Journal of Science and Medicine in Sport xxx (2018) xxx–xxx

Contents lists available at ScienceDirect

Journal of Science and Medicine in Sport

journal homepage: www.elsevier.com/locate/jsams

Original research

Modelling the relationships between volume, intensity and injury-risk in professional rugby league players

Cloe Cummins[a,b,*], Mitchell Welch[a], Brendan Inkster[c], Balin Cupples[c,d], Dan Weaving[b,e], Ben Jones[a,b,e,f,g], Doug King[a,h], Aron Murphy[a]

[a] School of Science and Technology, University of New England, Australia
[b] Institute for Sport Physical Activity and Leisure, Leeds Beckett University, United Kingdom
[c] Vodafone Warriors, New Zealand
[d] Sydney School of Education and Social Work, The University of Sydney, Australia
[e] Leeds Rhinos Rugby League club, United Kingdom
[f] Yorkshire Carnegie Rugby Union club, United Kingdom
[g] The Rugby Football League, United Kingdom
[h] Sports Performance Research Institute New Zealand (SPRINZ) at AUT Millennium, Faculty of Health and Environment Sciences, Auckland University of Technology, New Zealand

ARTICLE INFO

Article history:
Received 31 August 2018
Received in revised form 6 November 2018
Accepted 29 November 2018
Available online xxx

Keywords:
Injury prevention
Microtechnology
Team sport
Training load

ABSTRACT

Objective: This study aimed to: (a) identify the association between external-workloads and injury-risk in the subsequent week; and (b) understand the effectiveness of workload variables in establishing injury-risk.

Design: Retrospective cohort study.

Methods: Workload and injury data (soft-tissue) were collected from forty-eight professional male rugby league players. Load variables included duration (min), total distance (m), relative distance (m min^{-1}), high speed distance ([m]>20 km h^{-1}), very-high speed distance ([m]>25 km h^{-1}), acceleration and deceleration efforts (count) and PlayerLoad (Arbitrary Unit: AU). Cumulative two-, three- and four-weekly loads; Acute:Chronic Workload Ratio (ACWR); Mean-Standard Deviation Workload Ratio (MSWR) and strain values were calculated and divided into three equally-sized bins (low, moderate and high). Generalised Estimating Equations analysed relationships between workload variables and injury probability in the subsequent week.

Results: Injury-risk increased alongside increases in the ACWR for duration, total distance and PlayerLoad. Conversely, injury-risk decreased (Area Under Curve: 0.569–0.585) with increases in the four-weekly duration, total distance, accelerations, decelerations and PlayerLoad. For relative distance, high four-weekly workloads (high: >60 m min^{-1}) demonstrated a positive association with injury-risk, whilst high two-weekly loads (high: >82 m min^{-1}) were negatively associated.

Conclusions: A range of external workload metrics and summary statistics demonstrate either positive or negative associations with injury-risk status. Such findings provide the framework for the development of decision-support systems in which external workload metrics (e.g. total or high speed distance) can be uniquely and routinely monitored across a range of summary statistics (i.e. cumulative weekly loads and ACWR) in order to optimise player performance and welfare.

Practical applications

- External workload metrics demonstrate both positive and negative associations with injury-risk in the following week.
- In comparison to less consistent changes in workload, suitable and consistent increases in workload lead to a decreased risk of injury.
- The findings of our work support the integration of a range of variables to develop decision-support systems that provide an enhanced understanding of the aetiology surrounding injury-risk within rugby league.

* Corresponding author.
E-mail address: ccummin5@une.edu.au (C. Cummins).

https://doi.org/10.1016/j.jsams.2018.11.028

1. Introduction

Rugby league is an intermittent team-sport comprised of interspersed high and low intensity activity.[1] Additionally, players frequently engage in physically demanding collision and wrestle bouts.[2] The annual season for professional players is a multi-cyclical competition comprising of both a pre-season and competition phase. Typically, Australian rugby league players begin their pre-season training in November and finish in March. Players experience between match recovery periods that can vary from five to ten days.[3]

To meet the physical demands of match-participation, players undertake multi-modal training, structured to facilitate positive adaptations and performance improvements.[4] Such programs may specifically include speed and agility, conditioning as well as generic and positional based skills training.[5] As a consequence of the demanding training and match-play workloads, musculoskeletal injuries are common. Indeed, training injuries have been reported to occur at a rate of 12.6 per 1000 training hours, while match-play injuries occur at a rate of 148 injuries per 1000 match-play hours.[6] As such, high-performance and medical staff regularly assess each individual player's risk of injury and therefore, their availability to undertake training and match-play.

