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**Title:** The Dose-Response Relationship Between Training Load Measures and Aerobic Fitness in Elite Academy Soccer Players

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**Abstract**

The aim of the current study is to examine the dose-response relationships between training load (TL) measures and the consequent changes in aerobic fitness. Data were collected over the 6-week pre-season period in elite youth soccer players. Participants completed a lactate threshold test to identify changes in treadmill speed at 2 mmol·l$^{-1}$ (S2) and 4 mmol·l$^{-1}$ (S4). Internal TL was quantified with the following training impulse (TRIMP) methods: Banister TRIMP, Edwards TRIMP, Lucia TRIMP, individual TRIMP (iTRIMP) and rate of perceived exertion was also collected. External TL measures were total distance, PlayerLoad, high speed running (14.4-19.8 km·h$^{-1}$), very high-speed running (19.8-25.2 km·h$^{-1}$) and maximal sprint distance (>25.2 km·h$^{-1}$). Individual high-speed distance was derived from each participants treadmill speed at S4. Different Bayesian regression models were run with different likelihood functions. The best fitting models with both the lowest out-of-sample prediction error and the highest variance explained ($R^2$) were used. iTRIMP had the strongest relationships with changes in S2 (r=0.93, $R^2$=0.90) and S4 (r=0.88, $R^2$=0.82). Explained variance ranged from 10%-69% and 11%-38% for all other internal TL measures and external measures respectively. In summary, the iTRIMP method demonstrates a dose-response relationship with changes in aerobic fitness in elite youth soccer players.

## Introduction

Soccer is characterised by high intensity, intermittent activity that yields energy from anaerobic and aerobic pathways[1]. High intensity actions have previously been defined as running above 14.4 $km \cdot h^{-1}$ and accelerating/ decelerating above 3 $m \cdot s^{-2}$ [2,3]. Typically, 2-10% of the total distance (10,881 ± 885 m) will comprise of these high intensity actions and will also vary between positions within professional soccer[4,5]. To repeat these high intensity actions frequently, soccer players need to have adequate aerobic fitness[6]. Teams with higher aerobic fitness capabilities in soccer demonstrate an increased distance covered during match-play and an improved competitive ranking[7,8,9]. Increased $\dot{V}0_2max$ has also been shown to improve total distance covered (20%), involvements with the ball (23%) and the number of sprints (100%) during match-play[10]. Thus, designing and monitoring a training plan to improve aerobic capabilities in soccer players would be of interest to practitioners and coaches.

Training load can be defined as an input variable that is manipulated to elicit a desired training response[11]. To monitor the effectiveness of a training program, the theoretical framework provided by Impellizzeri, Rampinini and Marcora can be implemented[11]. The model demonstrates that the training outcome is the consequence of the internal load experienced, whereby, the internal load is influenced by individual characteristics and the external training load. Given that the internal load response is a consequence of the external load completed, it is plausible that these load measures will demonstrate a range of relationships against different training outcomes[12]. However, the fundamental principle of measuring dose-response relationships is essential to establishing an effective training process 13. This process utilises measurements and assesses them against a desired outcome to determine the measurements effectiveness. Internal load measurements are typically collected via heart rate (HR) monitoring and rate of perceived exertion (RPE). Recent advances in technology allow practitioners to quantify the external load by utilising Electromechanical Systems (MEMS) and Global Positioning Systems (GPS)[14]. External load measures typically provide data of the activity profile completed and can include measures such as total distance covered, high-speed distances, accelerations, decelerations and software-derived load measures.

To date, limited research has examined dose-response relationships between training load measures and aerobic fitness. To our knowledge, none have examined this relationship with a comprehensive range of internal and external TL measures in soccer. There are a few studies across a range of sports which provide dose-response data between internal load measures and aerobic fitness. Manzi et al.[15] utilised the individualised training impulse (iTRIMP) method to monitor the training process within elite premiership male soccer players. The iTRIMP method uses each player's own individual lactate profile to generate an exponential weighting factor for the TRIMP calculation (ΔHR x time x weighting factor). Manzi et al.[15] demonstrate a large to very large relationship between iTRIMP and percentage changes in $\dot{V}0_2max$, ventilatory thresholds, running speed at 4 mmol·l$^{-1}$ and Yo-Yo IR1 performance. Akubat et al.[16] employed a range of HR TRIMPs to assess the relationship between training load and aerobic performance in youth soccer players. Similar to Manzi et al.[15] iTRIMP showed the strongest relationships with aerobic performance, however, Akubat et al.[16] also examined the dose-response between other training load variables and performance. Session RPE (sRPE), Bannister's TRIMP (bTRIMP) and Stagno's TRIMP (tTRIMP) displayed a weak to moderate relationship with changes in aerobic fitness[16]. Unfortunately, no external load data was provided from either the Manzi et al. or Akubat et al. studies[15,16]. Previous data suggest that improvements aerobic fitness have been associated with high-speed running in amateur soccer players[16] and academy rugby union[17]. Moreover, practitioners are now utilising GPS/MEMS more than HR and establishing relationships with desired training outcomes are imperative[14].

