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ARTICLE

Quantifying the relationship between internal and external work in team sports: development of a novel training efficiency index

Jace A. Delaney[a], Grant M. Duthie [b], Heidi R. Thornton [c] and David B. Pyne[d,e]

[a]Institute of Sport Exercise and Active Living, Victoria University, Melbourne, Victoria, Australia; [b]School of Exercise Science, Australian Catholic University, Strathfield, New South Wales, Australia; [c]La Trobe Sport and Exercise Medicine Research Centre, La Trobe University, Melbourne, Victoria, Australia; [d]University of Canberra Research Institute for Sport and Exercise, Bruce, ACT, Australia; [e]Physiology, Australian Institute of Sport, Canberra, ACT, Australia

ABSTRACT

Objective: To establish whether a simple integration of selected internal and external training load (TL) metrics is useful for tracking and assessing training outcomes during team-sport training.
Methods: Internal [heart rate training impulse (HR-TRIMP), session rating of perceived exertion (sRPE-TL)] and selected external (global positioning systems; GPS) metrics were monitored over seven weeks in 38 professional male rugby league players. Relationships between internal and external measures of TL were determined, and an integrated novel training efficiency index (TE_I) was established. Changes in TE_I were compared to changes in both running performance (1.2 km shuttle test) and external TL completed.
Results: Moderate to almost perfect correlations (r = 0.35–0.96; ±~0.02; range ± 90% confidence limits) were observed between external TL and each measure of internal TL. The integration of HR-TRIMP and external TL measures incorporating both body mass and acceleration/deceleration were the most appropriate variables for calculating TE_I, exhibiting moderate (ES= 0.87–0.89; ±~0.15) and small (ES = 0.29–0.33; ±~0.07) relationships with changes in running performance and completed external TL respectively.
Conclusions: Combination of the TE_I and an athlete monitoring system should reveal useful information for continuous monitoring of team-sport athletes over several weeks.

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KEYWORDS
Player monitoring; fitness; global positioning systems; training load; validity

Introduction

Coaches and performance staff in team sports invest considerable time and resources into monitoring their athletes. Physical training can be described in terms of external load completed (i.e., work), and the acute responses and longer-term adaptions occurring as a consequence of training (i.e., internal response) (Impellizzeri et al. 2005). Typically, the internal response to training is quantified using a session rating of perceived exertion (sRPE), or a range of heart rate (HR) indices (Akenhead and Nassis 2016). Global positioning system (GPS) technology provides valuable information on the external demands imposed on the athletes, assessing adherence to prescribed loads, or reducing the risk of overtraining and soft-tissue injuries (Cummins et al. 2013). However, when used in isolation, external load monitoring cannot indicate an individual's physiological responses to training. Although two athletes may complete the same quantity of external work, their resulting internal response to that work may differ substantially due to variability in factors such as genetic background, or level of fitness (Bouchard and Rankinen 2001). Consequently, the imposed internal load differs between the two athletes (Impellizzeri et al. 2005). A solution for quantifying these differing responses would be the integration of both external training load (TL) and the concurrent acute internal response, thus providing a more holistic and informative approach to monitoring the physical status and training outcomes of team-sport athletes.

Maximal running tests are commonly utilised to measure team-sport athletes' adaptation to training. Although these tests provide useful and accurate information, they are often time consuming, and carry a substantial physical burden (Pyne et al. 2014). During periods of heightened competition loads, opportunities to perform fitness tests become scarce, as the focus of training shifts to the preparation for, and recovery from, scheduled matches. Consequently, submaximal running tests are commonly employed in a team-sport environment (Akenhead and Nassis 2016), as the shorter duration and lower intensity of these tests overcomes some of the limitations of maximal running protocols. As an example, the HR of elite Australian football players during a 4-min submaximal intermittent running test demonstrated a large correlation (r = −0.58 to −0.61) with distance covered during the Yo-Yo intermittent recovery 2 (YoYo IR2) test (Veugelers et al. 2016). More importantly, changes in the relationship between external work performed and internal response may indicate an athlete's adaptation to training. Unfortunately, HR-based testing may be influenced by factors as ambient conditions, running surface, wind resistance or hydration status (Akenhead and Nassis 2016), therefore, identifying other more robust methods is necessary.