Monitoring of the training process is important for understanding the implications on both physical and technical qualities as well as injury.[7] Despite this knowledge, until recently injury aetiology models only included internal risk factors such as body composition (i.e. body weight or anthropometric measures) or physical fitness (i.e. muscular strength or maximal oxygen uptake).[8] In addressing the previous oversight of external workloads, a new injury model has recently been proposed.[8] Such model highlights that the external workload (e.g. training and match-play workloads) contributes alongside both modifiable (e.g. strength and flexibility) and non-modifiable (e.g. age) factors to the multifactorial aetiology of injury-risk.[8] Indeed, there are several independent injury-risk factors (i.e. too-high or too-low [monthly] workloads[9] and insufficient recovery[10]) derived from the external load associated with injury-risk. Furthermore, large relative variations, or spikes, in workload (as assessed via the Acute:Chronic Workload Ratio [ACWR]) have been reported to precede an injury.[11] Players have an increased injury-risk for up to one month following such events.[12] In rugby league, low chronic workloads with concomitant high ACWR[13] and large fluctuations in week-to-week workloads[14] have also been posited as injury-risk factors. Therefore, monitoring of external workloads (training and match-play workloads) is considered essential in optimising workload and minimising the risk of injury.[7] Despite such findings, it's important to understand that it is not the external load directly that causes injury-risk, instead it's the resultant biomechanical strain incurred to joints, muscles and connective tissue (i.e. the internal load). Such strain however, cannot be measured directly during either training or competition and therefore, the external workload provides a surrogate measure in which to model injury-load relationships.

Researchers have begun identifying the association between individual workload metrics and injury-risk. Specifically, in rugby league it has been reported that the ACWR is associated with injury-risk.[15] Furthermore, it has been reported that injury-risk factors vary for positional groups, with the relative importance of each metric also varying among players.[4] Whilst this work has provided an insight into the association between workload metrics and injury-risk, and how injury-risk varies with each metric,[4] it has not addressed the relationship between specific thresholds of workload metrics and injury-risk. As such we aimed to identify: (a) the external workload metrics associated with an increased risk of "preventable" injury in the subsequent week; and (b) the effectiveness of workload variables in establishing injury-risk.

2. Methods

Participants: Data from forty-eight professional male rugby league players from a National Rugby League (NRL) team were attained for use within this study. Institutional ethics approval was granted by the University of New England.

Data were recorded for each player and included all on-field training sessions and games (trial and competition matches [$n = 1422$; average observations per player: 110 ± 46]). Data were collected daily across one season (November to September) from the first day of pre-season training until the last day of the respective, season. First grade, reserve grade and under 20-years professional rugby league players who undertook the same training regime (i.e. trained as part of the main training squad) are represented within the dataset.

Microtechnology devices: Player movements were assessed using microtechnology devices (OptimEye S5 device; Catapult Innovations, Melbourne, Australia). The devices record a 10-Hz Global Positioning System (GPS) sampling rate through the inbuilt GPS-chip. Additionally, the devices contain a tri-axial accelerometer, gyroscope and magnetometer which sample at 100-Hz. All data were downloaded and trimmed using proprietary software so that only data obtained during training and match-participation were retained for analysis (Openfield; Catapult Innovations, Melbourne, Australia). The S5 device has previously been reported to have a typical error (co-efficient of variation [CV]) of 1.9%, 4.7% and 10.5% for total distance, high speed running distance (>16.92 $km\,h^{-1}$) and very-high speed running distance (>20.01 $km\,h^{-1}$), respectively.[16] Furthermore, the tri-axial accelerometer within the device has acceptable within- (0.91–1.05%) and between-device (1.02–1.04%) reliability.[17]

Workload metrics: The following workload metrics were calculated: duration (min), total distance (m), relative distance ($m\,min^{-1}$), high speed distance ([m] >20 $km\,h^{-1}$), very-high speed distance ([m] >25 $km\,h^{-1}$) and acceleration (>1.5 $m\,s^{-2}$) and deceleration efforts (<−1.5 $m\,s^{-2}$) (count). Additionally, an accelerometer-derived load which represents the accumulation of accelerations in the mediolateral (x), anteroposterior (y) and vertical (z) directions was calculated (PlayerLoad; Arbitrary Unit [AU]).[18] The eight-workload variables were utilised to calculate summary statistics aimed at describing different aspects of workload that are linked to injury. The summary statistics utilised included the sum of each workload variable across two-week, three-week and four-week periods along with more complex ACWR, Mean-Standard Deviation Workload Ratio (MSWR) and strain values. The ACWR, is defined as the ratio between the one-week (acute) average of the daily load to the four-week (chronic) average of daily load calculated from a moving-window across the season. The ACWR is a well-established descriptive value, previously identified as an indicator for injury.[11,13] The MSWR provides a measure of training variability over a smaller period than that measured by the ACWR and is defined as the ratio of the mean to standard deviation over a single training week.[19] Strain, which is defined as the acute (one-week) load multiplied by the MSWR, directly measures the relationship between load and training monotony.[19]

Injury definition: "Preventable" injuries were defined as any soft-tissue injury that did not result from a collision or non-field related training session and rendered a player unable to complete full-training or match-play requirements. All injuries ($n = 36$) were diagnosed and recorded by medical staff at the club.

