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

Lorenzo Lolli[1], Alan M Batterham[1], Richard Hawkins[2], David M Kelly[2,3], Anthony J Strudwick[2], Robin T Thorpe[2,3], Warren Gregson[3], Greg Atkinson[1]

[1] Health and Social Care Institute, Teesside University, Middlesbrough, UK

[2] Medicine and Science Department, Manchester United Football Club, UK

[3] Football Exchange, Research Institute for Sport and Exercise Sciences, Liverpool John Moores University, Liverpool, UK

Correspondence:

Lorenzo Lolli
Health and Social Care Institute
School of Health and Social Care
Constantine Building
Teesside University
Middlesbrough, TS1 3BA, United Kingdom
e-mail: L.Lolli@tees.ac.uk
Telephone: +44 (0) 1642 342934

Word count: 950 words.

Items: 1 figure; 1 table.

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 (e.g., 7-day) increase in load, normalised to that person's prior "baseline" of chronic (e.g., 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 (e.g., preceding chronic load) that is perceived to have an important biological influence on the numerator variable (e.g., 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 *i)* there is a 'true' and 'proportional' *association* between numerator and denominator in the first place, and *ii)* 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 *i)* to scrutinise the assumptions that underpin the ACWR,[2] and *ii)* to compare the relative quality of twelve 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 thirty-eight 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 pre-season 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 (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* (i.e., 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 dataset.[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 datasets, 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 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 write, provide feedback, and revise critically the manuscript.

Competing interests

None declared

References

1. Bourdon PC, Cardinale M, Murray A, et al. Monitoring athlete training loads: consensus statement. *Int J Sports Physiol Perform* 2017;12(Suppl 2):S2161-S70. doi: 10.1123/IJSPP.2017-0208
2. Curran-Everett D. Explorations in statistics: the analysis of ratios and normalized data. *Adv Physiol Educ* 2013;37(3):213-19. doi: 10.1152/advan.00053.2013
3. Pearl J. Causal inference in statistics: an overview. *Statist Surv* 2009;3:96-146. doi: 10.1214/09-SS057
4. Lolli L, Batterham AM, Hawkins R, et al. Mathematical coupling causes spurious correlation within the conventional acute-to-chronic workload ratio calculations. *Br J Sports Med* 2017 doi: 10.1136/bjsports-2017-098110 [published Online First: 2017/11/05]
5. Batterham AM, George KP, Birch KM, et al. Growth of left ventricular mass with military basic training in army recruits. *Med Sci Sports Exerc* 2011;43(7):1295-300. doi: 10.1249/MSS.0b013e3182093300
6. Packard GC. Is complex allometry in field metabolic rates of mammals a statistical artifact? *Comp Biochem Physiol Part A Mol Integr Physiol* 2017;203:322-27. doi: 10.1016/j.cbpa.2016.10.005
7. Thorpe RT, Strudwick AJ, Buchheit M, et al. Tracking morning fatigue status across in-season training weeks in elite soccer players. *Int J Sports Physiol Perform* 2016;11(7):947-52. doi: 10.1123/ijspp.2015-0490
8. Bland JM, Altman DG. Calculating correlation coefficients with repeated observations: Part 1--Correlation within subjects. *BMJ* 1995;310(6977):446.

9. Murray NB, Gabbett TJ, Townshend AD, et al. Individual and combined effects of acute and chronic running loads on injury risk in elite Australian footballers. *Scand J Med Sci Sports* 2017;27(9):990-98. doi: 10.1111/sms.12719

10. Burnham KP, Anderson DR, Huyvaert KP. AIC model selection and multimodel inference in behavioral ecology: some background, observations, and comparisons. *Behav Ecol Sociobiol* 2011;65(1):23-35. doi: 10.1007/s00265-010-1029-6

