Title: The dose-response relationship between training load measures and changes in force-time components during a countermovement jump in male academy soccer players

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Abstract

Purpose: To manage physical performance in soccer, practitioners monitor the training load (TL) and the resulting fatigue. A method frequently used to assess performance is the countermovement jump (CMJ). However, the efficacy of CMJ to detect fatigue from soccer matches and training remains uncertain, as does the relationship between TL and change in CMJ performance. The aims of the present study are two-fold. One is to observe the changes of CMJ force-time components and jump height (JH). The second is to examine dose-response relationships between TL measures and CMJ over a 6-wk pre-season. **Methods:** Twelve professional male youth soccer players (17±1 year, 71.2±5.6 kg, 178±5.8 cm) were recruited. Daily changes in CMJ were assessed against baseline scores established before pre-season training, along with internal and external TL measures. A series of Bayesian random intercept models were fitted to determine probability of change above/below 0 and greater than the coefficient of variation (CV) established at baseline. Jumps were categorised into match-day minus (MD-) categories where the higher number indicated more time from a competitive match. **Results:** JH was lowest on MD-3 (28cm) and highest on MD-4 (34.6cm), with the probability of change from baseline CV highly uncertain (41% and 61% respectively). Changes to force-time components were more likely on MD-3 (21%-99%), which provided less uncertainty than JH. Bayes R2, ranged from 0.22-0.57 between TL measures and all CMJ parameters. **Conclusion:** Force-time components were more likely to change than JH. Practitioners should also be cautious when manipulating TL measures to influence CMJ performance.

INTRODUCTION

Physical performance at any given time has been purported to be a consequence of an individual's fitness status minus any accumulated fatigue[1]. The mechanisms of fatigue remain debated, but the practical measurement, categorization and management of fatigue has received some attention. Enoka and Duchateau[2] provided a taxonomy and categorised fatigue into 'performance fatigue' and 'perceived fatigue'. The performance fatigability strand from the taxonomy includes contractile function (e.g., force capacity) and muscle activation (e.g., neuromuscular propagation). In practice, this is often referred to as neuormuscular fatigue and can be typically assessed through decrements in performance tests[3]. Performance tests such as the countermovement jump (CMJ) have been proposed to detect neuromuscular fatigue, but there has been recent criticism on whether jump-height (JH) is a valid marker of neuromuscular fatigue[4].

JH can be calculated via two methods, the 'gold standard' for calculating JH is to utilise ground reaction force (GRF) which samples at an appropriate frequency (usually 1000Hz) and numerically integrates the GRF to establish velocity, and consequently displacement[5,6]. The additional benefit of using the GRF data to assess CMJ is the consequent force-time components and the JH obtained[7,8]. Typically, the CMJ is

broken down into unweighting, braking, propulsive, flight and landing with each phase having their respective force-time data calculated (e.g., time in each phase, impulse, power and velocity)[7]. However, a cheaper alternative is for practitioners to acquire JH data using the flight-time method. This is where JH is estimated from the distance travelled by the centre of mass (COM) and can be collected on equipment such as contact mats[9].

Due to its ease of administration and potentially low cost, numerous studies have characterised JH changes as a marker of neuromuscular fatigue following match-play[3]. Impairments in JH were suggested to occur immediately after the match and up to 72h [3]. Given that match-play is often the largest training load (TL) experienced within a training microcycle, it is perhaps not surprising to see JH diminish[3]. This is due to match play inducing transient inflammation, energy depletion and damage to muscle tissue[10,11,12]. However, when assessing JH following training (where TL is typically less than that of a match), it is unclear whether JH reduces when assessed before and after training sessions across a competitive microcycle[13]. Thorpe *et al.*,[14] have also shown that across a 17-day competitive microcycle, JH had low variation (4%), but negative changes in heart-rate variability and perceptions of fatigue were still

observed. These fundings suggest that JH alone may not detect neuromuscular fatigue which are observed by other measures.

Consequently, investigating the force-time components which underpin the performance output (JH) might provide a different insight into an athlete's state of fatigue and/or recovery. Gathercole *et al.*,[8] have provided reliability and sensitivity of the CMJ test in college-level athletes. Following a high-intensity fatigue protocol, there is evidence of a reduction in the athletes' force-time data in up to 19 CMJ variables. Of these 19 CMJ variables, there were larger changes (e.g., increased effect size) apparent with the force-time components as opposed to JH following the fatigue protocol. Changes in the force-time components as opposed to the JH could have contributed to impaired excitation–contraction coupling, stretch-reflex sensitivity related reduction in muscle stiffness or metabolic disturbances[15,16]. For example, decreased reflux sensitivity is thought to contribute to eccentric muscle function, which may explain the changes during the braking phase in the Gathercole et al., study[8]. Pasquet et al.,[17] also suggest that altered intracellular Ca^{2+} controlled excitation–contraction coupling processes during concentric contractions are present under neuromuscular fatigue. As such, eccentric and concentric force-time components may be affected differently when neuromuscular fatigue is present and consequently alter the

force-time components and/or JH. Although not related to a soccer-specific population, these findings highlight the potential added information on neuromuscular fatigue from the force-time components during the CMJ[8].

Regular monitoring of CMJ is now commonplace in elite performance environments. Moreover, the new software which utilises the force-time data can now give instant feedback and consequently information on the force-time components and the JH obtained. However, there is currently limited evidence measuring the force-time components in soccer players with research focussing only on match-play or simulation[3]. Furthermore, if the purpose of monitoring players' CMJ is to help inform programming decisions and manage the training process (e.g., if a player is demonstrating a decreased JH for their usual TL, then the training plan should be adjusted). This practice would suggest that a reduction in TL would impact JH. However, few studies have attempted to examine this dose-response relationship and have not considered a comprehensive range of internal and external TL in relation to the CMJ[3,18,19]. If this relationship is present, then practitioners can be more confident that a change in TL would impact CMJ and consequently manage neuromuscular fatigue better.