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Data analysis: Daily data were utilised to calculate chronological loads for each workload metric. Microtechnology data were uploaded to a PostgreSQL 9.6 database for pre-processing and summary statistics were calculated from daily values. Complete sets of the summary statistics were calculated by week for each player for the season. Metrics were not calculated for weeks not including any training sessions or games as an ACWR can't be calculated without data for the acute week. The incidence of soft-tissue injury in the following week were recorded against each set of summary statistics as a binary value for use in the analysis as the response variable.

Statistical analysis: A set of univariate Generalised Linear Models (GLM) were produced from the dataset. Generalised Estimating Equations (GEE) were used to calculate GLM parameters that model the relationship between individual summary variables and the probability of injury in the subsequent week. The GEE models were chosen as they provide a robust way to model a population averaged effect (in this case the probability of injury) across a dataset containing repeated, and possibly correlated, measures.[20]

The GEE models developed in the study utilised Bernoulli distribution to model the binary response variable (injured/not injured in the following week) coupled with the logit link function.[21] A First-Order Autoregressive (AR1) correlation structure was adopted with the player specified as the subject variable and the week of the training season as the single within-subject variable, representing the chronological relationship between sessions. This approach allowed the GEE models to correctly account for the changes exhibited by each individual player as training programs changed through the season (e.g. workload characteristics an individual player presents at the start of the season may not be correlated with those later in the season). The GEE approach has been applied across a range of areas for the analysis of longitudinal data (e.g. time-series data) because it has the advantage of being less sensitive to variance structure specification compared to generalised linear mixed models. The GEE models were implemented using the GEEQBOX toolkit[21] running within MATLAB 2017b (The MathWorks, USA).

The univariate models produced in this process were assessed and compared for their fit to the underlying data using Root Mean Squared Error (RMSE) values and *P*-values for the model coefficients. Receiver-Operator Characteristic Curves were produced for each model allowing the Area-Under-Curve (AUC) values to be calculated using the in-sample datasets to assess their performance for determining the association with injury. Ninety-five percent (95%) confidence intervals were calculated for the AUC values using the bootstrap sampling method. The values for each summary statistic (across each workload variable) were classified into three equally-sized bins spanning the range of the respective statistics (low, moderate and high). Modelled values based upon the centre of each bin were then utilised to produce injury odds ratios for the three bins within each summary statistic (Fig. 1). The odds ratio provides information on both the magnitude and direction of injury-risk. Specifically, in relation to magnitude the odds of being injured increases along the x axis, whereby at a value of 1 on the x axis there is a 1:1 odds ratio of being injured. The odds ratio also outlines two directions of injury-risk; (a) *positive relationship*: whereby there are negative effects or an increased risk of injury and (b) *negative relationship*: whereby there are beneficial effects or a decreased risk of injury.

Datasets for each variable were inspected to ensure their distribution was uni-modal (as required for the GEE) and the correlation matrix calculated for each variable was tested to ensure it was positive-definite, resulting in a valid GEE model for each variable. The AUC and RMSE values were utilised to select the top-performing summary statistics from the workload variables, for a bi-variate comparison utilising density heat-maps produced using a two-dimensional kernel density estimator. This analysis provides a comparison of the density of data points for pairs of variables (e.g. duration and total distance) and visually depicts differences in the distribution for particular variables between injured and non-injured datasets (i.e. separate density maps for injured and non-injured players; Fig. 2).

3. Results

The relationships and fit of the univariate models are shown in Table 1. The AUC and RMSE values ranged from 0.481 to 0.605 and 0.149 to 0.159, respectively. Strong relationships (AUC > 0.500) were observed for the ACWR of accelerations (AUC: 0.605; 95% CI = 0.533–0.680; p = 0.001), decelerations (AUC: 0.581; 95% CI = 0.503–0.650; p = 0.037) and duration (AUC: 0.580; 95% CI = 0.496–0.651; p = 0.009). Four-week workloads of PlayerLoad (AUC: 0.585; 95% CI = 0.482-0.672; p = 0.048) and distance (AUC: 0.578; 95% CI = 0.486–0.688; p = 0.062) also demonstrated strong generalised relationships. A significant positive relationship was also found for the two-week workload of relative distance (AUC: 0.595; 95% CI = 0.491–0.692; p = 0.044).

The association between external workload metrics and injury, for two-, three- and four-weekly loads, ACWR, MSWR and strain are shown in both Table 1 and Fig. 1. The density maps for injured and non-injured players are shown in Fig. 2.

For duration (Table 1; Fig. 1a) a high two-week duration (>600 min) was associated with an increased injury-risk in the following week, whilst a high four-week duration (>800 min) was associated with a decreased injury-risk. For total distance (Table 1; Fig. 1b) high two-week (>36,000 m) and strain (>100,000 AU) workloads were associated with an increased injury-risk in the following week. Conversely, high four-week loads (>60,000 m) were associated with a decreased injury-risk. For relative distance (Table 1; Fig. 1c) high two-week (>82 m min^{-1}) loads were associated with a decreased injury-risk, whilst high four-week (>60 m min^{-1}) loads were associated with an increased injury-risk in the following week. No clear associations were present for high speed distance (Table 1; Fig. 1d), whilst for very-high speed distance (Fig. 1e) high two-week loads (>1000 m), ACWR (>2.6 AU) and strain (>380 AU) were associated with an increased injury-risk. For accelerations (Table 1; Fig. 1f) a high ACWR (>1.4 AU) was associated with an increased injury-risk, whilst conversely a high MSWR (>3.2 AU) was associated with a decreased risk in the subsequent week. For decelerations (Table 1; Fig. 1 g) a high four-week load (>360 AU) was associated with a decreased injury-risk, whilst a high ACWR (>1.3 AU) was associated with an increased injury-risk. PlayerLoad (Table 1; Fig. 1h) demonstrated increased injury-risk for high ACWR (>1.2 AU) and strain (>6000 AU), whilst a high four-week (>3800 AU) load exhibited a decreased injury-risk in the subsequent week.