FIGURE LEGENDS

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

TABLE LEGENDS

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

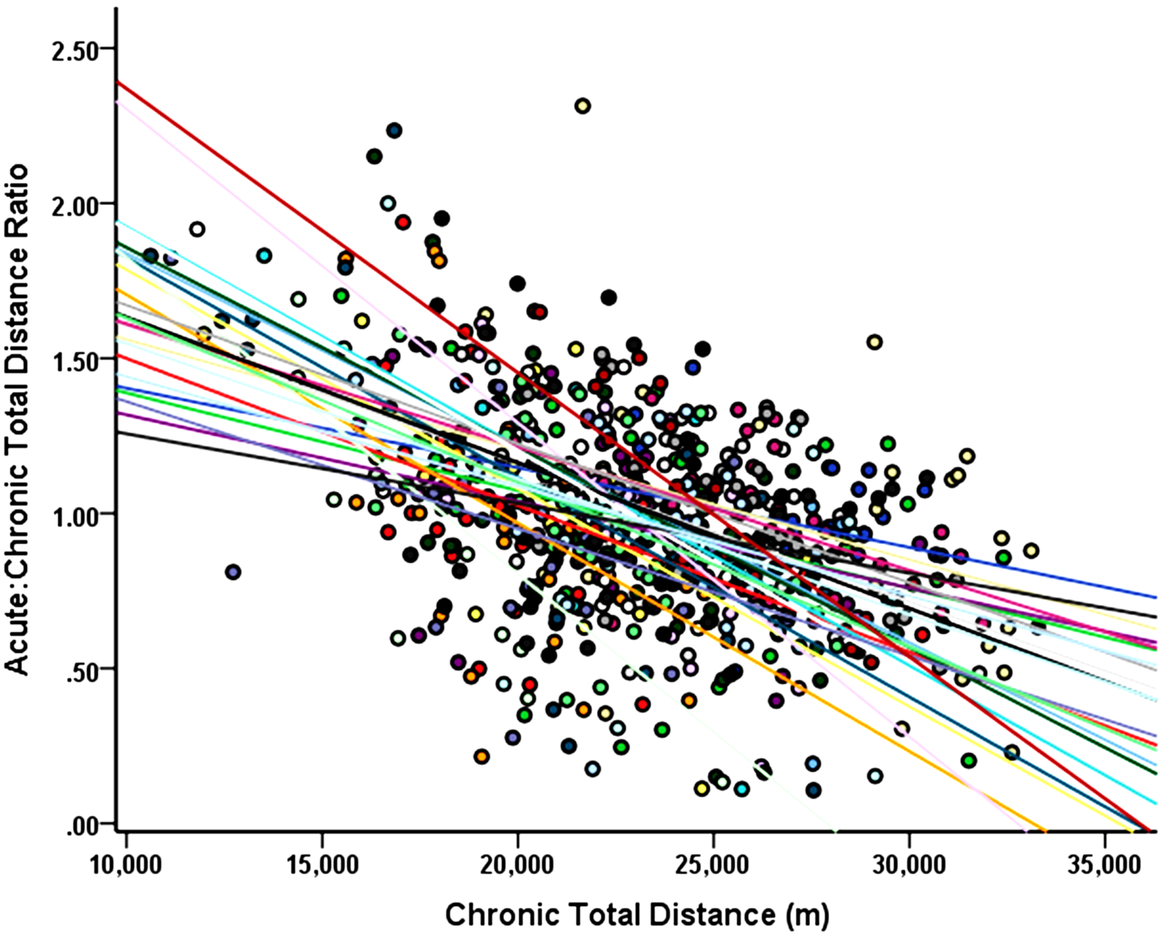

Figure 1. Each slope shown in the scatterplot represents the within-subject association between ACWR and chronic total distance load (m) for each participant in the present sample.

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

Model	AIC	ΔAIC	Inference
Straight line, no intercept, with lognormal heteroscedastic error	13919.56	352.96	no empirical support
Three-parameter power function with lognormal, heteroscedastic error	13825.72	259.12	no empirical support
Straight line, intercept, with lognormal heteroscedastic error	13823.78	257.18	no empirical support
Two-parameter power function with lognormal, heteroscedastic error	13823.74	257.14	no empirical support
Straight line, no intercept, with normal heteroscedastic error	13702.02	135.42	no empirical support
Straight line, no intercept, with normal homoscedastic error	13696.38	129.78	no empirical support
Three-parameter power function with normal, heteroscedastic error	13610.86	44.26	no empirical support
Three-parameter power function with normal, homoscedastic error	13604.72	38.12	no empirical support
Straight line, intercept, with normal, heteroscedastic error	13568.30	1.70	essentially equivalent
Straight line, intercept, with normal, homoscedastic error	13567.62	1.02	essentially equivalent
Two-parameter power function with normal, homoscedastic error	13567.60	1.00	essentially equivalent
Two-parameter power function with normal, heteroscedastic error	13566.60	0	best

AIC = Akaike's information criterion; ΔAIC = Akaike difference. Qualitative terms for the relative difference (ΔAIC) from the estimated best model (i.e., 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]