In the last 10 years or so, the availability of MEMS and GPS has increased descriptive research of soccer match play and training[4,5,19,20]. It has also led to the use of GPS/MEMS being the most prominent tools for monitoring training load in elite soccer[14].This GPS/MEMS technology has provided practitioners with a wealth of external load data which describes training and match activity[21]. According to Akenhead and Nassis, the external load measures which practitioners deemed the most appropriate to monitor were: accelerations, total distance, distance covered above 19.8 km·h$^{-1}$, estimated metabolic power and heart rate exertion[22]. Nevertheless, the rationale for these can be initiated by coaching staff and software used, but, are generally not informed by empirical evidence regarding dose-response relationships[22]. Multiple studies have also demonstrated that training and match exposure (duration in minutes) show associations with improved aerobic fitness[23,24,25]. However, no particular GPS/MEMS measure has provided further information (or improved explained variance) when examining the dose-response relationship between external load and aerobic fitness[20].

Fitzpatrick, Hicks & Hayes, provide both internal and external load data in relation to changes in aerobic performance[26]. They established that spending time above maximal aerobic speed (MAS) and time above 30% of anaerobic speed reserve had the strongest relationship with change MAS performance (1500m time trial). Distance and time spent above high-speed running velocities (17 km·h$^{-1}$ and 21 km·h$^{-1}$) were also assessed against MAS performance and these explained less variance. Similarly, sRPE and Edwards TRIMP (eTRIMP) demonstrate weaker relationships with change in MAS performance[22]. Whilst, Fitzpatrick, Hicks & Hayes[26] report associations between partial TL measures and aerobic fitness, equivocal findings have been established by Rabbani et al.[27]. They established that spending time above 90% of $HR_{max}$ provides 52% of the variance in changes in maximal velocity achieved in the 30-$15_{IFT}$ in professional soccer players[27]. Despite these associations existing, these cannot be used for complete prescription and monitoring of training that uses the whole intensity continuum i.e. soccer. Therefore, one must consider using a TL measure which has physiological credence and reflects the whole intensity continuum rather than just part of the intensity continuum

Currently, evidence suggests a range of HR-based measures demonstrates very weak to strong dose-response relationship with changes in aerobic fitness. These differences between studies could be due to the different criteria used to assess aerobic fitness (i.e. laboratory and field-based measures) and the dose measures used. Studies in other sports demonstrate that when a comprehensive range of internal and external load measures are assessed against a training outcome (i.e. change in aerobic fitness), the internal load measures have the strongest relationships and explain the most variance[17]. No such study currently exists within the soccer literature.

Therefore, given the sparsity of literature focussing on both internal and external dose-response (aerobic fitness) relationships within soccer, the aim of this is study is to examine the dose-response relationships between training load measures (internal and external) and the consequent changes in aerobic fitness.

## Methods

Fourteen professional youth soccer players agreed to participate in the study (mean±SD). However, due to injury, playing commitments and availability for re-testing the sample was reduced to nine (n=9, 17±1yrs, 179±5.6cm, 71.3±5.8kg). The study was approved by the departmental ethics committee and conformed to the Declaration of Helsinki. Informed consent was provided by the players, players' parents and the soccer club prior to the commencement of the study. All players compete within the category 2 format of Academy soccer provided by the English Premier League. Players trained 4±2 times per week with sessions ranging from 60-120 min with gym-based conditioning provided 3 times per week. Light tactical-based training preceded match fixtures with high-intensity training on a Tuesday and Thursday. Wednesday and Sunday's were typically recovery days.

Players performed laboratory testing on two occasions; once at the start of pre-season, the other at the end of pre-season with players avoiding strenuous exercise 48-hr prior to testing. Testing blocks were separated by 6 weeks of normal training and games. Players were instructed on arrival to lie supine for ten minutes with the lowest 5 seconds HR recorded (Polar T34, Polar Electro, OY, Finland) as their resting heart rate ($HR_{rest}$). To establish maximum HR ($HR_{max}$), maximal aerobic speed and the blood lactate relationship; players were required to complete 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 $km \cdot h^{-1}$ [16]. Each stage was four minutes in duration with a 1-minute rest period between stages. Following the 1-minute rest at 16 $km \cdot h^{-1}$, the protocol increased 0.5 $km \cdot h^{-1}$ every 30s 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).