The relationship between internal and external TL (i.e., HR to running speed index) has been investigated in recreationally trained endurance runners (Vesterinen et al. 2014), where a HR-running speed index was determined using each

CONTACT Jace A. Delaney jace.delaney@live.vu.edu.au

athlete's maximal HR, and running speed corresponding to VO_2max or HR_{max} during a baseline maximal running test. Changes in this index following 28weeks of marathon training had a moderate to large relationship

(r = 0.43–0.61) with changes in peak running speed during a maximal incremental treadmill test. However, this relationship in endurance athletes may lack specificity to the stochastic, intermittent nature of running evident in team sports (F. Hunter et al. 2015). In soccer players, a novel ratio of HR load to external work performed (either total or high-speed [>15 km·h^{-1}] running distance) using maximal treadmill running discriminated levels of fitness between players (Akubat et al. 2014). This study assessed these athletes at a single time point, and it remains unclear whether this metric can detect changes in fitness over time. Such information would provide deeper insight into the effectiveness of a prescribed training programme, and potentially a more practical alternative to maximal fitness testing. In team sports such as the football codes, athletes are limited in their ability to generate high running speeds, given a range of factors such as field dimensions or presence of opposition players (Kempton et al. 2015), and therefore acceleration abilities may be important to successful performance (Lockie et al. 2011). It is likely that these acceleration-based movements are predominant during training, contributing substantially to the load imposed on team-sport athletes (Varley and Aughey 2013). Consequently, a more global measure of external TL that incorporates both speed- and acceleration-based running is likely more appropriate for assessing the relationship between internal and external TL during training typical of team-sport athletes.

In tandem with advances in technology, sports scientists and performance coaches are in continual pursuit of best practice for monitoring their athletes' adaptation to training (Coutts 2014). While this search continues, high performance staff are faced with the challenge of selecting the most suitable variables to monitor. In a survey examining current practices in high-level soccer (football), all responders indicated they routinely collect both GPS and HR monitoring during sessions, and 68% of teams collected sRPE (Akenhead and Nassis 2016). Appropriate integration of these methods may reveal useful information regarding an individual's adaptation to a prescribed load, or their readiness to perform in upcoming sessions or matches (Weaving et al. 2014, 2017). The aim of the study was to establish a simple athlete tracking system for tracking the internal response to a prescribed external load during team-sport training, by integrating commonly used player monitoring methodologies.

Methods

Participants

Thirty-eight professional rugby league players (23 ± 3 years; 1.87 ± 0.06 m; 99 ± 10 kg; mean ±SD) competing for the same club in the Australian National Rugby League (NRL) competition participated in this study. Permission was granted from the NRL club to perform analyses on training monitoring data obtained during the 2016–2017 preseason period. Institutional ethics approval for a retrospective analysis of TL data was obtained prior to the commencement of the study, and all athletes provided written informed consent (HRE17–012).

Experimental design

To identify the most appropriate variables for deriving a novel Training Efficiency Index (TE_I) that incorporates both external and internal metrics, a range of external TL metrics were assessed for collinearity with measures of internal load. Second, we compared the changes in the TE_I against changes in performance during a commonly used field-based running test, to establish the concurrent validity of the metric. In addition, changes in the TE_I were assessed relative to the total external load completed during the preseason period, further confirming the most appropriate methods for calculating TE_I. We expected that global measures of running load incorporating the acceleration-based demands of team-sports training would be most appropriate for assessing relationships between internal and external TL.

Protocol

Training load data was collected during a 7-week general preparation phase, which typically included 4–5 (2 × conditioning and skills, 2 × speed, agility and skills and 0 or 1 skills-only) field-based sessions (ambient temperature 22.2 ± 2.9ºC), 4 strength sessions and 1–2 recovery and/or hydrotherapy sessions. For the purposes of this study, only field-based sessions (25 ± 3 per player) were included in the analyses. Prior to and following this period, a subset of 21 participants (23 ± 3 years; 1.89 ± 0.06 m, 104 ± 11 kg) completed a 1.2 km shuttle test (5 × 20–40–60 m shuttle runs) (Brew and Kelly 2014), from which the mean speed (m·s^{-1}) was used to determine changes in fitness. This test has been shown to exhibit strong test-retest reliability (intraclass correlation coefficient [ICC] = 0.98) (Brew and Kelly 2014). Movement data was recorded using GPS units with a raw sampling rate of 5 Hz (SPI HPU, GPSports, Canberra, Australia) fitted into a custom-made harness, located between the scapulae. Each player was assigned the same unit for the entirety of the collection period to minimise inter-unit variability (Buchheit et al. 2014). These units also recorded heart rate data to the device at 1 Hz, using a fitted chest strap worn beneath the participants' training garment (Polar T34, Kempele, Finland). During each session, a member of the research team recorded the details of each training drill completed by each participant, including start time, time of completion, and whether the drill included contact and/or wrestling. For the purposes of the present study, all drills including contact, wrestling or a large proportion (39% of all available drills) of other non-locomotor activity (i.e., kicking or jumping) were excluded from the analysis, due to the inability of GPS technology to accurately assess these demands. As this study was investigating the relationship between locomotor activity (i.e., external load) and the resulting internal response, only running-based activities were included. Last, within 30 min of the completion of each session, participants provided a rating of perceived exertion (sRPE), using Borg's CR-10 scale (Borg et al. 1985). All TL data were then downloaded and databased for further analysis by the same member of the research team.