Previous research has attempted to encapsulate this dose-response relationship, but has only used partial TL measurements (e.g., high-speed running)[14,19], acquired minimal observations (e.g., pre and post pre-season)[18], reported very weak relationships with JH[20], and only considered the JH rather than the force-time components[14,18,19]. Therefore, examining the force-time components alongside the JH with a combination of increased observations and extensive range of TL measurements (which consider the whole intensity continuum) may provide more information on the dose-response relationships between the TL and CMJ.

Consequently, the aims of the study are two-fold. One is to observe the longitudinal (6-weeks pre-season) changes with the force-time components and JH. The second is to examine dose-response relationships between TL measures and CMJ variables over the pre-season period.

METHOD

Participants

Twelve male academy soccer players were recruited to participate in the study. All players were part of a Category 2 academy under the Premier League guidelines. The physical characteristics (mean±SD) of the players were as follows: age 17±1yr, 71.2±5.6kg, 178±5.8cm. Written informed consent was given by each player, with the study being approved by the university ethics committee.

Procedure

To establish baseline measurements, each player completed 3 CMJ followed by a 24-h rest and then performed another 3 CMJ 4-days prior to pre-season. All players were familiarised with the CMJ protocol and were instructed to perform a CMJ without arm-swing given its greater reliability compared to with arm-swing[21].

The coefficient of variation (CV%) was calculated for each player at baseline and used in the statistical analysis as a practical threshold to change above this value rather than as a covariate in the statistical models. The CV% was calculated by dividing the SD by the mean multiplied by 100 to give a percentage. The mean CV% for each player was then calculated from both tests and the final CV% used for analysis was the mean squad CV%

for each variable (table 1). The best CMJ (highest JH) from three trials was taken for analysis as this had been previously deemed an acceptable monitoring method for CMJ performance[22].

CMJ was monitored using dual PASCO force plates (PASCO scientific, Roseville, CA, US) which sampled at 1000Hz. Players were asked to jump on the morning prior to each training session (and 3 home match fixtures) from 45-60 min prior to outdoor training/ match-play following a standardised warm-up utilising dynamic stretches over the 6-wk period. CMJ data collection and analysis followed guidelines previously set out by Owen *et al.*,[23] CMJ variables collected adhere to previous definitions provided by Gathercole *et al.*,[8] and McMahon *et al.*,[7]. JH was calculated using the impulse-momentum method[24], while net-force was integrated with respect to time to obtain net impulse which was summed over the eccentric and concentric phases[23]. There were a total of 244 jumps collected (22±5 observations per player) over the 6-weeks of pre-season. Should a participant have missed a CMJ during data collection, it was simply not included in the analysis and no imputation methods were used.

Training sessions (n=26) and matches (n=7) were categorised in relation to the days before the match (i.e., match-day minus [MD-]). Thus, there were 6 categories broken down into MD-5 (5-days prior to match), MD-4 (4-days prior to match), MD-3 (3-

days prior to match), MD-2 (2-days prior to match), MD-1 (1-day prior to match) and MD (match-day). When matches were on a Saturday, players would typically jump every morning including Saturday's (home fixture only) but not Sunday (MD+1). There was one occasion where players played 2 games in one week with the TL and CMJ categorised (MD) appropriately and MD+1 always remaining a non-training day.

**Table 1 near here – Coefficient of Variation (CV) of all jump measures at baseline **

To monitor the player's internal TL, heart rate was collected via heart rate monitors which sampled at 10Hz (TeamPro, Polar Electro, OY, Finland) with the raw data being exported for analysis. All raw HR data was inspected visually for abnormal spikes, but these were not apparent in the current data collection. A comprehensive range of training impulse (TRIMP) methods were included and calculated in the following manor. The Bannister TRIMP (bTRIMP) was calculated based on training duration, HR and a weighting factor using the following formula:

bTRIMP= duration training (minutes) x ΔHR x $0.64e^{1.92x}$

where ΔHR = (HRex – HRrest)/(HRmax – HRrest), e equals the base of the Napierian logarithms, 1.92 equals a generic constant for males and x equals ΔHR. Edwards TRIMP (eTRIMP) was

calculated based on time spent in five HR zones and multiplied by a zone-specific weighting factor: duration in zone 1 (50–59% of HRmax) multiplied by 1, duration in zone 2 (60–69% HRmax) multiplied by 2, duration in zone 3 (70–79% HRmax) multiplied by 3, duration in zone 4 (80–89% HRmax) multiplied by 4 and duration in zone 5 (90–100% HRmax) multiplied by 5. Summating the scores from each zone results in the final eTRIMP[25]. A modified luTRIMP was employed by multiplying the time spent in three HR zones based around HR at fixed blood lactate accumulation at 2 and 4 mmol · L^{-1} [26,27]. The RPE training load (sRPE-TL) was calculated by multiplying the duration of the session by the CR-10 score[28]. Participants were familiar with CR-10 method as they had previously used it for 4 seasons prior to data collection. sRPE-TL was recorded on pen and paper by verbally asking each player for their score immediately following sessions.

iTRIMP was calculated in the same manor is bTRIMP, but instead of the generic exponential weighting factor, each player would generate their own weighting factor as stated by Manzi et al.,[29]. To generate individual weighting factors, each player completed an incremental lactate threshold test on a motorised treadmill (h/p cosmos mercury 4.0; h/p Cosmos, Nussdrof-Traunstein, Germany). The protocol consisted of five stages at 8, 10, 12, 14 and 16 km · h^{-1} [30]. Each stage was 4 min in duration

with a 1-min rest period between stages. Following the 1-min rest at 16 km · h−1, the protocol increased 0.5 km · h−1 every 30 s until the player reached volitional exhaustion. During all rest periods and following the final stage, a 20 µl fingertip capillary blood sample was taken. The blood sample was diluted in a lactate-glucose haemolysing solution and then taken for analysis (Biosen C-Line, EKF Diagnostics, Germany). To establish a fixed blood lactate accumulation at (S4) mmol·l^{-1} the Lactate-E software was used[31].