Fig. 2, visually compares the bi-variate relationships of four-week distance, four-week PlayerLoad, two-week relative distance and ACWR for duration to the ACWR for accelerations and decelerations for injured and non-injured datasets. Observation of the location of the highest density point (as indicated by the brighter colouring) can be used to highlight differences in the load distributions. Collectively, when examining injured and non-injured datasets (a vs i, b vs j, c vs k and d vs l, respectively), it can be observed that the centre of the highest density point is shifted slightly to the right, thereby indicating an increased ACWR for the injured players. Compared to non-injured players, the interaction between two-week relative distance and ACWR for accelerations, indicates a skewness towards higher relative distance (two-week) and acceleration (ACWR) workloads for injured players (Fig. 2 g and o), i.e. injury-risk increases as the number of accelerations increases. For four-week PlayerLoad, the interaction with the ACWR for accelerations demonstrates that a lower PlayerLoad is indicative of an increased injury-risk (Fig. 2a and i), whilst the relationship with decelerations is not as clear (Fig. 2b and j).

4. Discussion

Through this study we identify that a range of external workload metrics and summary statistics demonstrate either a positive or negative association with "preventable" injury-risk status. Such findings provide the framework for the development of decision-support systems in which external workload metrics (e.g. total or high speed distance) can be uniquely and routinely monitored in order to optimise player performance and welfare.

When examined over a series of summary statistics (two-, three- and four-week loads; ACWR; MSWR and strain) most external workload metrics demonstrated an association with injury-risk. However, the associative power of the models developed within this study varied across each individual workload metric and summary statistic (Fig. 1 and Table 1). Specifically, for duration, total distance, accelerations, decelerations and PlayerLoad, as the four-week load increases the injury-risk decreases. Conversely as the ACWR for duration, total distance and PlayerLoad increases, so too does injury-risk. The larger load for total distance, accelerations, decelerations, PlayerLoad and longer total durations likely correspond to a consistent training program with consistently high workloads, whereas the higher ACWR and lower four-week loads may correspond to a less consistent program with workload increasing in the week prior to injury. The association between the overall stability of workload and decreased injury-risk is similar to that observed in other codes.[22]

For relative distance, injury-risk decreases as the two-weekly load increases, however, injury-risk increases with a higher four-week load. This finding is suggestive of the fact that continued increases in intensity (via relative distance) contribute to an enhanced risk of injury. For high speed distance, only the MSWR demonstrated a moderate association with injury-risk, highlighting that injury-risk increases alongside increases in the MSWR for high speed distance. This indicates that consistently high total high speed distances over a one-week period are likely associated with a higher injury-risk. Injury-risk also rises alongside increases in both the two-week, three-week, ACWR, MSWR and strain for very-high speed distance. This suggests that injury-risk increases as very-high speed distance increases within all summary statistics, with the exception of the four-week load where the risk remains stable. Collectively, the data indicates that short-term spikes in very-high speed distance are associated with an increased injury-risk.

For duration and total distance, a high two-weekly load increased injury-risk in the subsequent week, whilst a high four-weekly load demonstrated a reduced injury-risk. Conversely, a