Internal load measures

Upon completion of each session, data were downloaded using proprietary software (Team AMS v 2016.1., GPSports, Canberra, Australia). Heart rate traces were checked for errors such as drop out or losing contact with the skin, and where necessary removed from further analysis (18% of dataset). Raw heart rate data (b·min^{-1}) were reported relative to the participants' 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 (Banister, 1991). The duration of each drill was multiplied by the individual's sRPE to compute the training load (sRPE-TL).

External load measures

After the initial download of data by the proprietor's software (Team AMS v 2016.1., GPSports, Canberra, Australia), instantaneous speed data were imported into customised software (R Studio, v 3.1.3.). This software assesses both the total and high-speed running (HS, >5.5 m·s^{-1}) distances (Rampinini et al. 2007). Acceleration demands were calculated by averaging the absolute change in speed over the duration of a drill, regardless of the direction of change (i.e., acceleration or deceleration), and multiplying by that duration. This method has been shown to be a valid and reliable marker of acceleration-based load during team sports activity (J.A. Delaney et al. 2017). In addition, metabolic power (P_{met}) was estimated, using methods detailed previously (Osgnach et al. 2010). This technique has been the topic of debate (Osgnach et al. 2016) given its inability to accurately assess the metabolic demands of activities such as kicking, jumping and tackling (Buchheit et al. 2015). However, given the focus of this study on the running demands of training, the theoretical basis of these calculations, and the accuracy (Rampinini et al. 2015) and reliability (Buchheit et al. 2015) of this metric, the P_{met} technique was deemed appropriate for this analysis. The distance covered over a predefined high-metabolic-power threshold (HP, >20 W·kg^{-1}) was included to quantify high-intensity running, accounting for both accelerated/decelerated and HS movements (Osgnach et al. 2010). Metabolic work was estimated using the average metabolic power (P_{met}, W·kg^{-1}) (Osgnach et al. 2010) sustained throughout the drill, multiplied by the participants' body mass, to elicit the average absolute metabolic load for the drill. This value was then multiplied by the duration of that drill to estimate the total metabolic load imposed upon the athlete.

In line with a recent review by Winter et al. (2016), and given that only the running demands of the activity in question were quantified, we quantified the mechanical requirements of training as:

$$Impulse = Ft \quad (1)$$

where F represents the mean force (calculated by multiplying the participants' body mass by the instantaneous absolute acceleration), and t is the duration of the activity. This method was chosen to indicate the acceleration-based requirements of the activity. In addition, total mechanical work ($Work_{mech}$) was estimated as:

$$Work_{mech} = Fd \quad (2)$$

where d signifies distance (calculated by multiplying the participants' speed by time). Pilot data from our laboratory suggests that these variables (Impulse and $Work_{met}$) are suitable for comparisons between players (coefficient of variation [CV] = 5.6–6.5%). Although the physiological and biomechanical characteristics of training load are likely independent of one another (Vanrenterghem et al. 2017), we and others (Halson 2014) propose that integrating these components reveals valuable information on the training status of team-sport athletes. For each external TL measure examined, a 4-week exponentially weighted moving average (EWMA) was calculated (J. S. Hunter 1986), representative of the participants' recently completed TL.

Training efficiency index

To determine the most appropriate TL variables used to calculate the TE_I, repeated measures linear regression was employed to examine the relationship between log-transformed measures of internal (n = 2; sRPE-TL and HR-TRIMP) and external load (n = 7; Distance, HS Distance, Acc/Dec Load, HP Distance, $Work_{met}$, Impulse and $Work_{mech}$). Back-transformation yields a function of external and internal work in the form E/I^x, where E = external work, I = internal work, and x is a constant derived as the average slope of the relationship between log-transformed variables. Similar to previous modelling of anthropometric measures to establish a lean mass index (Slater et al. 2006), we interpret this function as a training efficiency index (TE_I), as it tracks changes in external work, controlled for changes in internal work. This method was then repeated for each combination of internal and external TL metrics. Concurrent validity of the TE_I for each external and internal load index was determined through comparison with changes in 1.2 km shuttle performance. In addition, this validity was further assessed by determining the relationship between changes in TE_I and the volume of external TL (for each respective TL metric) completed throughout the 7-week period.