External TL was measured with a GPS/MEMS device worn between the players scapula (GPS 10 Hz, Tri-axial accelerometer 100Hz; Catapult S5, firmware 6.75, Catapult Innovations, Melbourne, Australia). These devices have previously demonstrated reliability (1.9-6% CV) for instantaneous velocity, high-speed running (4.7% CV)[32] and sufficient sensitivity to accelerations, decelerations, and constant velocity[33]. Data were processed using Sprint 5.1 (Catapult Innovations, Melbourne, Australia). The thresholds used for high-speed running (HSR) distances were 14.4-19.8 km·h^{-1}, very high-speed running (VHSR) was 19.8-25.2 km·h^{-1} and maximal sprint distance was >25.2 km·h^{-1}. High-intensity accelerations (HiAccel) and decelerations (HiDecel) thresholds were set at distance covered at or above 3 m·s^{-2}. Total distance (TD) and PlayerLoad^{TM} (PL) were also collected for each session.

Additionally, each player had their own individual high-speed threshold (iHSD) which was derived from the speed of which a fixed blood lactate concentration of 4 mmol·L^{-1} occurred (13±2 km·h^{-1}) on the incremental treadmill test[27]. A mean number of 12±13 satellites recorded sessions where the horizontal dilution of precision recorded at 0.8 ± 0.4 and minimum effort dwell time was set to 1 s (default settings).

Statistical Analysis

Given recent concerns over null-hypothesis significance testing, the wide misinterpretation of traditional p-values and confidence intervals, as well as the need for random samples for their accurate calculation, in the present study, Bayesian analysis was used rather than traditional frequentist analysis. This type of analysis avoids these issues, is better suited for making inferences on small sample sizes given informative prior information and provides direct probabilities of differences or relationships. An added advantage of using Bayesian probability is that direct probabilities are not limited to calculating a probability above or below zero, but a probability above any value that a researcher might consider important. In the present study, we calculated differences above natural variation in jump performance using the coefficient of variation as a proxy for this. The output of Bayesian analysis is known as a posterior distribution, which is essentially a probability distribution that is

a combination of prior knowledge and the likelihood function using the data. This distribution captures all the information about parameter values and their uncertainty.

Rather than conducting a series of hypothesis tests, the data were modelled in different ways and the best models chosen in terms of how well the model performed on unseen data, known as out-of-sample prediction accuracy. Leave-One-Out cross validation information criterion (LOOIC) was used for this purpose, where the pointwise out-of-sample prediction accuracy was determined using log-likelihoods from posterior simulations of parameters. The best models are reported, and all passed an agreed threshold for a metric that determines reliability of estimates obtained from Markov-Chain Monte-Carlo (MCMC) chains ($\hat{r}=1$). Both force-time components and JH were assessed against baseline and this was modelled over time using the match-day minus categories. A series of Bayesian models were fitted where the intercept for each participant was allowed to vary, allowing a partial pooling strategy with all of the intercepts informing each other[34]. These models not only capture the central tendency of the trends across time but also trends for each player. Given time between jumps differed (24 hrs and 48-72hrs) with players sometimes not playing on Wednesday or Sundays, time between each jump was included as a covariate to control for this. Estimated marginal

means (Lenth et al., 2020, emmeans, v1.4.8) were calculated from the best fitting models with pairwise comparisons made between time categories reported along with their associated 95% Highest Posterior Density (HPD) — the Bayesian equivalent of a confidence interval. Probability was calculated for both change above or below 0 depending on the most probable direction (probability of direction), and a change greater than the CV% established at baseline (practical significance in that it gives probability above natural variation) using bayestest package in R. The models used appropriate weakly informed priors as a starting point as these can help regulate the posterior distribution by reducing the effect of any extreme values in the data[35]. In order to check that the chosen priors had a reasonable constraining effect without biasing estimates, prior predictive checks were used and found to be appropriately weakly informative across estimates before the collected data were included in the models. In order to check that the final models simulated the actual data in terms of distribution, variance and central tendency, posterior predictive checks were used and showed (using draws from a model's posterior distribution), that the simulated data aligned well with the observed data.

To establish relationships between the previous days' TL and next-day jump, all CMJ data (height and force-time components) were subtracted from baseline to give a change from baseline score. The previous day's load was then modelled with the change in force-time variables or jump height. Again, a series of Bayesian random intercepts models were fitted, with participant's intercepts allowed to vary. Different response distributions were used to model the dependent variable ranging from Gaussian (normal) to Skew normal. Time between jumps was again used as a covariate within the model. A Bayesian version of R^2 was calculated as an estimate of the proportion of variance explained for future predictions along with 95% HPDs. All analyses were conducted in R (Core Team, 2020) and analysed using the Bayesian Regression Models in Stan (brms; Buerkner, 2017) package which uses Stan (Stan development team, 2018) to implement a Hamiltonian Markov Chain Monte Carlo with a No-U-Turn Sampler with the default settings (number of chains, iterations, thinning and burn-in) used. Code is available as a supplementary file.

RESULTS

Tables 2 and 3 show the weekly mean TL data experienced over the 6-weeks according to each match-day category. Table 4 indicates that JH was reduced on MD and MD-3 with all other days showing small increases or minimal change from baseline. Countermovement depth (CMD) was reduced on MD-3 with all other days showing small changes from baseline (0.2 to 1.5cm) as shown in Table 5. Braking phase time was increased on all training and match days but the probability of this occurring above the CV% is uncertain ranging from 0 to 71% (table 5). Table 5 also shows that mean power was reduced in the braking phase across all categories with differences from baseline ranging from small (62W) to large (290W). Net impulse was reduced during the braking phase with the largest change on MD-3 and measures in the propulsive phase remain relatively unchanged from baseline (table 5). Overall, the braking phase force-time components suggest a higher probability of a practical change (more than CV%) compared to JH.