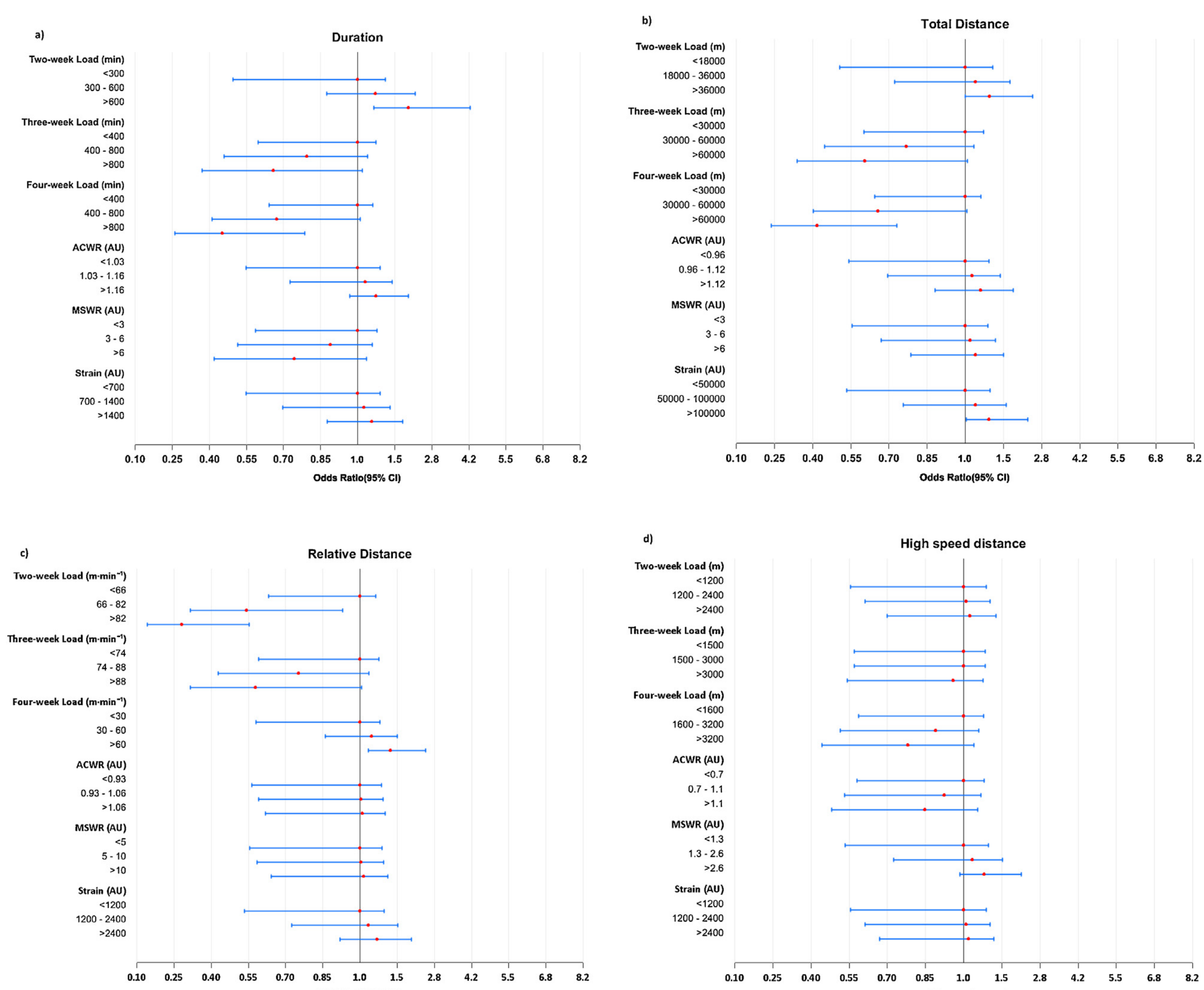

Fig. 1. The association between external workload metrics and injury, for two-, three- and four-weekly loads, ACWR = Acute:Chronic Workload Ratio; MSWR = Mean-Standard Deviation Workload Ratio and strain.

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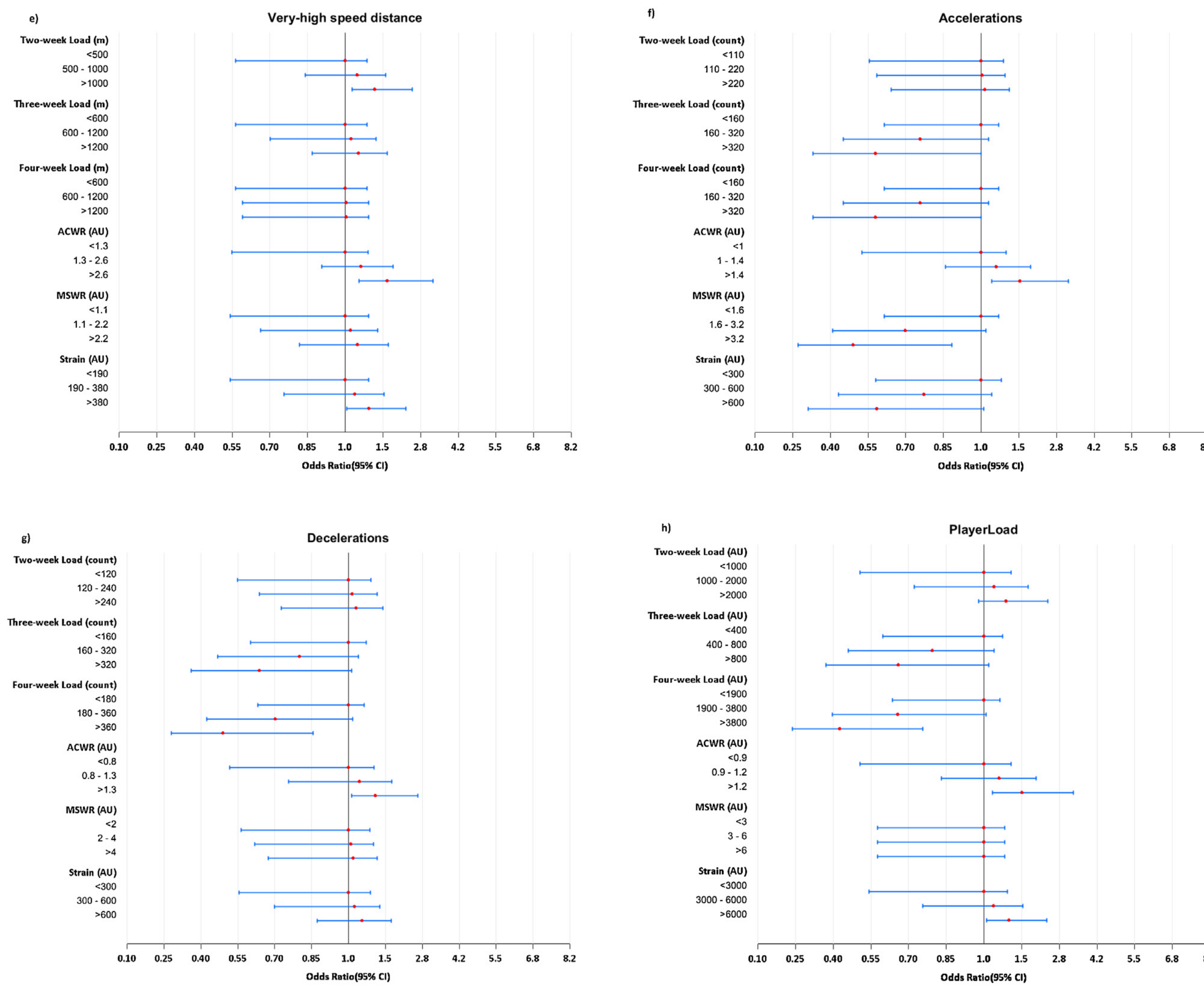