Statistical analyses

All data were log-transformed prior to analyses. Relationships between TL measures were established using repeated-measures linear regression, and the slope of this relationship was then used to calculate the TE_I. Correlation coefficients were interpreted as <0.1, trivial; 0.1–0.3, small; 0.3–0.5, moderate; 0.5–0.7, large; 0.7–0.9, very large; 0.9–0.99, almost perfect; and 1.0, perfect (W. G. Hopkins 2007). A mixed-model reliability analysis was used to calculate between- and within-participant SD for each training load, fitness or TE_I metric. Between-participant SD were extracted as the SD of the random effect, whilst the residual SD represented the true within-participant SD.

To determine the effect of changes in fitness on the TE_I, pre and post measures of TE_I were derived from the linear relationship between TE_I and training day for a subset of 27 players. Therefore, the equation of this line was solved for the first and last day of the study period, allowing these data to be aligned with the day on which the fitness test was performed. A linear mixed model was then constructed, where fitness was modelled as a function of TE_I, and the slope of this relationship was multiplied by two within-participant SD in the predictor (TE_I), representative of the change from a typically low to a typically high value. This change was then converted to an effect size (ES) and the associated 90% CI by dividing by one between-participant SD of the outcome variable (fitness). Similarly, TE_I was modelled as a function of each respective external TL metric, and the slope of the relationship was multiplied by two within-participant SD in the predictor (TL), and then converted to an ES using the true between-participant SD. Effect sizes were interpreted as <0.2, trivial; 0.2–0.6, small; 0.6–1.2, moderate; 1.2–2, large; and >2.0, very large (W. G. Hopkins 2007). All correlations were considered substantial where the likelihood of the relationship being greater than the smallest worthwhile change (i.e., 0.1 for correlations, 0.2 for ES) exceeded 75% (W. Hopkins et al. 2009).

Results

Associations between measures of internal and external TL are presented in Table 1. Relationships between sRPE-TL and external load measures ranged from moderate to almost perfect (r = 0.35–0.93; ±~0.02; r-value; 90% CL). When considering HR-based measures these correlations strengthened, with five of the seven measures of external TL exhibiting almost perfect relationships with HR-TRIMP (Distance, Acc/Dec Load, $Work_{met}$, Impulse and $Work_{mech}$; r = 0.93–0.96; ±~0.01).

An example of the mean change in TE_I over the 7-week period is illustrated in Figure 1, where each individual's score is converted to a Z-score, averaged across the squad, and presented as a trend over time. Only sessions involving >75% of the participant cohort are represented in Figure 1. The effect of TE_I on changes in fitness is illustrated in Figure 2. The TE_I variables calculated using the HR-TRIMP metric were most consistently associated with changes in fitness, with all seven combinations classified as *moderate*. Similarly, Figure 3 illustrates that five TE_I measures ($Work_{met}$, $Work_{mech}$, Distance, HS Distance and HP Distance) using the HR-TRIMP method were substantially related to TL completed.

Table 1. Relationship between markers of internal and external training load, collected from 38 professional male rugby league players during a 7-week block of intensified training.

Internal load	External load	Slope coefficient (± SD)	Correlation coefficient (r)
sRPE-TL (AU)	Distance (m)	0.75 ± 0.06	0.87; ± 0.01, *very large*
	HS Distance (>5.5 $m \cdot s^{-1}$, m)	0.61 ± 0.22	0.35; ± 0.05, *moderate*
	Acc/Dec Load (AU)	0.79 ± 0.07	0.93; ± 0.01, *almost perfect*
	HP Distance (>20 $W \cdot kg^{-1}$, m)	0.77 ± 0.09	0.73; ± 0.03, *very large*
	$Work_{met}$ (J)	0.75 ± 0.06	0.89; ± 0.01, *very large*
	Impulse (N.s)	0.79 ± 0.07	0.93; ± 0.01, *almost perfect*
	$Work_{mech}$ (J)	0.75 ± 0.06	0.91; ± 0.01, *almost perfect*
HR TRIMP (AU)	Distance (m)	0.87 ± 0.06	0.93; ± 0.01, *almost perfect*
	HS Distance (>5.5 $m \cdot s^{-1}$, m)	0.67 ± 0.24	0.35; ± 0.05, *moderate*
	Acc/Dec Load (AU)	0.88 ± 0.06	0.95; ± 0.01, *almost perfect*
	HP Distance (>20 $W \cdot kg^{-1}$, m)	0.92 ± 0.09	0.80; ± 0.02, *very large*
	$Work_{met}$ (J)	0.86 ± 0.04	0.95; ± 0.01, *almost perfect*
	Impulse (N.s)	0.86 ± 0.06	0.95; ± 0.01, *almost perfect*
	$Work_{mech}$ (J)	0.86 ± 0.03	0.96; ± 0.00, *almost perfect*