Explained variance for future predictions between all TL (internal and external) measures and JH ranged from 0.22-0.25 (95%CI: 0.13-0.39). For CMD the R^2 values ranged from 0.43-0.47 (95%CI: 0.35-0.53) across all TL. The R^2 values for all TL and the braking phase time, mean power and net impulse were 0.55-0.57 (95%CI: 0.47-0.62), 0.38-0.40 (95%CI: 0.30-0.47) and

0.39-0.43 (95%CI: 0.31-0.49) respectively. The R^2 values for all TL and the propulsive phase time, mean power and net impulse were 0.38-0.45 (95%CI: 0.30-0.52), 0.37-0.39 (95%CI: 0.28-0.46) and 0.40-0.42 (95%CI: 0.32-0.49) respectively. Figure 1 shows one of the highest R^2 relationship to give visual indication of the uncertain relationships between TL and CMJ. Relationships for each TL measure are available as a supplementary file within Tables 6 and 7.

Table 2 near here – Internal load measures for each of the categories across the 6-week pre-season (mean ± SD)

Table 3 near here - External load measures for each of the categories across the 6-week pre-season (mean ± SD)

**Table 4 near here – Change in jump height (cm) from baseline for each category across the 6-week pre-season. **

**Table 5 near here - Change in force-time components from baseline for each category across the 6-week pre-season **

**Figure 1 near here

DISCUSSION

The present study aims were two-fold: 1) to determine if the force-time components and JH change over the pre-season period and 2) to establish potential dose-response relationships between TL measures and the force-time components or JH. JH was at its lowest on MD-3 (28cm) and its highest on MD-4 (34.6cm), but the chance of any change from baseline CV is highly uncertain (41% and 61% respectively). There was more consistent evidence for force-time components changing from baseline on MD-3 (see table 5). Braking phase time (+49ms), mean power (-290W) and net impulse (-30N·s^{-1}) were more likely to change on MD-3, with the CMD (+6.2cm) also not lowering as normal. Propulsive phase force-time components changes were less pronounced, suggesting that the players maintained the ability to concentrically produce force across each MD- category. Therefore, the main finding from this particular study is that braking phase force-time components show a higher probability to change compared to JH during a soccer pre-season. However, in terms of measuring a dose-response relationship between TL measures and the CMJ (JH and force-time components), it is unlikely the previous days TL

influences the next day CMJ (with explained variance ranging from 23% to 57% across all TL measures). Thus, practitioners looking to manage neuromuscular fatigue via the CMJ method should look to investigate changes during the braking phase but remain cautious in adjusting their training plan based on the previous day's TL measures (internal or external).

Similar to previous research[13,14], JH was preserved over the pre-season period and did not seem to be affected by soccer training (given the uncertainty of the dose-response data and low probability of change >CV). Given the inconclusive evidence regarding JH as a marker of neuromuscular fatigue soccer training, our findings highlight the potential of the force-time components to change more than the JH, and they may want to be considered within the training monitoring process. This study suggests that on MD-3 during pre-season, the force-time data was more like to reduce in the braking phase across all components (71-99% chance of changing) than both the JH (41% chance of reducing) and all propulsive phase components (3-58% chance of changing). This is similar to the acute studies within the soccer literature[14], been observed elsewhere[8]

and could potentially be due to decreased reflux sensitivity[15,16].

However, an interesting observation from the present study is that MD-4 represents the highest internal (iTRIMP=280±135 AU) and external load (TD=9739±2137m) experienced over the pre-season (such TL is higher than the MD due to players routinely rotating their match playing time which can be common during the pre-season period). Following the training on MD-4, the recorded CMJ variables on MD-3 represent the largest reductions in both JH (2.8cm) and braking phase force-time components. However, given the uncertainty in the dose-response relationships between all TL measures and all CMJ parameters, these changes may not be influenced by the previous day TL.

Previous dose-response research which has examined TL and JH over a pre-season period show uncertain relationships[18,19]. But unlike the present study, they did not measure CMJ daily or consider the force-time components. Studies that have utilised the force-time component have followed match-play and only considered a few isolated metrics and not the temporal force-time components[36,37]. Although the current study

tried to address these limitations, no credible dose-response relationships were found between the previous days TL and next-day CMJ. Figure 1 shows one of the strongest (some were very similar, see table 6 & 7 supplementary file) dose-response relationships, which was between HSR and change in braking phase time. This figure, along with the other dose-response data, show the importance of developing these dose-response relationships. For example, it highlights that when some players complete more HSR, some spend longer in the braking phase and others spend less (and vice versa). Therefore, this makes it difficult for the practitioner to adjust the training plan (based on the previous day TL) with less uncertainty.

Previous research has also considered accumulated HSR (>14.8 km·s^{-1}) over 2, 3 and 4 days, with the results suggesting unclear relationships (r=0.18-0.28)[14]. Thus, along with this study, there appears to be a growing body of evidence to suggest that soccer training may not induce neuromuscular fatigue which is captured via the CMJ method, or the soccer training itself is effective at preserving CMJ performance. This is perhaps due to CMJ being a performance measure that can theoretically be affected by different training

methods (cardiovascular, strength or skill) and non-physical factors (psychological) as posited by the multicomponent model presented by Calvert *et al.,*[38]. Consequently, one potential explanation for JH and the force-time data to change, but not display a dose-response relationship between TL measures is the use of different training modalities within soccer. Thus, future studies should consider how each training modality (e.g., on-field or gym-based) may affect the force-time components. Such data may provide clarity on why the force-time components and JH may change, when the relationship between CMJ and the previous day TL is uncertain.

