Training efficiency and athlete wellness in collegiate female soccer.

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Headline

The training efficiency index (TE_I) is a simple index where internal load is assessed controlling for the amount of external work completed (1). This measure has been shown to be related to both changes in fitness (ES = 0.87-0.89; ± ≈0.15) and the quantity of training load completed (r = 0.29-0.33; ± ≈0.07) (1). However, it is unknown if the TEI is affected by acute training status (fatigue, muscle soreness, sleep quality or acute training loads). Knowledge of these relationships may reveal whether the TEI is reflective solely of chronic adaptations, or if it is also useful for assessing acute training outcomes.

Aim. The purpose of this investigation was to investigate whether changes in the TEI were associated with pre-training athlete status, including a subjective wellness questionnaire and previously completed external training loads.

Methods

Athletes. Data were collected from 21 female players (age: 20 ± 1 yrs) from a Division 1 collegiate soccer program over 9 weeks. Players provided written informed consent at their annual medical, indicating that de-identified, wellness or performance data may be used for research. The study conformed to the recommendations of the Declaration of Helsinki.

Design. A retrospective observational research design was employed, where players were assessed as part of their regular in-season training program, with no additional interventions arising as a result of this study.

Protocol

Wellness measures. Players completed a customised wellness questionnaire each day upon waking on their own smartphone. The information collected comprised of three questions: self-reported hours of sleep; muscle soreness (0 = no soreness; 10 = extremely sore) and stress (0 = no stress; 10 = highly stressed).

Internal load. During all field-based sessions (49 ± 6 sessions per player, mean duration 85 ± 9 min), players were fitted with a chest-worn device that sampled HR data at 1 Hz intervals (Polar Team Pro, Kempele, Finland). Further, these units provided 10 Hz position data from a global positioning system, a sampling rate that has been shown to be adequate for assessing team-sport movement profiles (2). Upon completion of each session, data were analysed using customised software (R Studio, v 3.1.3.). Specifically, this software analysed all speed ($m.s^{-1}$) and HR ($b.min^{-1}$) data concurrently. In the case of errors (i.e. drop out or losing contact with skin), the software removed both HR and GPS data, leaving only clean data traces remaining. Raw heart rate data ($b.min^{-1}$) were reported relative to the subject's peak heart rate, taken as the highest heart-rate recorded throughout all preseason testing and training. These values were then used to calculate training impulse (HR-TRIMP) for each individual training drill, using methods detailed previously (3). Sessions incorporating less than 30 min of "clean" data were removed from analysis.

External load. Using the instantaneous speed trace, the running-based mechanical requirements of training were quantified (4). Firstly, as a representation of the acceleration-based movement profile of training, Impulse was calculated as:

$$Impulse = Ft \quad [1]$$

where F represents the mean force (calculated by multiplying the subject's body mass by the instantaneous absolute acceleration), and t is the duration of the activity. Secondly, total mechanical work (Work_{mech}) was estimated as:

$$\text{Work}_{mech} = Fd \quad [2]$$

where d signifies distance (calculated by multiplying the subject's speed by time). For each of the two chosen external load metrics an exponentially-weighted moving average (EWMA) was calculated for time periods of 3 and 21 days (5), reflective of acute and chronic training load, respectively.

Training Efficiency Index (TE_I). The training efficiency index (TE_I) tracks changes in external work controlled for changes in internal work. The details of this metric can be found elsewhere (1), although it is calculated as:

$$TE_I = \frac{E}{I^x} \quad [3]$$

where E = external work, I = internal work, and x is a constant derived as the average slope of the relationship between each combination of log-transformed internal and external load variables. This was calculated using both external load markers on a daily basis ($TE_{IImpulse}$, TE_{IWork}). To account for between-session variability in HR responses (6), rolling 5- and 7-day loads were used to calculate each TE_I measure ($TE_{IImpulse5}$, TE_{IWork5}, $TE_{IImpulse7}$ and TE_{IWork5}), which were then used to assess associations with wellness the following day.