Data are effect size correlation (r) and 90% confidence limits (90% CL), unless otherwise stated. Slope coefficient represents average slope of the relationship between internal and external training load, which forms the exponent ("x") of the TE_I calculation.

sRPE-TL: session rating of perceived exertion-training load; AU: arbitrary units; m: metre; HS: high speed; HP: high metabolic power; $m \cdot s^{-1}$: metres per second; J: joules; N.s: Newton seconds; $W \cdot kg^{-1}$: Watts per kilogram.

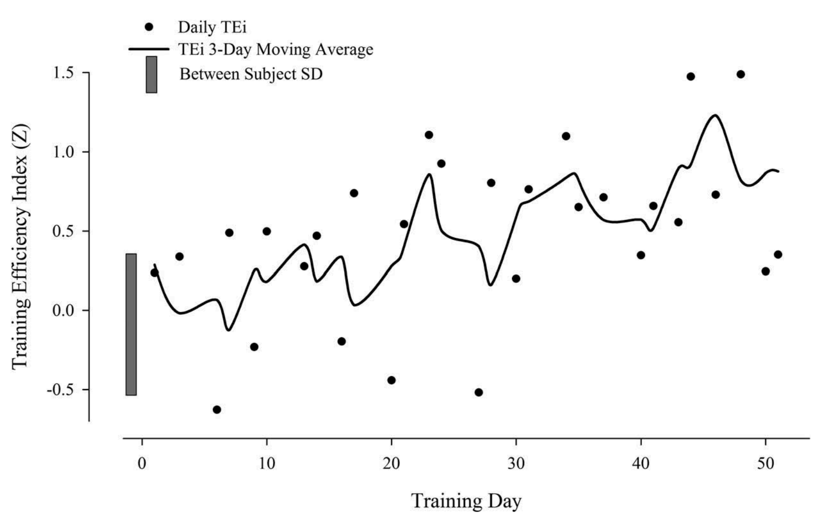

Figure 1. Example of changes in the training efficiency index (TE_I) calculated as mechanical work/HR $TRIMP^{0.87}$ over a 7-week training period for 38 professional rugby league players. Changes are expressed as a z-score, and averaged across the squad. Thin black line denotes a 3-day rolling average. Only sessions involving >75% of the training cohort were included (mean number of players = 28 ± 8).