HR was collected via heart rate monitors which sampled at 10Hz (TeamPro, Polar Electro, OY, Finland) with the raw data being export for analysis. bTRIMP was calculated based on training duration, HR, and a weighting factor using the following formula[28]:

$$\text{bTRIMP} = \text{duration training (minutes)} \times \Delta HR \times 0.64e1.92x$$

where $\Delta HR = (HRex - HRrest) / (HRmax - HRrest)$, $e$ equals the base of the Napierian logarithms, 1.92 equals a generic constant for males and x equals ΔHR. A modified luTRIMP was employed by multiplying time spent in three HR zones based around HR at fixed blood lactate accumulation at 2 and 4 $mmol \cdot l^{-1}$ [17]. 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[30]. 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.[15]. The RPE training load (sRPE) was calculated by multiplying the duration of the session by the CR-10 score[31].

External training load was measured with a GPS/MEMS device (GPS 10 Hz, Tri-axial accelerometer 100Hz; Catapult S5, firmware 6.75, Catapult Innovations, Melbourne, Australia). Varley et al.[32] has demonstrated the reliability for speed and distance using these GPS devices (1.9-6% CV). GPS/MEMS devices were worn in a tight fitted vest with the unit placed between the players scapula. Data were processed using Sprint 5.1 (Catapult Innovations, Melbourne, Australia). The GPS data provided information on total distance (TD), high speed running (HSR) and PlayerLoad™ (PL). The thresholds used for high-speed running were 14.4-19.8 $km \cdot h^{-1}$, very high-speed running (VHSR) was 19.8-25.2 $km \cdot h^{-1}$ and maximal sprint distance (MS) was >25.2 $km \cdot h^{-1}$. Additionally, each player had their own individual high-speed threshold (iHSD) which was derived from the speed of which a fixed blood lactate of 4 $mmol \cdot l^{-1}$ occurred on the treadmill test. Minimum effort dwell time was set to 1s (default settings) with the mean horizontal dilution of precision recorded at 0.8 ± 0.4 with a mean number of 12 ± 3 satellites recording sessions.

To establish a fixed blood lactate accumulation at 2 (S2) and 4 (S4) $mmol \cdot l^{-1}$ the Lactate-E software was used[33]. The final treadmill velocity was deemed the maximal aerobic speed (MAS). The independent variables were the total mean load (internal and external) for players over the 6- week pre-season data collection period. Three different types of analysis were conducted, 1) Bayesian regression models to establish the unstandardised relationships between aerobic fitness and total mean load, 2) Bayesian correlations to explore standardised linear relationships between these variables and 3) Bayesian t-tests to estimate differences between pre and post measures for the start and end of the pre-season training. Bayesian analysis was used given widescale misinterpretation of traditional p-values and confidence intervals, along with serious issues identified with Magnitude Based Inference (MBI)[34,35,36,,37].

Different Bayesian regression models were run with different response distributions ranging from Gaussian linear to non-linear and using mildly informative priors. Model fit was evaluated using the leave-one-out (LOO) criterion[38]. A Bayesian version of $R^2$ was also calculated as an estimate of the proportion of variance explained for new data[39]. Graphical posterior predictive checks were used to compare simulated data from the models to the observed data to check for discrepancies[40]. Effect size for differences were calculated in a similar way to standardised difference tests such as Cohen's d with Bayesian posteriors as input values.

All models were fitted using R (Core Team, 2020) regression models fitted using the brms package which uses Stan (Stan development team, 2018) to implement a Hamiltonian Markov Chain Monte Carlo with a No-U-Turn Sampler. All models were checked for convergence ($\hat{r}=1$), and graphical posterior predictive checks used conducted using bayesplot (Gabry, Mahr, and Buerkner; bayesplot, version 1.5.0, 2018). Bayesian paired t-test and associated effect sizes were fitted using the BEST (Bayesian Estimation Supersedes the t-Test) package[41]. Bayesian correlations were modelled using the Bayesian First Aid package (Baath, Bayesian First Aid, 2013).

## Results

During the 6-week data collection period there were a total of 257 observations for training and matches and correlations between TL measures are presented in table 2. Table 1 shows the change in running speed at the corresponding 2 and 4 mmol·l$^{-1}$ lactate thresholds for individuals. The mean S2 changed from 9.87 ± 2.51 km·h$^{-1}$ to 11.9 ± 1.7 km·h$^{-1}$ with a 98% chance of improving (ES=0.83). Mean S4 increased from 13.3 ± 2.8 km·h$^{-1}$ to 15.0 ± 1.6 km·h$^{-1}$ with a 94% chance of improvement (ES=0.59). Mean MAS improved from 18.6 ± 2.1 km·h$^{-1}$ to 19.2 ± 2.2 km·h$^{-1}$ with 95% probability of change (ES=0.63).