The present study is not without its limitations. The current sample size is somewhat low, but this was the maximum number of players that could be used for analysis at the present time and had the most observations. Despite the small sample size, the HPD intervals capture the uncertainty and are reflected within the results. Moreover, there were only 2 occasions (out of 7) where CMJ data could be collected on MD. The ability to assess CMJ the next day following training or matches was not always possible due to players having a rest day, which increased time

between jumps. However, this was accounted for within the data analysis by adding time between jumps as a covariate.

Practical application

The current study provides evidence that the CMJ force-time data (particularly during the braking phase) has a higher probability of practical change (more than the CV) over a longitudinal period than measuring JH. This indicates that monitoring CMJ force-time components rather than JH may be more beneficial for practitioners. Practitioners should also be mindful of the CV% for each measure and consider some form of error threshold when looking at changes, rather than simply looking at changes above zero. Researchers should also aim to explore similar applied concepts using dose-response relationships to help identify actionable information for practitioners.

Conclusions

To summarise, whilst there were indications on MD-3 that the CMJ force-time data and JH altered, there was no credible dose-response relationship with the previous days TL. This is in line with previous soccer literature, which has also examined CMJ in relation to

TL across different time periods. As such, it remains uncertain as to whether the CMJ is influenced by the TL. Other modalities such as resistance exercise may play a further role in modifying acute CMJ variables as discussed previously, and future research may wish to examine to what extent resistance exercise impairs CMJ performance compared to field-based training and matches.

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Table 1 – Coefficient of Variation (CV) of all jump measures at baseline

	JH (cm)	CMD (cm)	BPT (ms)	BMP (W)	BNI ($N \cdot s^{-1}$)	PPT (ms)	PMP (W)	PNI ($N \cdot s^{-1}$)
CV	3.3	5.3	42	157	18	36	120	12
CV%	5.4	20.3	23.9	20.4	16.1	13.9	7.6	4.8

Notes: JH= jump height, CMD= countermovement depth, BPT= braking phase time, BMP = braking mean power, BNI= braking net impulse, PPT= propulsive phase time, PMP = propulsive mean power, PNI= propulsive net impulse

Table 2 – Internal load measures for each of the categories across the 6-week pre-season (mean ± SD)

	sRPE (AU)	iTRIMP (AU)	bTRIMP (AU)	luTRIMP (AU)	eTRIMP (AU)
MD	915 ± 479	220 ± 128	158 ± 131	193 ± 65	302 ± 103
MD -1	587 ± 245	129 ± 81	89 ± 39	174 ± 49	219 ± 82
MD -2	714 ± 324	192 ± 122	141 ± 67	217 ± 97	324 ± 143
MD -3	929 ± 424	207 ± 122	139 ± 68	213 ± 68	320 ± 138
MD -4	1105 ± 272	280 ± 135	182 ± 56	279 ± 68	418 ± 97
MD -5	605 ± 181	147 ± 68	122 ± 45	182 ± 48	280 ± 84

Notes: AU= arbitrary units, MD= match-day, iTRIMP=individualised TRIMP, bTRIMP= Banister TRIMP, luTRIMP= Lucia TRIMP, eTRIMP= Edwards TRIMP

Table 3 - External load measures for each of the categories across the 6-week pre-season (mean ± SD)

	TD (m)	PL (AU)	HiDec (m)	HiAcc (m)	iHSD (m)	HSR (m)	VHSR (m)	Sprint Dist (m)
MD	8396 ± 2593	772 ± 227	195 ± 71	276 ± 92	6147 ± 2114	1134 ± 435	370 ± 195	125 ± 157
MD -1	5514 ± 515	564 ± 118	128 ± 53	212 ± 69	4383 ± 891	550 ± 409	226 ± 282	62 ± 127
MD -2	7756 ± 3846	674 ± 359	191 ± 105	288 ± 155	6336 ± 3238	776 ± 438	348 ± 313	81 ± 106
MD -3	7104 ± 2852	768 ± 288	154 ± 67	263 ± 109	5330 ± 962	880 ± 609	486 ± 414	23 ± 50
MD -4	9739 ± 2137	961 ± 201	227 ± 93	364 ± 127	6744 ± 2323	1416 ± 433	982 ± 482	117 ± 148
MD -5	7312 ± 1149	709 ± 134	172 ± 50	265 ± 60	5793 ± 1037	1011 ± 381	277 ± 251	48 ± 42

Notes: AU= arbitrary units, MD= match-day, TD=total distance, PL=PlayerLoad™, HiDec=high-intensity decelerations, HiAcc=high-intensity accelerations, iHSD=individualised high-speed distance, VHSR=very high-speed running, Sprint Dist= sprint distance.

Table 4 – Change in jump height (cm) from baseline for each category across the 6-week pre-season.

	Baseline	MD	MD-1	MD-2	MD-3	MD-4	MD-5
EMM [HPD]	30.9 [27.7 to 34.3]	29 [25.4 to 32.3]	31.3 [28.2 to 34.5]	32.3 [29.1-35.5]	28 [24.1-32.4]	34.6 [31.4-38]	30.3 [26.7-34.6]
ΔEMM [HPD]		-1.9 [-4.8 to 0.6]	0.4 [-1.9 to 2.7]	1.3 [-1.1 to 3.8]	-2.8 [-6.5 to 0.6]	3.7 [-1.3 to 6.4]	0.1 [-3.8 to 2.6]
P		0.92	0.62	0.86	0.94	0.99	0.65
P>CV		0.17	0.01	0.06	0.41	0.60	0.05

Notes: EMM= Estimated marginal means, MD= Match-day, CV= coefficient of variation, P=probability, P>CV= probability is greater than the CV, HPD=highest posterior density (set at 95%).