Analysis

To confirm the relationship between the chosen internal and external load metrics, within-subject correlations (r) were calculated between internal load (HR-TRIMP) and each external load metric (Impulse and Workmech, respectively), and interpreted according to Hopkins (7). The relationships between each wellness/training load metric and TE_I (daily, 5-day and 7-day for both Impulse and Work_{mech}, respectively) were assessed using linear mixed models, to control for within-subject repeated measures. When assessing relationships between TEI

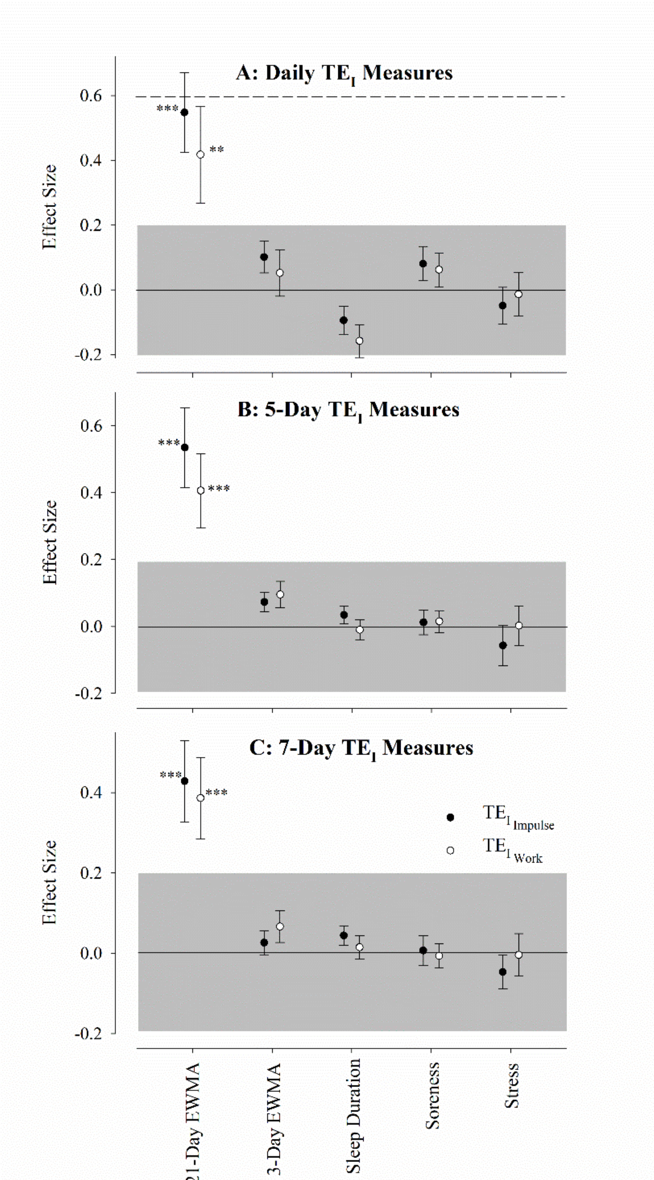

Fig. 1. Association between each calculation of Training Efficiency Index (TE_I) and both self-report athlete wellness measures and the respective training load metric amongst female collegiate soccer players (n = 21). * = effect likely > 0.2; ** = effect very likely > 0.2; *** = effect almost certainly > 0.2.

and external TL, only the corresponding (rescaled) EWMA measures were inputted into the model (i.e. the same TL metric was used to calculate both the TEI and the respective EWMA measure). Relationships were standardised by multiplying the final model slope by 2 × the between-subject standard deviation (SD), obtained from the raw data. This method results in the expected change in the outcome measure given a change from a typically low to a typically high value (8). This change was then converted to an effect size (ES; ±90% CI) using the between-subject SD and was interpreted using a magnitude-based approach.

Results

There were almost perfect within-subject relationships between HR-TRIMP and both Impulse (r = 0.93; ±0.04) and