ACWR = Acute:Chronic Workload Ratio; MSWR = Mean-Standard Deviation Workload Ratio; AU = Arbitrary Unit.

Fig. 1. (*Continued*)

high four-weekly relative distance was positively associated with injury-risk, whilst a high two-weekly load was negatively associated. Such findings suggest that appropriate and consistent increases in total workload (duration and distance) contribute to a decreased injury-risk within rugby league players. Whilst sustained increases in intensity through relative distance ($\mathrm{m\,min^{-1}}$) contribute to an enhanced injury-risk. Such information is important in guiding the development of monitoring-systems that examine individual workload metrics across acute (≤one-week) and chronic (≥two-week) durations. Such analysis enables better understanding of each individual athlete's injury-risk.

Within our study, the ACWR appears to be effective in determining associations between individual workload metrics and injury-risk. The caveat is that the ACWR demonstrated no meaningful relationships in regard to injury-risk within the subsequent week for high speed distance (>20 $\mathrm{km\,h^{-1}}$). This finding is in contrast to recent work within soccer,[10] where high ACWR's (>1.18) for distance covered at high speed (>20 $\mathrm{km\,h^{-1}}$) were reported to increase injury-risk. Such discrepancy may be related to the inherent differences between the two codes, for example variances in the volume of high speed running undertaken throughout match-play.[23] Furthermore, using simulated data Lolli et al. recently reported that metrics used in calculating the ACWR are mathematically coupled and therefore, any associations between the ACWR and injury-risk could be a result of spurious correlations.[24] As such, the authors recommend care be taken when utilising the ACWR method to interpret injury-risk and proposed a modified ACWR calculation. Future research is warranted utilising real external training load data to examine how associations with injury-risk differ between the original and modified ACWR calculations.

As demonstrated in these data, the complex and variable nature of workload and injury data supports the provision of athlete monitoring-systems that are able to calculate and examine individual workload measures across a range of summary statistics. This would enable teams to better understand not only which measures demonstrate an association with injury-risk, but to determine those, which possess the strongest associative power (AUC > 0.500). Such systems are vital in optimising the periodisation strategy and workload management of individual athletes and teams, in an attempt to enhance athletic performance whilst mitigating injury-risk.

A limitation of our study is that the data are from one professional rugby league team. Therefore, whilst the data analysis and statistical methods utilised within our study have direct, immediate applications and transferability to other rugby league teams, and indeed other team-based sports, the specific injury-risk associations which have been reported will likely vary. As previously acknowledged,[5,25] relatively small sample sizes or individual teams