Dose-response relationships between percent changes in aerobic fitness and internal training load measures are presented in table 3. The strongest relationships with percent changes at S2 are iTRIMP (r=0.93,$R^2$=0.90) and luTRIMP (r=0.75,$R^2$=0.60). Similar findings are apparent with S4 as iTRIMP (r=0.88,$R^2$=0.82) and luTRIMP (r=0.82,$R^2$=0.69) explained the most variance. Figure 1 demonstrates the linear relationship between iTRIMP and aerobic fitness. The weakest relationships (r=0.03 to 0.37) and lowest explained variance ($R^2$=0.11 to 0.24) were observed when examining the dose-response relationship between training load measures and MAS.

Dose-response relationships between percent changes in aerobic fitness and external training load measures are presented in table 4. PL demonstrates the strongest relationship and explains the most variance across all changes in aerobic fitness (S2, r=0.49 & $R^2$=0.30; S4, r=0.51 & $R^2$=0.31; MAS r=0.56 & $R^2$=0.38). All other external training load measures demonstrate weaker relationships and are highly uncertain ranging from negative to positive relationship values (table 4).

**Table 1 –** Individual changes of fitness following a 6-week pre-season period

| | S2 | | | S4 | | | MAS | | |
|---|---|---|---|---|---|---|---|---|---|
| **Participant** | **Pre** | **Post** | **Change** | **Pre** | **Post** | **Change** | **Pre** | **Post** | **Change** |
| **1** | 10.1 | 13 | 2.9 | 14 | 16 | 2 | 19.5 | 20.5 | 1 |
| **2** | 10.7 | 11.1 | 0.4 | 12.4 | 11.6 | -0.8 | 17 | 16 | -1 |
| **3** | 11.5 | 14 | 2.5 | 15.6 | 16.3 | 0.7 | 19.5 | 20 | 0.5 |
| **4** | 12.4 | 12.5 | 0.1 | 15.9 | 16.3 | 0.4 | 21.5 | 22 | 0.5 |
| **5** | 8.1 | 13 | 4.9 | 10.9 | 15.3 | 4.4 | 16 | 18 | 2 |
| **6** | 5.6 | 11.5 | 5.9 | 7.8 | 14.2 | 6.4 | 18 | 19 | 1 |
| **7** | 6.6 | 8.6 | 2 | 11.9 | 14.9 | 3 | 16 | 16 | 0 |
| **8** | 12.4 | 13.2 | 0.8 | 16.1 | 16.4 | 0.3 | 22 | 22 | 0 |
| **9** | 11.4 | 10.4 | -1 | 14.9 | 14.9 | -1.2 | 18 | 19 | 1 |

*Notes: All values are expressed as $km \cdot h^{-1}$, S2 = speed at 2 $mmol \cdot l^{-1}$, S4 = speed at 4 $mmol \cdot l^{-1}$, MAS= maximal aerobic speed.*

**Table 2 –** Correlation matrix of training load measures.

| | **iTRIMP** | **bTRIMP** | **luTRIMP** | **eTRIMP** | **TD** | **HSR** | **VHSR** | **iHSD** | **MS** | **PL** |
|---|---|---|---|---|---|---|---|---|---|---|
| **sRPE** | 0.67 | 0.79 | 0.82 | 0.83 | 0.82 | 0.71 | 0.58 | 0.76 | 0.31 | 0.84 |
| **[95% CI]** | [0.59-0.75] | [0.74-0.84] | [0.77-0.87] | [0.78-0.87] | [0.77-0.87] | [0.63-0.77] | [0.48-0.67] | [0.69-0.82 | [0.18-0.43] | [0.79-0.88] |
| **iTRIMP** | | 0.78 | 0.84 | 0.76 | 0.65 | 0.50 | 0.44 | 0.50 | 0.26 | 0.69 |
| **[95% CI]** | | [0.72-0.83] | [0.80-0.88] | [0.70-0.82] | [0.56-0.73] | [0.39-0.60] | [0.32-0.55] | [0.39-0.61] | [0.12-0.39] | [0.62-0.76] |
| **bTRIMP** | | | 0.80 | 0.98 | 0.79 | 0.65 | 0.51 | 0.71 | 0.24 | 0.81 |
| **[95% CI]** | | | [0.75-0.86] | [0.97-0.98] | [0.73-0.84] | [0.56-0.73] | [0.41-0.61] | [0.63-0.78] | [0.10-0.37] | [0.76-0.81] |
| **luTRIMP** | | | | 0.85 | 0.81 | 0.59 | 0.46 | 0.71 | 0.27 | 0.85 |
| **[95% CI]** | | | | [0.80-0.88] | [0.75-0.86] | [0.49-0.68] | [0.34-0.56] | [0.64-0.78] | [0.13-0.39] | [0.81-0.89] |
| **eTRIMP** | | | | | 0.84 | 0.67 | 0.51 | 0.77 | 0.23 | 0.85 |
| **[95% CI]** | | | | | [0.79-0.88] | [0.59-0.75] | [0.40-0.60] | [0.71-0.82] | [0.10-0.37] | [0.81-0.89] |