Table 5 - Change in force-time components from baseline for each category across the 6-week pre-season

	CMD (cm)	Braking PT (ms)	Braking MP (W)	Braking NI ($N \cdot s^{-1}$)	Propulsive PT (ms)	Propulsive MP (W)	Propulsive NI ($N \cdot s^{-1}$)
B-EMM [HPD]	-29.9 [-33.8 to -26]	170 [138 to 203]	876 [763 to 982]	123 [103 to 137]	252 [216 to 287]	1664 [1545 to 1813]	258 [245 to 272]
MD-EMM [HPD]	-30.2 [-34.1 to -26.2]	193 [159 to 224]	810 [709 to 922]	120 [104 to 133]	258 [220 to 292]	1596 [1461 to 1725]	251 [237 to 264]
ΔEMM [HPD]	-0.2 [-2.6 to 3.1]	24 [4 to 42]	-64 [-152 to 12]	-3 [-13 to 7]	1 [-15 to 26]	-69 [-157 to 15]	-6 [-15 to 3]
P>0	0.58	0.99	0.93	0.75	0.71	0.95	0.92
P>CV	0.00	0.03	0.02	0.00	0.00	0.13	0.12
MD-1 EMM [HPD]	-28.5 [-31.9 to -24.7]	188 [157 to 218]	763 [665 to 860]	114 [99 to 126]	261 [229 to 298]	1672 [1552 to 1793]	260 [247 to 272]
ΔEMM [HPD]	1.5 [-1 to 3.8]	19 [2 to 34]	-113 [-185 to -40]	-10 [-19 to -1]	1 [-10 to 25]	7 [-72 to 78]	2 [-6 to 9]
P>0	0.88	0.99	0.99	0.99	0.84	0.57	0.67
P>CV	0.00	0.00	0.12	0.04	0.00	0.00	0.00
MD-2 EMM [HPD]	-28.6 [-32.3 to -25]	188 [153 to 217]	775 [673 to 879]	115 [100 to 127]	256 [223 to 293]	1645 [1524 to 1774]	256 [243 to 269]
ΔEMM [HPD]	1.4 [-1.1 to 3.9]	18 [1 to 34]	-102 [-175 to -25]	-9 [-18 to 1]	1 [-13 to 23]	-20 [-98 to 61]	-1 [-10 to 7]
P>0	0.85	0.98	0.99	0.97	0.67	0.70	0.63
P>CV	0.00	0.00	0.07	0.03	0.00	0.00	0.01
MD-3 EMM [HPD]	-23.6 [-28.1 to -19.1]	219 [181 to 253]	586 [462 to 715]	93 [76 to 108]	264 [227 to 303]	1536 [1387 to 1679]	250 [235 to 266]
ΔEMM [HPD]	6.2 [2.7 to 9.7]	49 [26 to 72]	-290 [-400 to -188]	-30 [-42 to -17]	12 [-12 to 38]	-131 [-27 to -246]	-8 [-19 to 4]
P>0	0.99	1.00	1.00	1.00	0.82	0.99	0.90
P>CV	0.69	0.71	0.99	0.97	0.03	0.58	0.21
MD-4 EMM [HPD]	-30.2 [-33.9 to -26.5]	188 [155 to 218]	814 [708 to 922]	119 [104 to 132]	241 [207 to 276]	1724 [1607 to 1863]	258 [244 to 270]
ΔEMM [HPD]	-0.2 [-2.4 to 2.8]	18 [1 to 35]	-62 [-143 to 22]	-5 [-15 to 5]	-11 [-29 to 9]	58 [-27 to 141]	1 [-9 to 8]
P>0	0.57	0.97	0.93	0.82	0.88	0.91	0.50
P>CV	0.00	0.00	0.01	0.01	0.00	0.08	0.00
MD-5 EMM [HPD]	-29.4 [-33.4 to 25.1]	198 [162 to 230]	789 [670 to 911]	118 [102 to 133]	253 [213 to 289]	1637 [1497 to 1772]	256 [240 to 269]
ΔEMM [HPD]	0.4 [-2.6 to 3.8]	28 [1 to 50]	-88 [-190 to 14]	-5 [-17 to 7]	0 [-23 to 23]	-29 [-126 to 75]	-2 [-13 to 9]
P>0	0.61	0.99	0.95	0.79	0.52	0.71	0.67
P>CV	0.00	0.11	0.09	0.02	0.00	0.04	0.04

Notes: B=baseline, MD=Match day, EMM=estimated marginal means, HPD=highest posterior density (set at 95%), ΔEMM=change in EMM from baseline, P=probability, P>CV= probability is greater than the CV, HPD=highest posterior density (set at 95%), *CMD=countermovement depth, PT=phase time, MP=mean power, NI=net impulse.*

Table 6 – The dose-response relationship between the internal training load and the different countermovement jump variables. Bayesian R^2 with [95% credible intervals].

	Δ Jump Height (cm)	**Δ CMD (cm)**	**Δ Braking PT (s)**	**Δ Braking MP (W)**	**Δ Braking NI ($N \cdot s^{-1}$)**	**Δ Propulsive PT (s)**	**Δ Propulsive MP (W)**	**Δ Propulsive NI ($N \cdot s^{-1}$)**
sRPE	0.23	0.44	0.57	0.40	0.42	0.45	0.37	0.40
	[0.15-0.32]	[0.37-0.51]	[0.50-0.62]	[0.31-0.47]	[0.34-0.49]	[0.37-0.52]	[0.28-0.44]	[0.32-0.48]
iTRIMP	0.22	0.43	0.55	0.38	0.40	0.38	0.37	0.40
	[0.13-0.39]	[0.35-0.50]	[0.47-0.61]	[0.30-0.45]	[0.32-0.47]	[0.30-0.46]	[0.29-0.44]	[0.32-0.48]
bTRIMP	0.22	0.43	0.56	0.39	0.41	0.45	0.37	0.40
	[0.13-0.30]	[0.35-0.50]	[0.50-0.61]	[0.30-0.46]	[0.33-0.48]	[0.38-0.52]	[0.29-0.44]	[0.32-0.47]
luTIRMP	0.22	0.43	0.56	0.38	0.41	0.45	0.37	0.40
	[0.13-0.31]	[0.36-0.50]	[0.50-0.61]	[0.30-0.46]	[0.33-0.48]	[0.38-0.52]	[0.28-0.45]	[0.32-0.48]
eTRIMP	0.22	0.43	0.56	0.38	0.39	0.45	0.37	0.40
	[0.13-0.30]	[0.35-0.50]	[0.50-0.62]	[0.30-0.46]	[0.31-0.47]	[0.37-0.52]	[0.28-0.44]	[0.33-0.47]