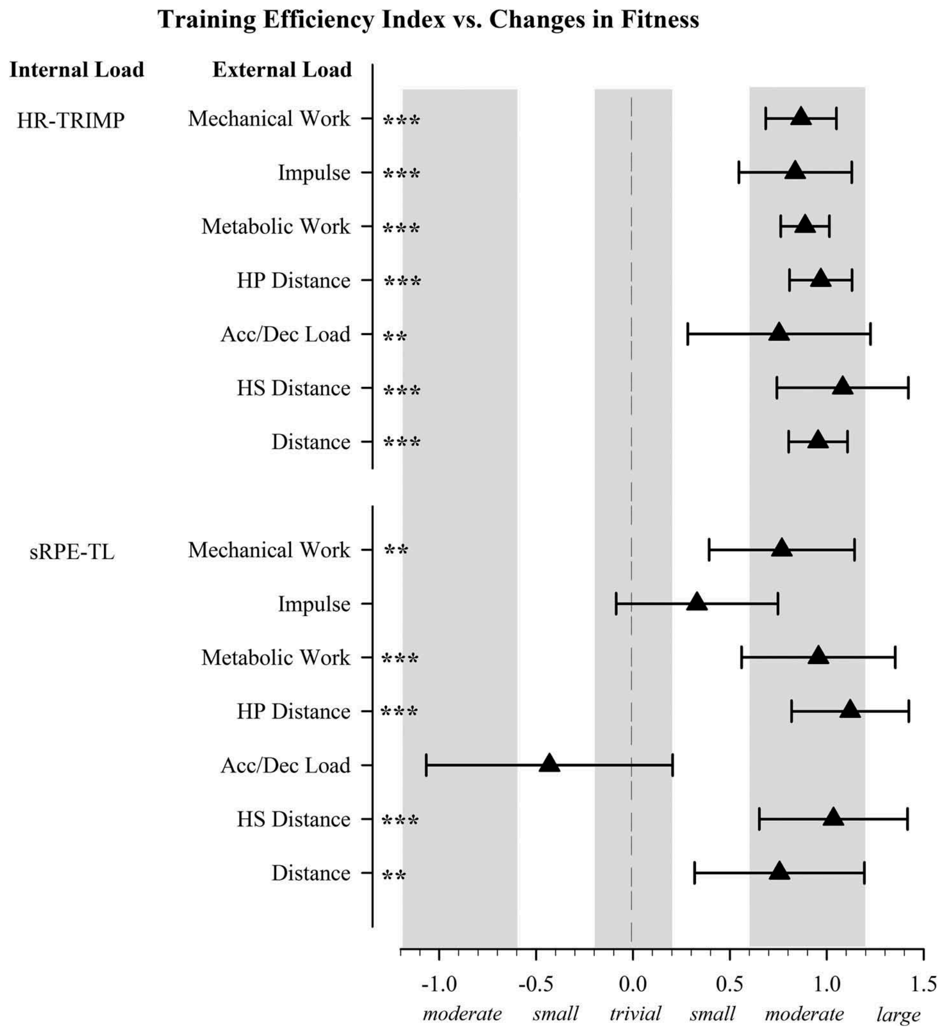

Figure 2. Relationships between the training efficiency index (TE_I) calculated using each combination of internal/external training load, and changes in fitness (1.2-km shuttle) over a 7-week training period (n = 27). *Denotes likelihood of observed effect being >0.2 exceeding 75%. HR: heart rate; HP: high metabolic power, >20 W·kg^{-1}; Acc/Dec: acceleration/deceleration; HS: high speed, >5.5 m·s^{-1}.

Discussion

The primary outcome of the present study was that the TE_I, appears useful for tracking individual responses to a pre-season training period in team-sport athletes, provided the most appropriate internal and external TL variables are selected. Integration of a HR-based measure of internal load (HR-TRIMP) with both speed- and acceleration-based running load ($Work_{met}$, $Work_{mech}$) was the most appropriate method for calculating the TE_I in this team-sport cohort. Moderate relationships were evident between changes in the TE_I and improvements in fitness (1.2 km shuttle), while small relationships were observed between the TE_I and volume of running completed over a four week period. Taken together, the TE_I provides useful information for assessing individual adaptations to a prescribed training programme, and presumably the risk of excessive fatigue, injury or illness. The TE_I presents as a valid, practical tool that can be simply integrated into a team sport's monitoring programme.

The sRPE-TL method represents a simple and cost-free method for assessing the internal TL of team-sports athletes, thus warranting its inclusion in the present study. The primarily strong relationships between sRPE-TL and measures of external TL (6/7 metrics exhibited r > 0.7) observed within the present study are comparable with other studies investigating team-sport athletes (Lovell et al. 2013; Scott et al. 2013; Scanlan et al. 2014). However, the almost perfect correlations observed between various external TL measures (5/7 metrics) and HR-TRIMP are inconsistent with a previous study examining professional soccer players (r = 0.40–0.78) (Scott et al. 2013), which may be reflective of the stringent inclusion criteria we employed in the current study. Given that GPS technology cannot adequately assess the physical requirements of non-locomotor activity such as kicking, jumping or wrestling, drills that contained these activities were removed from the present analyses. This step may also have somewhat compromised the sRPE-TL method used in this study, as the sRPE-TL response provided by participants was reflective of the session as a whole, whereas HR-based intensity measures were only representative of the included drills. Nonetheless, removal of these drills was unavoidable considering the training requirements of the current cohort, and future research may benefit from investigating these relationships in a non-contact, running-based team sport.