*Notes: All values (r) derived from a Bayesian correlation consisting of 257 observations. 95% CI = 95% credible intervals, TD= total distance, HSR= high speed running, iHSD= individualised high-speed distance, VHSR= very high-speed running, MS= maximal sprinting distance, PL = PlayerLoad™.*

**Table 3** – Dose-response relationships between internal load and changes in aerobic fitness.

| | | **sRPE** (AU) | **iTRIMP** (AU) | **bTRIMP** (AU) | **luTRIMP** (AU) | **eTRIMP** (AU) |
|---|---|---|---|---|---|---|
| | Mean ± SD | 3797 ± 346 | 916 ± 430 | 623 ± 129 | 1005 ± 201 | 1443 ± 235 |
| **% Δ S2** | Bayes r *[95% CI]* | -0.17 *[-0.77 to 0.50]* | 0.93 *[0.74 to 1]* | 0.33 *[-0.33 to 0.87]* | 0.75 *[0.26 to 0.98]* | 0.17 *[-0.49 to 0.77]* |
| | Bayes $R^2$ *[95% CI]* | 0.12 *[0.00 to 0.40]* | 0.90 *[0.76 to 0.93]* | 0.23 *[0.00 to 0.54]* | 0.60 *[0.12 to 0.75]* | 0.13 *[0.00 to 0.42]* |
| **% Δ S4** | Bayes r *[95% CI]* | -0.16 *[-0.76 to 0.51]* | 0.88 *[0.62 to 0.99]* | 0.18 *[-0.48 to 0.81]* | 0.82 *[0.44 to 0.99]* | 0.00 *[-0.65 to 0.67]* |
| | Bayes $R^2$ *[95% CI]* | 0.12 *[0.00 to 0.39]* | 0.82 *[0.51 to 0.88]* | 0.16 *[0.00 to 0.46]* | 0.69 *[0.20 to 0.81]* | 0.10 *[0.00 to 0.35]* |
| **% Δ MAS** | Bayes r *[95% CI]* | 0.37 *[-0.27 to 0.88]* | 0.37 *[-0.28 to 0.87]* | 0.03 *[-0.59 to 0.66]* | 0.26 *[-0.41 to 0.83]* | 0.08 *[-0.57 to 0.69]* |
| | Bayes $R^2$ *[95% CI]* | 0.24 *[0.00 to 0.55]* | 0.22 *[0.00 to 0.52]* | 0.11 *[0.00 to 0.38]* | 0.16 *[0.00 to 0.47]* | 0.11 *[0.00 to 0.38]* |

*Note: S2 = speed at 2 mmol·l$^{-1}$, S4 = speed at 4 mmol·l$^{-1}$, MAS= maximal aerobic speed, AU= Arbitrary Units, 95% CI = 95% credible intervals.*