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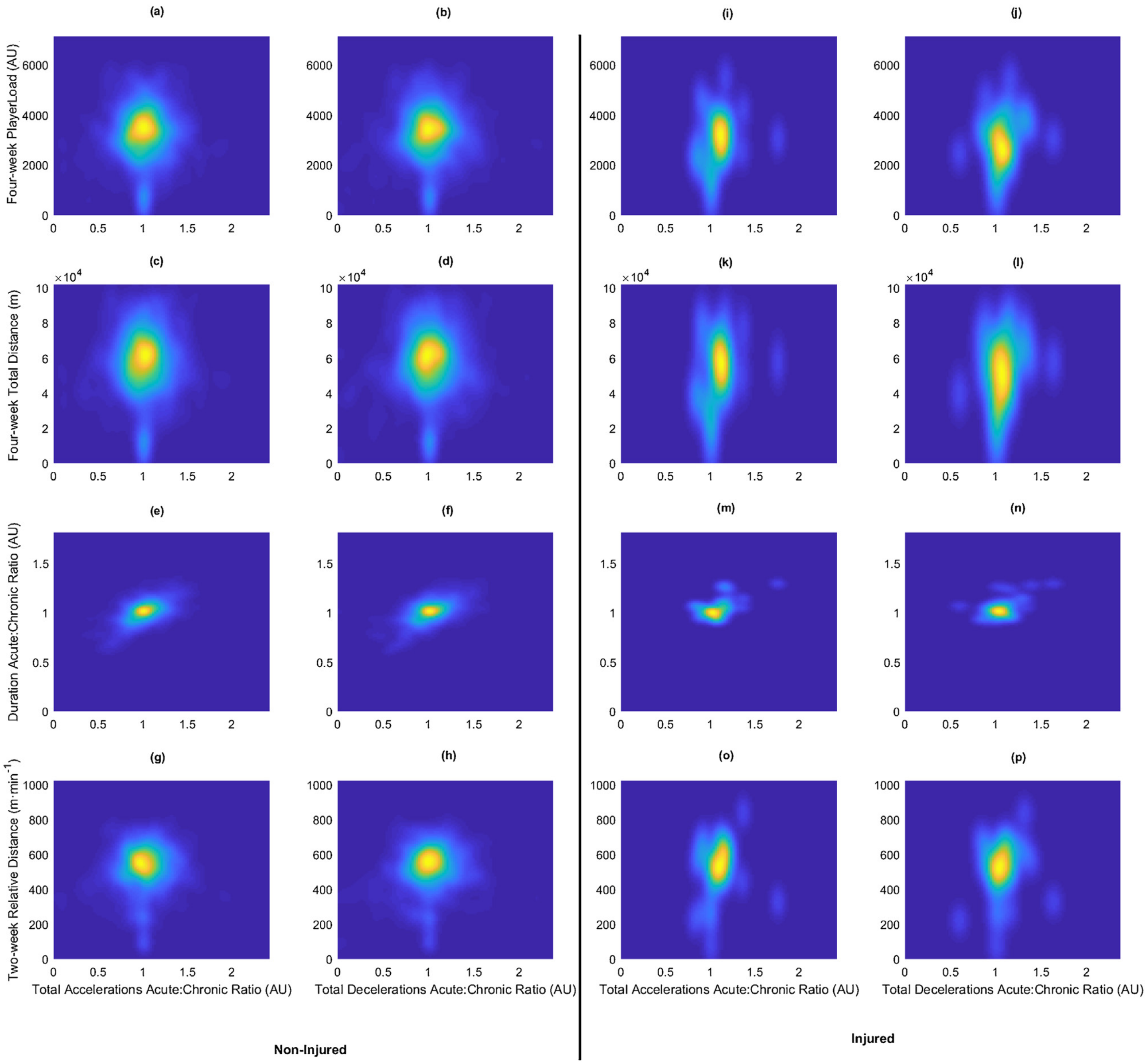

Fig. 2. The following heat-maps provide a two-dimensional visual comparison between injured and non-injured combinations for four-week distance, four-week PlayerLoad, two-week relative distance and ACWR for duration compared to the ACWR for accelerations and decelerations for injured and non-injured data sets.
ACWR = Acute:Chronic Workload Ratio; MSWR = Mean-Standard Deviation Workload Ratio; AU = Arbitrary Unit

is somewhat unavoidable, as the potential to share workload monitoring and injury surveillance data between competing teams rarely occurs. In line with this, the relatively small sample size prohibits analysis of the relationships between external workload metrics and injury-risk within specific phases of the season (i.e. pre-season and competition phases). Despite this potential limitation, it is important to note that our paper examines the conditions that led to a player being injured and therefore, it is not essential that data be separated into specific phases. Additionally, whilst the current analysis reports on acceleration and deceleration counts, it is unknown whether it is the number or intensity of such variables that contribute to injury. Given the metabolic cost of such movements,[26] future research should examine the relationship between intensity derived mechanical variables and injury-risk.

Whilst our study provides a model in which to better understand the multifactorial aetiology of rugby league injury-risk, it should be noted that the model identifies individual risk factors associated with injury as opposed to recognising patterns that can determine injury-risk. Due to the complexity that surrounds overuse injuries, there may be multiple different workload configurations that lead to similar injuries.[27] The results obtained from the highest performing univariate model presented here only achieve a modest AUC of 0.605 (1.000 is a perfect classification, whilst 0.500 represents a chance). While this is evidence of an association, it only describes part of the overall complexity within the data and has limited predictive power. Future research should look to employ machine learning algorithms that can handle and combine the information (or variance) provided by multiple workload variables that concurrently share a large proportion of common and unique information (or variance).[28,29] Whilst the utilisation of machine learning algorithms may facilitate injury predictions from similar datasets, the current analysis is important to practitioners in that it provides a context to such findings.