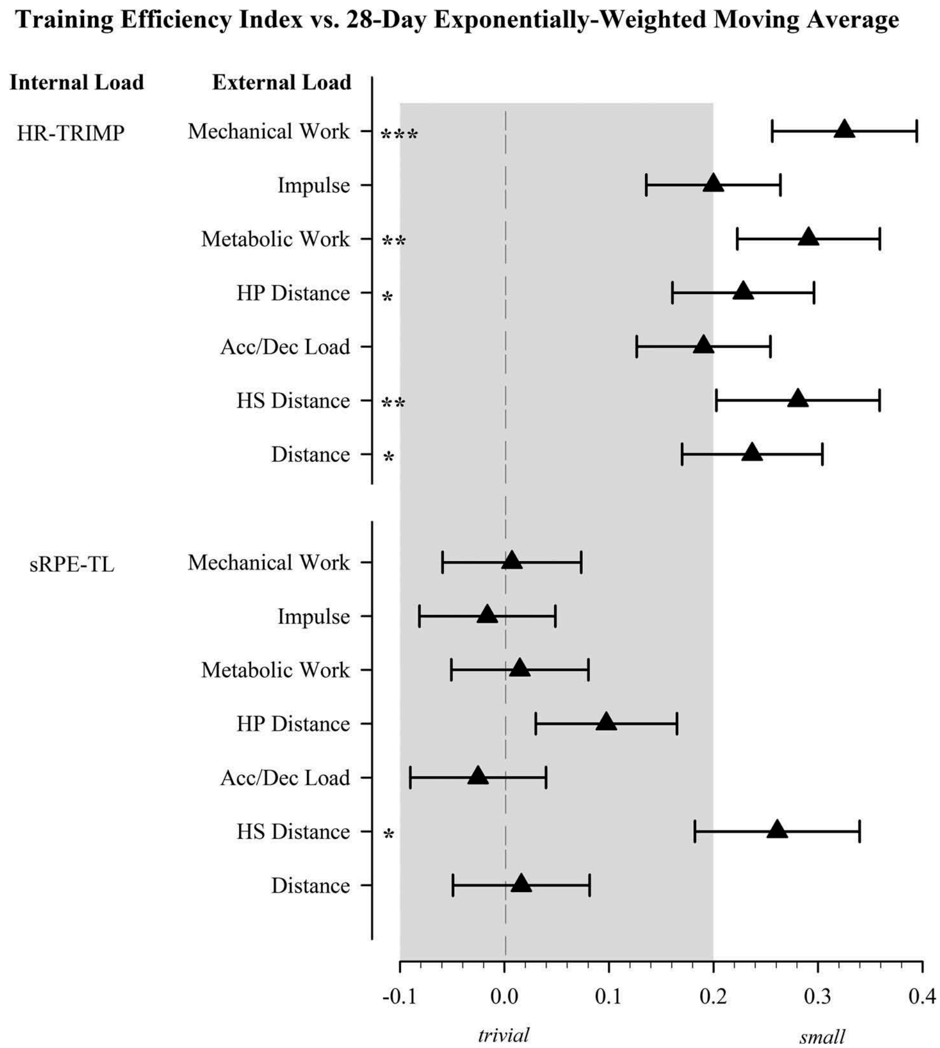

Figure 3. Relationships between the training efficiency index (TE_I) calculated using each combination of internal/external training load, and 4-week exponentially weighted moving average of the respective external training load (n = 27). *Denotes likelihood of observed effect being >0.2 exceeding 75%. HR: heart rate; HP: high metabolic power, >20 W·kg^{-1}; Acc/Dec: acceleration/deceleration; HS: high speed, >5.5 m·s^{-1}.

Several studies have described the relationship between measures of internal and external TL (Lovell et al. 2013; Scott et al. 2013; Scanlan et al. 2014). However, we contend that changes in this relationship are more important to the practitioner. Figure 1 illustrates a trend in TE_I, across a squad, over the pre-season period. This figure is representative of the trend across the entire squad, and large changes between sessions are evident. These differences could be attributed to a myriad of factors including accumulated fatigue from previous sessions or the concurrent strength programme, or the athletes' acute readiness to perform (i.e., perceived muscle soreness). However, the present study assessed the ability of the TE_I metric to assess chronic adaptations to a training programme, and therefore this area warrants further investigation.

The outcomes of the present study support the assertion that external TL variables encompassing speed- and acceleration-based running are most appropriate for calculating TE_I. While all TE_I metrics calculated using the HR-TRIMP metric exhibited moderate relationships with changes in running performance, $Work_{met}$ and $Work_{mech}$ were most strongly related to 4-week EWMA training loads, and among the variables most highly correlated with internal load. Both $Work_{met}$ and $Work_{mech}$ are inclusive of the participants' body mass, indicating that the increased physiological cost associated with accelerating and decelerating a greater body mass (J. A. Delaney et al. 2015), resulted in greater performance improvements over this training block. This outcome has implications for team sports, such as rugby league, where players of different positions (e.g., forwards and backs) vary substantially in body mass (Johnston et al. 2014). For example, prescription of a training session based on traditional external TL metrics (e.g., total distance) may result in a substantially different physical load for players of diverse body mass. Body mass is an important consideration that may have been overlooked in the past by practitioners and/or researchers using traditional load monitoring techniques. Subsequently, this finding has implications for injury risk, or development of position-specific conditioning programmes.