**Table 4** - Dose-response relationships between external load and changes in aerobic fitness

| | | **TD (m)** | **HSR (m)** | **VHSR (m)** | **iHSD(m)** | **MS (m)** | **PL (AU)** |
|---|---|---|---|---|---|---|---|
| | Mean ± SD | 38003 ± 3559 | 4655± 807 | 1770 ± 556 | 30759 ± 7835 | 541 ± 461 | 3754 ± 269 |
| **% Δ S2** | Bayes r *[95% CI]* | -0.14 *[-0.74 to 0.51]* | -0.45 *[-0.90 to 0.17]* | -0.25 *[-0.81 to 0.41]* | -0.01 *[-0.73 to 0.56]* | -0.22 *[-0.80 to 0.43]* | 0.49 *[-0.13 to 0.90]* |
| | Bayes $R^2$ *[95% CI]* | 0.12 *[0.00 to 0.40]* | 0.27 *[0.00 to 0.57]* | 0.18 *[0.00 to 0.49]* | 0.12 *[0.00 to 0.40]* | 0.15 *[0.00 to 0.44]* | 0.30 *[0.01 to 0.58]* |
| **% Δ S4** | Bayes r *[95% CI]* | -0.11 *[0.74 to 0.54]* | -0.45 *[-0.89 to 0.19]* | -0.33 *-0.86 to 0.32* | -0.12 *[-0.71 to 0.56]* | -0.15 *[-0.76 to 0.49]* | 0.51 *[-0.10 to 0.92]* |
| | Bayes $R^2$ *[95% CI]* | 0.11 *[0.00 to 0.37]* | 0.27 *[0.00 to 0.56]* | 0.22 *[0.00 to 0.54]* | 0.12 *[0.00 to 0.40* | 0.13 *[0.00 to 0.42]* | 0.31 *[0.00 to 0.59]* |
| **% Δ MAS** | Bayes r *[95% CI]* | 0.34 *[-0.30 to 0.85]* | 0.11 *[-0.52 to 0.73]* | -0.06 *[-0.69 to 0.58]* | 0.27 *[-0.37 to 0.82]* | -0.10 *[-0.74 to 0.54]* | 0.56 *[-0.34 to 0.94]* |
| | Bayes $R^2$ *[95% CI]* | 0.21 *[0.00 to 0.51]* | 0.12 *[0.00 to 0.39]* | 0.12 *[0.00 to 0.39]* | 0.16 *[0.00 to 0.47]* | 0.12 *[0.00 to 0.39]* | 0.38 *[0.01 to 0.63]* |

*Note: S2 = speed at 2 mmol·l$^{-1}$, S4 = speed at 4 mmol·l$^{-1}$, MAS= maximal aerobic speed, TD= total distance, HSR= high speed running, VHSR= very high speed running, iHSD=individualised high-speed distance, MS= maximal sprinting distance, PL = PlayerLoad™, AU= Arbitrary Units, 95% CI = 95% credible intervals.*

