The acute-to-chronic workload ratio: an inaccurate scaling index for an unnecessary normalisation process?

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INTRODUCTION

An important question for researchers and practitioners is whether an individual's risk of injury increases if they make prior changes to their training load.[1] In this field of research, 'load' typically refers to in-training distances covered, speed and accelerations.[1] Attention has generally focused on whether a person's acute (eg, 7 day) increase in load, normalised to that person's prior 'baseline' of chronic (eg, 28 day) load, predicts injury.[1] To obtain this normalised predictor, acute load is typically divided by chronic load to provide the acute-to-chronic workload ratio (ACWR).[1]

Fundamentally, simple ratios (Y/X) are formulated to '*control for*' a denominator variable (eg, preceding chronic load) that is perceived to have an important biological influence on the numerator variable (eg, acute load).[2] Within this notion of '*control for*',[3] it is generally posited that the denominator is a 'nuisance' variable that is associated with the numerator of interest.[2] Logically, a simple ratio index provides meaningful *relative* measures for clinical and prognostic purposes only if (1) there is a 'true' and 'proportional' *association* between numerator and denominator in the first place, and (2) the ratio normalises for the denominator in a consistent manner for all individuals in the measurement range.[2]

We have demonstrated recently that the typical practice in the current literature[1] of including, for example, 7-day load within the 28-day load calculation can generate problems of 'relating of a part to a whole' and provide biased ACWR estimates.[4] In the context of the ACWR, 'within-subjects' (repeated-measures) analyses are also critical to quantify the degree of any *relative* increase or decrease in the acute load experienced by a given player while controlling for any variation in prior chronic load in that same player.[5] This is assuming that acute and chronic load are truly, non-spuriously, associated.[4] Therefore, we aimed (1) to scrutinise the assumptions that underpin the ACWR,[2] and (2) to compare the relative quality of 12 linear and non-linear functions for modelling the longitudinal within-subjects relationships between acute load and chronic load.[5 6]

ARTEFACTUAL RATIO CORRELATION COMPOUNDED FROM UNRELATED MEASUREMENTS

We analysed the data collected as part of a previous study, which received Institutional Ethics approval.[7] A sample of English Premier League players (n=24) were monitored over 38 in-season weeks. General linear models were used to derive the overall within-player correlations over the multiple in-season weeks by regressing acute load (or the ACWR) on chronic load, with participant entered as a categorical factor.[8] Total distance (m) acute load was designated as the most recent 7-day period, whereas the 28-day period defining chronic load was calculated separately[4] as a conventional rolling average.[9] As recommended, data collected during preseason were not included in the chronic load calculation.[9] Only data from players with four complete measurements prior to the fifth acute period were analysed.

We found only a trivial within-subject correlation of −0.04 (95%CI −0.44 to 0.37) between acute and chronic load. Second, we found a large and inverse within-subject correlation between the ACWR and its chronic load denominator; r= −0.50 (95%CI −0.71 to −0.18). Specifically, this meant that the use of the ACWR biased a person's status of acute total distance as too low when prior chronic total distance loads were high and vice versa (figure 1). Such bias will naturally occur, especially in this case where the association between numerator and denominator is trivial.[2]

Therefore, because within-person variations in prior chronic load were not influential on subsequent within-person variations in acute load,[2] it is possible that the ACWR

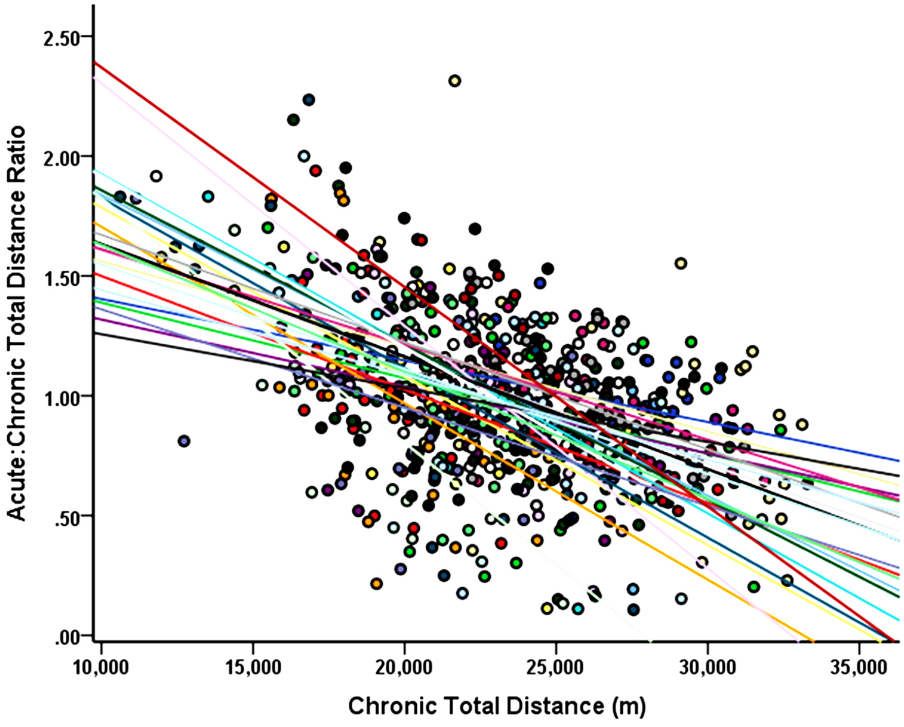

Figure 1 Each slope shown in the scatterplot represents the within-subject association between acute-to-chronic workload ratio (ACWR) and chronic total distance load (m) for each participant in the present sample.