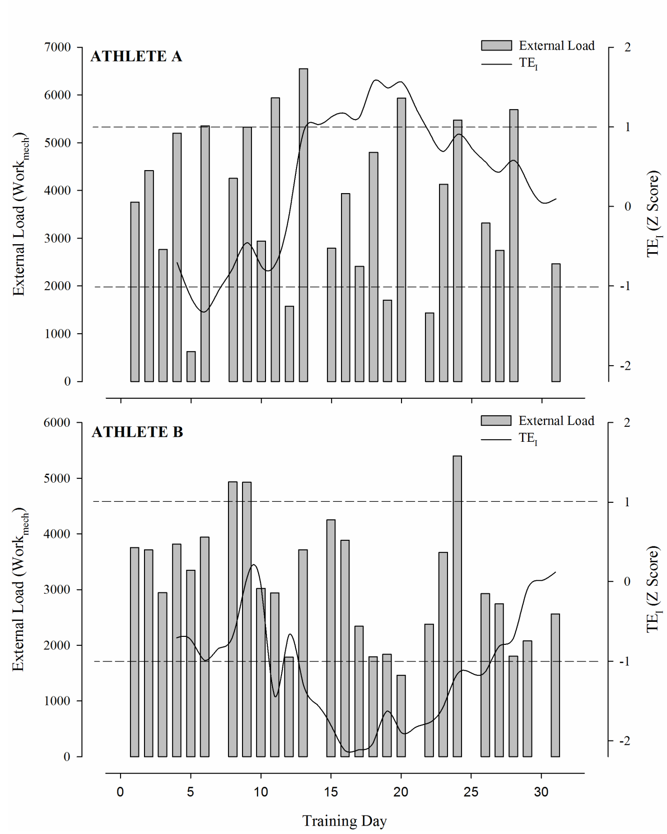

Fig. 2. Example of two athletes' training workload ($Work_{mech}$) and the concurrent TE_I measure, presented as a Z-score over the in-season period (31 days).

Workmech (r = 0.91; ±0.05). The slope of these relationships (0.73 ± 0.07 and 0.88 ± 0.07, respectively) represented the coefficient (x) that was used to calculate the TE_I (Eq. 3). Figure 1 illustrates that the TE_I was poorly associated with both wellness and acute TL, while small relationships with chronic TL were observed. Figure 2 demonstrates an example of the TE_I (7-day average, plotted as a Z-score) in the context of external TL completed for two separate athletes.

Discussion

This study investigated the association of selected athlete monitoring measures with a novel TE_I metric amongst female collegiate soccer players. Whilst it was hypothesised that the TE_I could provide objective information regarding an athlete's acute training status, relationships between all wellness measures and the TEI were found to be trivial. Similarly, 3-day EWMA shared trivial relationships with the TEI when calculated using each external load measure, while in contrast 21-day EWMA loads exhibited small associations with TE_I. Taken together, these data would indicate that the TE_I does not provide further insight into the daily stress state of individual athletes, but may be useful for assessing chronic adaptations to training.

Throughout a team-sport training program, coaches are interested in tracking their athletes' response to training, but allocating time for isolated fitness assessments during certain phases of the season (i.e. competitive phase) can be challenging (9). The daily integration of internal and external training loads may provide a more practical alternative, where each training session completed reflects a testing data point. Interestingly, 3-day EWMA external loads were not related to TE_I in any capacity, whereas 21-day EWMA external loads were related to all TE_I measures (ES = 0.39 to 0.55), in agreement with a similar investigation amongst male professional rugby league players (1). Together, these findings may suggest the TE_I provides further insight into the fitness state of team-sport athletes, though changes must be considered within the context of the completed training load. As an example, data for the TE_I and training load for two athletes over the first month of a pre-season training program are shown in Figure 2, where the TE_I is plotted as a Z-score. In this case, Athlete A appears to be responding well to the prescribed training load, resulting in an increase in training efficiency over this phase. In contrast, Athlete B's response throughout this period is far less favourable, despite performing a similar amount of work. From a practical perspective, this information could be acted upon for Athlete B, and an intervention may be required.

Our findings are similar to those reporting in Australian Football players, where pre-session wellness was not related to a ratio between external load and RPE (10). Given that TE_I is calculated from athletes' internal HR responses during exercise, it is possible that the absence of a relationship between TE_I and acute measures of wellness and training load can be attributed to other confounding factors such as exercise-induced plasma expansion (11), ambient conditions, running surface, wind resistance or hydration status (12). As such, these findings suggest that the use of HR measures to examine daily TE_I is limited in assessing the daily stress state of individual athletes.

Practical Applications

- The small relationships between external work completed over a 21-day period and TE_I observed in the present study indicate that the TE_I may assist in monitoring an athlete's response to training, however it is important to consider the context of the training load completed.
- Daily fluctuations in TE_I are not related to changes in athlete wellness, as quantified using a pre-training self-report questionnaire, suggesting it is not appropriate for the basing decisions upon on a daily basis.
- Although the TE_I does not replace traditional fitness testing, it provides a simple, holistic assessment of athletes' status that can be collected during all training sessions.

Limitations

- The findings of the present study are specific to the female collegiate-aged athletes investigated. No consideration was given to hormonal alterations that occur as a result of the menstrual cycle, which may have been a confounding factor.
- No attempt was made to control for caffeine consumption or hydration status, which could have altered results. However, this decision was made based on the fact that these factors are not always monitored in a team-sport setting, therefore increasing the practical application of these findings.

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