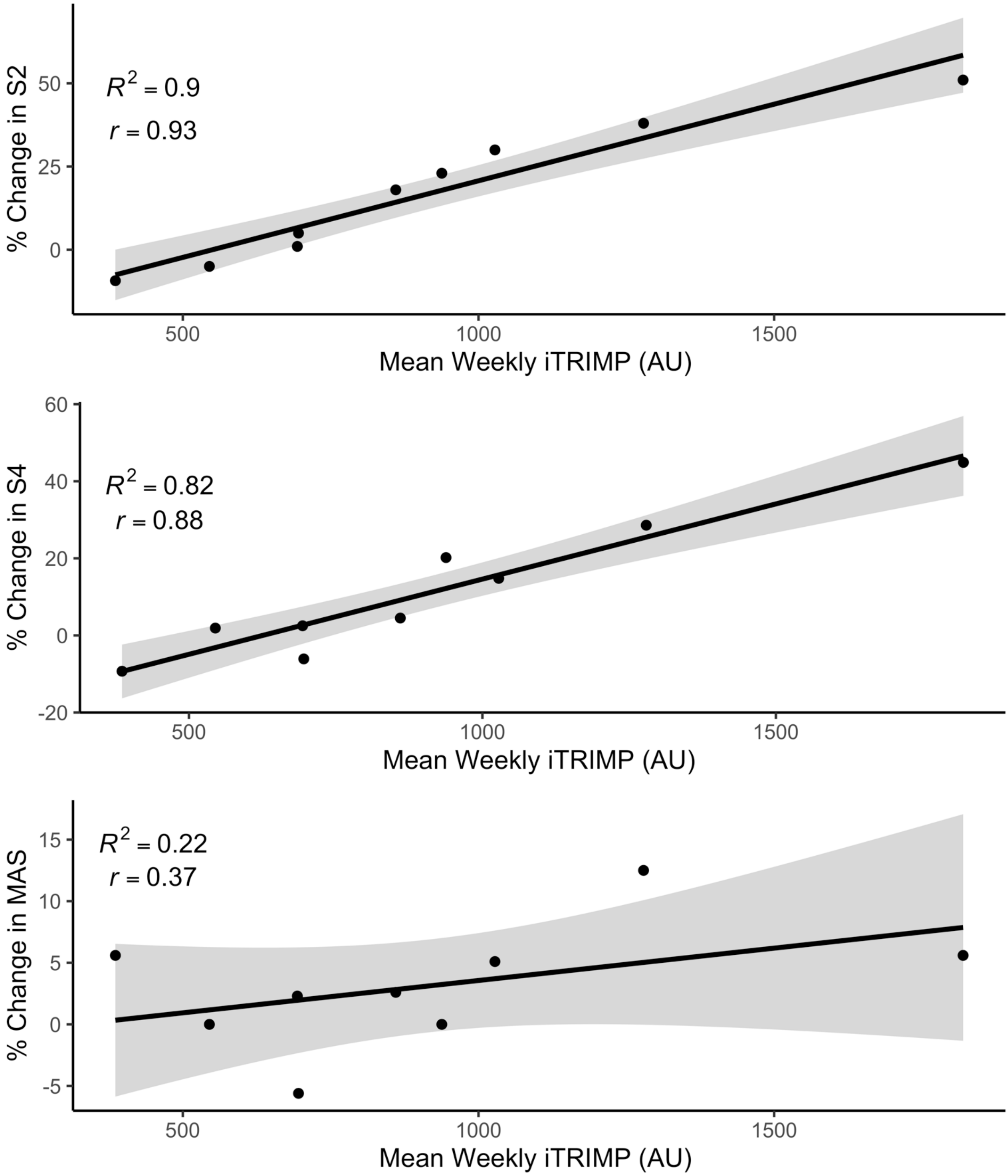


**Figure 1** – Relationship between iTRIMP and changes in aerobic fitness

## Discussion

The aim of the present study was to examine the dose-response relationship across a comprehensive range of TL measures and the consequent change in aerobic fitness during a 6-wk pre-season period. The key finding from this study was iTRIMP explained 82% and 90% of the variance of changes in S2 and S4 respectively. TL measures which had the least individualised calculations (sRPE, eTRIMP and bTRIMP) showed the weaker relationships (r = 0.08 to 0.37) and explained less variance ($R^2$ = 0.10 to 0.24) between the TL measure and training outcome. Correlations between all TL measures ranged from r=0.23 to r=0.98 and demonstrate covariance. This is perhaps due to TL measures sharing similar formulae but are distinguished by how they determine intensity and/or weighting factors. Consequently, TL methods which utilised the lactate data (luTRIMP and iTRIMP) present a stronger relationship. External TL measures displayed a range from negative to positive relationships with changes in aerobic fitness. However, of the GPS/MEMS measures, PL demonstrated the strongest relationship and explained 30%, 31% and 38% of the variance of changes in S2, S4 and MAS respectively. Since the strongest dose-response relationships were observed with internal TL measures (i.e. iTRIMP), these data support the use of a TL method which incorporates individual physiological characteristics (i.e. HR–blood lactate relationship).

As per the model by Impellizzeri et al., it is suggested that internal TL is influenced by individual factors such as genetics and fitness status[11]. Given that iTRIMP utilises the HR-blood lactate relationship, it is not surprising that incorporating these individual factors into the TL measure results in a stronger dose-response relationship. Despite similar findings in previous research, practitioners have still chosen to use sRPE as their main monitoring tools in elite soccer[14]. This is perhaps due to the low cost, ease of administration and the relationships with improved aerobic fitness outside of soccer[19,31]. sRPE has shown relationships with improved aerobic fitness in cycling[42], healthy volunteers[43] and during strength training[44]. sRPE also demonstrates a relationship with intensity (%$HR_{max}$) during continuous incremental exercise suggesting it to be a valid marker of intensity[45]. There is also emerging evidence that using differential RPE may provide practitioners on changes in aerobic fitness in soccer players[46] with similar findings across a range of tests apparent in rugby union players[47]. However, despite previous relationships and practical benefits our data indicates that sRPE only provides 12% to 24% of the variance explained for changes in aerobic fitness. The influence of fatigue on sRPE has previously been reported and is perhaps why there is a reduced dose-response relationship with fitness[45]. This is reaffirmed by the updated training process model as psychological status (i.e. perception of effort) can influence the perceived internal load, but it is not a measure of internal load[11].

bTRIMP and eTRIMP have previously been reported as criterion HR based measures to validate internal and external training load measures[11,27,31]. However, the current investigation presents data that neither bTRIMP or eTRIMP demonstrate a credible relationship with changes in aerobic fitness (table 3). There a few explanations to why these may not relate to the training outcome. bTRIMP uses mean HR to calculate TL and does not reflect the intermittent nature of training and match play[48]. Whilst only 2-10% of the total distance is covered at high speed, the mean HR during soccer match play is 85% $HR_{max}$ and can also reach 100% $HR_{max}$[4,49,50,51]. Thus, the use of mean HR within a stochastic sport such as soccer would not be appropriate. Furthermore, eTRIMP uses arbitrary linear weighting zones which do not reflect individual physiological characteristics[30]. Therefore, it poses the question of validity when using these measures as a criterion of TL as previous research has done [11,27,31].

