was found to be a greater predictor of injury than either acute or chronic workload separately in elite Rugby League players.[28] Together, these findings suggest that sudden increases in load should be avoided, and that loads should instead be systematically increased relative to each player's cumulative load (as described by component one).[28]

The third component identified by the PCA only contained one highly-weighted factor, daily sRPE training load, which may be considered a measure of 'acute' workload. This variable described an additional 9% of total variance. The acute (or recent) workloads undertaken by players are likely to reflect the current level of fatigue in their system,[30] and so should be monitored to ensure that workloads prescribed in the ensuing period are appropriate with respect to the variables described in components one and two (i.e., cumulative loads and changes in load, respectively).

To select one training load measure to represent each component, it is recommended that the univariate associations between each measure and injury risk be compared (e.g., using generalised linear mixed-effects models). Both linear and non-linear relationships between these load measures and injury risk should be explored, as a number of recent studies have reported non-linear associations.[11,24] Using this approach in the current study, 4-week cumulative load was selected as the measure representing component one (cumulative load), acute:chronic workload was selected as the measure representing component two (changes in load), whilst daily training load was the only variable highly correlated with component three (acute load) and so was automatically selected as the representative variable for this component. The specific variables chosen are likely to be unique to the current dataset, but the process outlined here may be used to select and monitor the most pertinent variables in other settings. In the current study, this process resulted in the selection of three training load measures (4-week cumulative load, acute:chronic workload, and daily training load) for further analysis and monitoring, from an initial group of ten possible measures, and would thus simplify the load monitoring analysis process, whilst still capturing the unique components of 'load' in this cohort. In addition, the process outlined here could also be applied to select the most pertinent variables for other training load measures (e.g., GPS and accelerometer data) for both injury risk and performance monitoring.

Practical Applications

- For those collecting sRPE data in elite collision sport athletes, a measure of cumulative load, change in load, and acute load should be monitored for injury risk management purposes.
- In other sports settings, the data reduction and variable selection procedures outlined in the current study may be similarly applied to extract key measures for the specific environment, in order to optimise the training load monitoring process.

Conclusions

The current study has outlined a systematic process of data reduction and variable selection that may be used to simplify the analysis of training load measures in team sport settings. Three principal components were identified in this elite rugby union dataset to monitor injury risk, representing measures of cumulative loads, changes in loads, and acute loads. Selecting one measure to represent each of these components enables practitioners to monitor the most parsimonious set of variables, whilst still retaining the variation and unique components within the data.

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Table and Figure Captions

Table 1. Summary of training load measures investigated within the current study, including their calculation and use in existing literature.

Figure 1. Scree plot for Principal Component Analysis, displaying the presence of three principal components.

Table 2. Descriptive data for internal sRPE training load measures for each team over the study period.

Table 3. Data reduction procedure; rotated component matrix of the training load measures.

Table 4. Variable selection procedure; univariate relationships between training load measures and injury risk. *, variable explaining the largest amount of variation in injury risk, and therefore selected as the representative measure for this component.

Table and Figures

Table 1.

Training load measure	Calculation	Supporting literature
Daily training load	Session RPE x session duration [minutes].	Foster [2]
1,2,3,4 -weekly cumulative loads	Sum of previous (7, 14, 21, 28) days’ training load values	Gabbett et al. [6,29,31-33] Rogalski et al.[10] Colby et al.[9]
Week-to-week change	Absolute difference between current and previous week’s training load totals	Rogalski et al.[10] Cross et al.[24]
Training monotony	A measure of the day-to-day consistency of a player’s training load within a given week: daily mean/standard deviation	Foster [2]
Training strain	Weekly training load x training monotony	Foster [2]
Acute:chronic workload	Calculated by expressing a player’s acute workload [1-week load] as a percentage of their chronic workload [four-week rolling average]	Hulin et al.[11,12]
Exponentially-weighted moving average	*f* x (previous day’s training load) + (1-*f*) *x* (cumulative load up to that point), where f is a decay factor with value between 0 and 1. An f value of 0.1 was adopted for the calculation of the exponentially-weighted moving average of training load, based upon a previous study using a comparable population[13]. The resulting cumulative load is effectively smoothed with a time constant of 10 d.	Holt[34]; Kara[13]

Table 2.

sRPE Training Load Measure	Team A	Team B	Team C	Team D	Mean ± Between Team SD
Daily training load [AU]	218	293	226	244	245 ± 33
1-week cumulative load [AU]	1528	2048	1556	1692	1706 ± 239
Two-week cumulative load [AU]	2259	3479	2644	2677	2765 ± 513
Three-week cumulative load [AU]	3047	4757	3529	3682	3754 ± 721
Four-week cumulative load [AU]	3891	6030	3892	4262	4518 ± 1022
Week-to-week change [AU]	4	-17	-5	-63	-34 ± 30
Training monotony [AU]	0.81	0.67	0.98	0.85	0.83 ± 0.13
Training strain [AU]	1256	1439	1511	1329	1384 ± 113
Acute:chronic workload [%]	87	127	112	95	103 ± 18
Exponentially-weighted moving average [AU]	240	251	166	209	188 ± 38

Table 3.

Training load measure	Component		
	1 [Cumulative]	2 [Changes in load]	3 [Acute]
Daily training load	0.15	0.14	**0.98**
1-week cumulative load	**0.84**	0.47	-0.21
2-week cumulative load	**0.95**	-0.02	0.14
3-week cumulative load	**0.94**	-0.22	0.12
4-week cumulative load	**0.88**	-0.34	0.12
Week-to-week change	0.08	**0.88**	-0.16
Training monotony	0.68	0.47	-0.16
Training strain	**0.79**	0.50	-0.21
Acute:chronic workload	-0.19	**0.86**	0.00
Exponentially-weighted moving average	**0.98**	-0.01	-0.08

Note, factor loadings >.70 appear in bold.

Table 4.

Training load measure	Conditional R^2_{GLMM}	
	Linear model	Non-linear model
Component 1		
1-week cumulative	37.48%	38.15%
2-week cumulative	38.01%	38.97%
3-week cumulative	38.88%	38.70%
4-week cumulative*	41.51%	**42.67%**
Exponentially-weighted moving average	38.47%	38.86%
Training strain	38.63%	38.94%
Component 2		
Week-to-week change	41.20%	41.22%
Acute:chronic workload*	42.12%	**42.15%**
Component 3		
Daily training load*	**36.97%**	36.77%