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Table 1 Within-subject statistical models fitted to untransformed acute and chronic load data over 38 in-season weeks

Model	AIC	ΔAIC	Inference
Straight line, no intercept, with lognormal heteroscedastic error	13,919.56	352.96	No empirical support
Three-parameter power function with lognormal, heteroscedastic error	13,825.72	259.12	No empirical support
Straight line, intercept, with lognormal heteroscedastic error	13,823.78	257.18	No empirical support
Two-parameter power function with lognormal, heteroscedastic error	13,823.74	257.14	No empirical support
Straight line, no intercept, with normal heteroscedastic error	13,702.02	135.42	No empirical support
Straight line, no intercept, with normal homoscedastic error	13,696.38	129.78	No empirical support
Three-parameter power function with normal, heteroscedastic error	13,610.86	44.26	No empirical support
Three-parameter power function with normal, homoscedastic error	13,604.72	38.12	No empirical support
Straight line, intercept, with normal, heteroscedastic error	13,568.30	1.70	Essentially equivalent
Straight line, intercept, with normal, homoscedastic error	13,567.62	1.02	Essentially equivalent
Two-parameter power function with normal, homoscedastic error	13,567.60	1.00	Essentially equivalent
Two-parameter power function with normal, heteroscedastic error	13,566.60	0	Best

Qualitative terms for the relative difference (ΔAIC) from the estimated best model (ie, the model with the lowest AIC value; ΔAIC=0) were assigned according to the following scale: 0–2, essentially equivalent; 2–7, plausible alternative; 7–14, weak support; >14, no empirical support.[10]
AIC, Akaike's information criterion; Δ AIC, Akaike difference.

(or indeed any normalisation approach) essentially incorporates the 'noise' of an unrelated denominator to the numerator of interest.

To demonstrate how a researcher should formulate and evaluate appropriate scaling models, we used the MODEL procedure in *SAS OnDemand for Academics* to perform within-subject, non-linear regression analyses of untransformed acute and chronic total distance load measurements. We fitted three sets of four models assuming multiplicative, log-normal, heteroscedastic error and additive, normal, homoscedastic or heteroscedastic error, respectively.[5 6] The relative quality of each candidate model was determined using an information-theoretic approach.[10]

Notably, all the *ratio models* (ie, straight line, no intercept models) had no empirical support in this model comparison (table 1). The allometric exponent (95% CI) describing the relationship between acute and chronic load was 0.058 (95% CI 0.040 to 0.063) and 0.061 (95% CI 0.045 to 0.077) for the two-parameter power function with normal, homoscedastic or heteroscedastic error, respectively. These two models, alongside the straight lines, intercept and normal homoscedastic or heteroscedastic error, were clearly more appropriate than ratio normalisation for our data (table 1). Nevertheless, these allometric exponents were close enough to zero for us to question, again, the fundamental need to normalise acute load for chronic load using any statistical approach whatsoever in this particular data set.[2 5 6]

PRACTICAL IMPLICATIONS AND FUTURE DIRECTIONS

Collectively, the results of our previous[4] and present study suggest that acute load itself could be a useful predictor of injury in *absolute terms* and may not necessarily require normalisation for chronic load via a ratio or different statistical approaches (table 1). It is, therefore, difficult to conceive a causal pathway between changes in chronic load and changes in acute load if these variables are, in fact, not associated with each other,[3] as we found in the present study.

If the lack of a 'true' within-person association between acute and chronic load is confirmed in other, larger data sets, then formulation of the ACWR may merely add undesired 'noise' to an injury prediction model. We suggest that different scaling models should be appraised carefully before the ACWR is naturally assumed to be a suitable exposure for injury risk. Until this appraisal is completed and appropriate epidemiological models are evaluated, the current use of the ACWR to identify at-risk athletes and manage them athletes may be premature. Future research appears necessary to establish the optimal analytical approach for training load monitoring and injury prediction in everyday practice.

Contributors LL, AMB and GA developed the study concept and design. All authors contributed to the writing, provided feedback and revised critically the manuscript.

Funding The authors have not declared a specific grant for this research from any funding agency in the public, commercial or not-for-profit sectors.

Competing interests None declared.

Patient consent Not required.

Ethics approval Liverpool John Moores University.

Provenance and peer review Not commissioned; externally peer reviewed.

To cite Lolli L, Batterham AM, Hawkins R, *et al*. *Br J Sports Med* Epub ahead of print: [*please include* Day Month Year]. doi:10.1136/bjsports-2017-098884

Accepted 23 May 2018

Br J Sports Med 2018;**0**:1–2.
doi:10.1136/bjsports-2017-098884

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