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Table 1
The relationship and fit of the univariate models.

	Two-week load[a]	Three-week load[a]	Four-week load[a]	ACWR (AU)	MSWR (AU)	Strain (AU)
Duration (min)						
Area-Under-Curve (95% CI)	0.578 (0.471–0.669)	0.521 (0.393–0.600)	0.571 (0.471–0.677)	0.580 (0.496–0.651)	0.529 (0.426–0.647)	0.543 (0.428–0.647)
Root Mean Squared Error	0.155	0.155	0.155	0.155	0.158	0.156
P	0.205	0.507	0.087	0.009	0.538	0.333
Distance (m)						
Area-Under-Curve (95% CI)	0.556 (0.452–0.650)	0.535 (0.449–0.655)	0.578 (0.486–0.688)	0.549 (0.473–0.646)	0.524 (0.416–0.631)	0.542 (0.413–0.658)
Root Mean Squared Error	0.155	0.155	0.155	0.155	0.156	0.151
P	0.287	0.404	0.062	0.097	0.609	0.303
Relative distance (m min^{-1})						
Area-Under-Curve (95% CI)	0.595 (0.491–0.692)	0.556 (0.443–0.653)	0.575 (0.464–0.692)	0.492 (0.406–0.585)	0.505 (0.413–0.609)	0.556 (0.463–0.640)
Root Mean Squared Error	0.155	0.155	0.155	0.155	0.153	0.156
P	0.044	0.408	0.188	0.811	0.778	0.333
High speed distance (m)						
Area-Under-Curve (95% CI)	0.543 (0.449–0.633)	0.481 (0.380–0.582)	0.516 (0.429–0.619)	0.504 (0.426–0.590)	0.535 (0.424–0.639)	0.553 (0.456–0.637)
Root Mean Squared Error	0.155	0.155	0.155	0.155	0.156	0.154
P	0.621	0.921	0.449	0.525	0.361	0.625
Very-high speed distance (m)						
Area-Under-Curve (95% CI)	0.555 (0.434–0.639)	0.539 (0.420–0.646)	0.512 (0.406–0.604)	0.543 (0.445–0.638)	0.546 (0.439–0.654)	0.576 (0.464–0.679)
Root Mean Squared Error	0.155	0.155	0.155	0.155	0.149	0.149
P	0.220	0.460	0.937	0.205	0.389	0.123
Accelerations (count)						
Area-Under-Curve (95% CI)	0.540 (0.416–0.640)	0.536 (0.417–0.625)	0.573 (0.467–0.676)	0.605 (0.533–0.680)	0.576 (0.473–0.660)	0.538 (0.450–0.632)
Root Mean Squared Error	0.155	0.155	0.155	0.155	0.157	0.155
P	0.774	0.214	0.044	0.001	0.014	0.198
Decelerations (count)						
Area-Under-Curve (95% CI)	0.538 (0.436–0.639)	0.535 (0.432–0.631)	0.569 (0.468–0.679)	0.581 (0.503–0.650)	0.490 (0.380–0.587)	0.509 (0.415–0.593)
Root Mean Squared Error	0.155	0.155	0.155	0.155	0.157	0.155
P	0.627	0.348	0.073	0.037	0.754	0.467
PlayerLoad (AU)						
Area-Under-Curve (95% CI)	0.565 (0.472–0.646)	0.545 (0.442–0.647)	0.585 (0.482–0.672)	0.561 (0.460–0.656)	0.504 (0.411–0.596)	0.551 (0.437–0.660)
Root Mean Squared Error	0.155	0.155	0.155	0.155	0.159	0.153
P	0.164	0.284	0.048	0.116	0.989	0.161

[a] Unit of measurement is indicated beside the external workload metric; ACWR = Acute:Chronic Workload Ratio; MSWR = Mean-Standard Deviation Workload Ratio; AU = Arbitrary Unit; 95% CI = 95% Confidence Interval.

5. Conclusion

Our research identifies that both beneficial and harmful associations exist between external workload metrics and injury-risk. Specifically, for duration and total distance, a high two-weekly load increased injury-risk in the subsequent week, whilst a high four-weekly load demonstrated a reduced injury-risk. Conversely, a high four-weekly relative distance was positively associated with injury-risk, whilst a high two-weekly load was negatively associated. Such findings suggest that appropriate and consistent increases in total workload (duration and distance) contribute to a decreased injury-risk within rugby league players. Whilst sustained increases in intensity through relative distance (m min^{-1}) contribute to an enhanced injury-risk.

Further, our research demonstrates that external workload metrics routinely collected within team-sports such as rugby league, can provide insight into understanding injury-risk. Collectively, this work provides the framework for the development of a decision-support system that can facilitate an enhanced understanding of the complex aetiology surrounding the risk of injury.

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Please cite this article in press as: Cummins C, et al. Modelling the relationships between volume, intensity and injury-risk in professional rugby league players. *J Sci Med Sport* (2018), https://doi.org/10.1016/j.jsams.2018.11.028

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