Notes: iTRIMP=individualised TRIMP, bTRIMP= Banister TRIMP, luTRIMP= Lucia TRIMP, eTRIMP= Edwards TRIMP CMD=Countermovement depth, PT=phase time, MP=mean power, NI=net impulse

Table 7 – The dose-response relationship between the external training load and the different countermovement jump variables. Bayesian R^2 with [95% credible intervals].

	Δ Jump Height (cm)	**Δ CMD (cm)**	**Δ Braking PT (s)**	**Δ Braking MP (W)**	**Δ Braking NI ($N \cdot s^{-1}$)**	**Δ Propulsive PT (s)**	**Δ Propulsive MP (W)**	**Δ Propulsive NI ($N \cdot s^{-1}$)**
TD	0.23	0.46	0.56	0.40	0.42	0.45	0.37	0.40
	[0.14-0.32]	[0.35-0.53]	[0.50-0.62]	[0.31-0.46]	[0.34-0.49]	[0.37-0.52]	[0.29-0.44]	[0.32-0.47]
PL	0.23	0.47	0.56	0.40	0.43	0.45	0.37	0.40
	[0.14-0.32]	[0.39-0.53]	[0.50-0.62]	[0.31-0.47]	[0.34-0.49]	[0.38-0.52]	[0.28-0.44]	[0.32-0.47]
HiDec	0.24	0.46	0.56	0.39	0.42	0.45	0.37	0.40
	[0.15-0.33]	[0.39-0.53]	[0.50-0.62]	[0.31-0.47]	[0.34-0.49]	[0.37-0.52]	[0.28-0.44]	[0.32-0.48]
HiAcc	0.24	0.47	0.56	0.40	0.42	0.45	0.37	0.40
	[0.15-0.32]	[0.40-0.53]	[0.50-0.62]	[0.31-0.47]	[0.34-0.49]	[0.37-0.52]	[0.29-0.44]	[0.32-0.48]
iHSD	0.24	0.47	0.56	0.39	0.41	0.45	0.37	0.40
	[0.15-0.32	[0.40-0.53]	[0.50-0.62]	[0.30-0.46]	[0.33-0.48]	[0.37-0.52]	[0.29-0.44]	[0.32-0.47]
HSR	0.25	0.47	0.57	0.39	0.42	0.45	0.39	0.41
	[0.16-0.33]	[0.40-0.53]	[0.51-0.62]	[0.31-0.47]	[0.34-0.49]	[0.37-0.52]	[0.30-0.46]	[0.33-0.48]
VHSR	0.24	0.45	0.57	0.39	0.42	0.45	0.39	0.41
	[0.15-0.33]	[0.38-0.52]	[0.51-0.62]	[0.31-0.47]	[0.34-0.49]	[0.37-0.52]	[0.30-0.46]	[0.33-0.48]
Sprint	0.24	0.45	0.57	0.39	0.41	0.45	0.38	0.42
Dist	[0.16-0.33]	[0.37-0.52]	[0.50-0.62]	[0.30-0.46]	[0.33-0.49]	[0.37-0.52]	[0.30-0.46]	[0.33-0.49]

Notes: CMD=Countermovement depth, PT=phase time, MP=mean power, NI=net impulse, TD=total distance, PL=PlayerLoad™, HiDec=high-intensity decelerations, HiAcc=high-intensity accelerations, iHSD=individualised high-speed distance, VHSR=very high-speed running, Sprint Dist= sprint distance.