The TE_I established from either $Work_{met}$ or $Work_{mech}$ can be useful in examining the interaction between external work and the ensuing internal response. Theoretically, the $Work_{met}$ metric estimates the metabolic requirement of an activity, by equating the energetic cost of uphill running at a constant speed with accelerated running on flat terrain (Di Prampero et al. 2005). However, we sought to differentiate individual's internal response to a given load, using either sRPE-TL or HR-TRIMP. In that regard, the $Work_{met}$ is not representative of an actual metabolic cost, but rather an estimated cost given the movement profile of the activity. As expected, this measure exhibited strong relationships with both changes in running performance and volume of running completed over a 4-week period. However, simple integration of body mass, running speed and acceleration ($Work_{mech}$) based on a first principles analysis (Winter et al. 2016) was equally, if not more useful, for this purpose. Given limitations of the metabolic power method (Brown et al. 2016; Highton et al. 2016), it may be that simple first principles calculation is preferred.

There are several limitations that must be acknowledged when interpreting the results of this investigation. Given the contact-based nature of rugby league, a large proportion of the original dataset (~50%) was excluded from analysis, due to either non-locomotor activity such as kicking or wrestling, or inconsistencies in the HR trace. The application of external loads, the concurrent internal response, and the derived TE_I, may be limited during the in-season or competition period, where the proportion of running-only activities is reduced. Throughout periods of limited isolated running such as in-season, adaptations are a result of other training and match activities such as contacts and wrestling, therefore decreasing specificity of this technique. The sRPE-TL method is a more useful technique for monitoring the players' responses to the contact-based activities typical of rugby league training and competition, which are particularly evident in competition periods. Nonetheless, as no additional interventions are required, infrequent bouts of isolated running may be sufficient to track these athletes longitudinally. Moreover, the TE_I may have superior application to sports with a lower proportion of contact situations, such as Australian football, field-hockey or football (soccer), though this assertion requires further investigation.

In line with the limitations of monitoring HR-based indices in a team-sport environment (Lamberts et al. 2004), we did not control factors such as caffeine intake, within-session hydration status or ambient temperature. We present a robust metric that can be used to track the physiological response to training amongst several athletes longitudinally, with no additional burden to the athlete, nor the performance staff. It is possible the outcome could have been improved had these factors been accounted for, however from a practical perspective, it is logistically difficult to systematically address these issues in a team-sport environment. Further, using more data points (i.e., training days) with the TE_I may attenuate some of these limitations in HR monitoring methods. These limitations may have less influence on the sRPE-TL method, however the sRPE-TL method is unable to differentiate between drills within the same session, given only one rating is provided per session, which contributes substantially to the better utility of within-session HR monitoring.

Practical applications

We have developed a novel training efficiency index, the TE_I, for assessing athletes' individual responses to a prescribed training programme. Our results indicate the TE_I has both acceptable face validity, where the index covers both external load and internal response metrics in a way understandable to coaches and conditioning staff, and convergent validity, with high correlations between the two constructs of the index and changes in fitness. Coaches and practitioners can use the TE_I to provide regular feedback on the physiological adaptations that may occur as a result of training. Heart rate monitoring is superior to the sRPE-TL method for computing the TE_I, given its ability to differentiate the intensity of different drills within the same session. However, if HR monitoring is unavailable, sRPE-TL remains a suitable alternative. In addition, it seems that global measures of external TL that incorporate body mass, speed- and acceleration-based running are most effective for tracking of the TE_I. Importantly, it is the responsibility of the practitioner to differentiate between changes that may be considered positive (i.e., an increase in fitness), or are early indications of the onset of fatigue. When considered in context with typical training load monitoring practices, the TE_I should be useful for team-sport practitioners to assess the acute response to training, providing further insight into the training status of the athlete. In conclusion, the TE_I is a simple, cost-effective and practical monitoring tool to track adaptations to a team-sport training programme, reduce the risk of injury and illness, or assist in maximising performance.

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Disclosure statement

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ORCID

Grant M. Duthie http://orcid.org/0000-0001-5920-0363
Heidi R. Thornton http://orcid.org/0000-0002-5818-4450

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