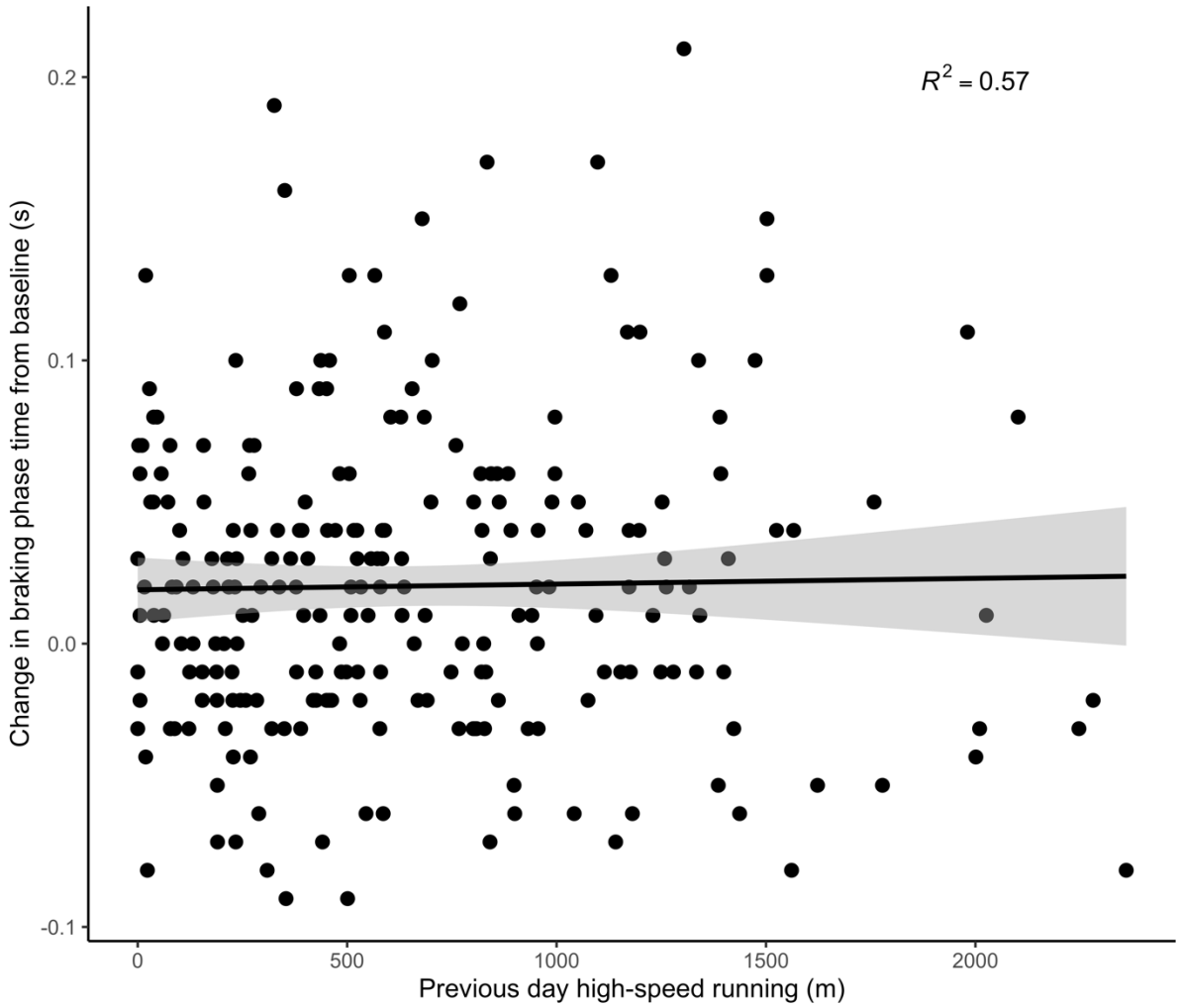

Figure 1 – Relationship between the previous days high-speed running (m) and change in braking phase time (s)

Supplementary code for R

```
# Point working directory to csv file
# Read in CSV file
data <-read.csv("named_file.csv")


# load packages
if (!require(brms)) {
  install.packages("brms")
}
library(brms) # note that for the brms package to run,
#rstan https://mc-stan.org/users/interfaces/rstan will need to be installed

if (!require(emmeans)) {
  install.packages("emmeans")
}
library(emmeans)

if (!require(bayestestR)) {
  install.packages("bayestestR")
}
library(bayestestR)

# A separate id number is assigned to each player so these numerical values need to be
#set as a factor rather than an integer
data$id <- as.factor(data$id) # set the id variable to a factor

# Check structure of the data
str(data)

# The initial model build used brms package default priors — Improper flat priors were
   # used for all b coefficients in the model. The priors for standard deviation and sigma
   # were restricted to be non-negative, using a half student-t prior with 3 degrees of
   # freedom, a zero location and a scale parameter that is 2.5 or the median absolute
   # deviation of the response variable of greater than 2.5.
# The default response distribution is a Gaussian distribution but numerous additional
   # distribution families available
   # see https://paul-buerkner.github.io/brms/reference/brmsfamily.html
# Given a number of data points were not independent — players were measured multiple
   # times — each model fitted used (1 | id) to allow the intercept for each participant
   # to vary and allows for correlation between different observations for the same player
# time between jumps was added as a covariate
# This model was used to look at the dose-response relationships between training loads
   # and jump performance

Model_name <-
```

```
  brm(Dependent_variable ~ predictor + covariate + (1 | id), data = data)
# If a model did not converge adjustments were made adapt delta and change treedepth
e.g:
#for the dose-response training load data there were a total of 28/104 models that required
this
Model_name <-
  brm(
    y ~ x + covariate + (1 |id),
    data = data,
    control = list(adapt_delta = 0.99, max_treedepth = 15)
  )

# Posterior predictive checks were conducted to see how closelyY simulated from the model
compared to the Y in the data
pp_check(Model_name, ndraws = 50)
pp_check(Model_name, "stat")
pp_check(Model_name, "stat_grouped", group = "match")


# build and check weakly informed prior
#below is the example of the jump height prior with a lower bound set to 0
prior_name<-prior(normal(0, 0.5), class = b, lb=0)

Model_prior <-
  brm(y ~ x + covariate+ (1 | id),
      data = data,
      prior = prior_name,
      sample_prior = "only")
pp_check(Model_prior, ndraws = 50)

# you can increase the simulations by increasing the ndraws, for this study ndraws of 50 was
used
pp_check(Model_prior, "stat")
pp_check(Model_prior, "stat_grouped", group = "match")
# build model with prior

Model_with_prior <-
  brm(y ~ x + covariate+ (1 | id),
      data = data,
      prior = ("insert prior name"))
# Efficient approximate leave-one-out cross-validation for each fitted models was
    # calculated

loo1 <- loo(Model_name)
loo2 <- loo(Model_with_prior)
print(compare(loo1, loo2), digits = 3)
```

```
# Bayesian R squared was calculated for each model which is a data-based estimate of the
  # proportion of variance explained for new data.
bayes_R2(model_with_prior)

# Estimated marginal means were calculated for jump parameters.
Em_model_with_prior <- emmeans(model_with_prior ~ time)

# pairwise comparisons were calculated for each model
Pairs_em_model_with_prior <- pairs(Em_model_with_prior)

# Probability of the posterior distribution above or below 0 was calculated for the
   # best model (as determined by LOO)
bayestestR::p_direction(Pairs_em_model_with_prior)

# Probability of the posterior distribution above the coefficient of variation was calculated.
CV% was calculated manually on excel using the baseline measures.
bayestestR::p_significance(Pairs_em_model_with_prior, threshold = 0.0333965)
```