Whilst GPS/MEMS may be popular to use amongst practitioners, our data questions its use for prescribing and monitoring for changes in aerobic fitness. The distances (weekly total mean) completed are presented in table 4 and represent similar values to descriptive studies[52]. The external TL measures ranged from 11% to 38% explained variance with changes in aerobic fitness (table 4). In attempt to individualise the high-speed running, we used the treadmill speed at S4 to create an iHSD for each player[17]. In spite of this, it only explained 12% for changes in S2, S4 and 16% for changes in MAS respectively, with similar findings have been observed elsewhere[17]. The lack of a dose-response relationship might be explained by the current studies test selection. Previous studies have found a relationship with external training load and field-based sport-specific measures of aerobic fitness. Rabbani et al.[27] found relationships with 'BodyLoad' and changes in $30\text{-}15_{IFT}$, whereas, Fitzpatrick, Hicks and Hayes[26] established relationships with time spent above MAS and >30% ASR with MAS time-trial performance. Consequently, certain dose measures (internal and/or external) may relate better to different fitness tests (i.e. field or lab-based) and this remains to be explored in a comprehensive manner.

The strongest relationship with the external TL measures and aerobic fitness was observed with PL. PL explained 30% (r=0.49, 95% CI = -0.13 to 0.19), 31% (r=0.51, 95% CI= -0.10 to 0.92) and 38% (r= 0.56, 95% CI= -0.34 to 0.94) of variance with S2, S4 and MAS respectively. Given that PL attempts to encapsulate the whole session, quantify the range of intensities experienced and is largely influenced by duration it is not surprising this measure had the stronger relationship. Nevertheless, PL still only explained 30-38% of variance with aerobic measures with considerably large credible intervals compared to internal TL measures. Thus, whilst there might be potential to use this measure there is still considerable uncertainty with its dose-response relationship with changes in aerobic fitness. However, potential for GPS/MEMS measures might exist for monitoring the fatigue dose-response given the associations with changes in neuromuscular performance[53]. If one could better understand the fitness-fatigue paradigm by using a range of internal and external measures, this would benefit practitioners within elite soccer.

There a few limitations to the current study. Unfortunately, the sample size was reduced (n=9) due to availability for rest through injury and/or illnesses. However, Bayesian analysis is better suited for making inferences on small sample sizes given informative prior information, as the MCMC methods used to produce posterior distributions do not depend on asymptotics the same way that traditional frequentist methods do[54]. There was also no field test conducted during the pre-season period, however, other studies have found that individualised TL methods relate to improvements in both field and laboratory measurements[15]. Data from Malone et al. also suggest that relationships between TL measures and training outcomes will change dependent on the type of test[12]. Thus, whilst this study identifies a relationship between iTRIMP and aerobic fitness, it is important to establish each measurement with appropriate outcomes[11,12]. The use of a lactate threshold test also provides insight into adaptation across the intensity continuum which is imperative for the pre-season period (table 1).

A practical application from the regression analysis revealed that for a change of zero (i.e. maintenance of fitness) to occur at S2 and S4, a mean weekly training load (iTRIMP) of 571 AU (95%CI= 169-896 AU) or 643 AU (95%CI= 170-981 AU) would be required. This is slightly different to that of Manzi who established a mean iTRIMP load of 454 AU would elicit zero change at S4[15]. One explanation could be that Manzi used senior premiership footballers who would possess a higher level of fitness compared to developing elite youth soccer players. Both regressions demonstrate the practical use of identifying dose-response relationships and how this can be implemented in training. The current data also demonstrates the considerable range at which a change of 0% would occur. Thus, it is imperative to monitor training using individualised TL measures and consider them on an individual basis. The current data cannot be generalised beyond this stage of the season (pre-season), but it is important to recognise the practical process and certainty of establishing dose-response measures with training outcomes. Such measures would have to be recalibrated and repeated throughout the season for practitioners to maintain their understanding of the dose-response relationship. Further data are warranted over a longer period of time in order to capture both the preparative and competitive phases of the season as the dose-response relationship has the potential to change i.e. to non-linear[17]. Moreover, establishing a field-based lactate test would remove practical barriers for soccer clubs and further research are required in this area.

This is the first study to the authors' knowledge to comprehensively examine the dose-response relationships of internal and external TL measures with aerobic fitness in elite soccer. Similar to previous research, iTRIMP demonstrates the strongest relationship and explains the most variance to changes in aerobic fitness. Linear relationships were also observed between TL measures and changes in aerobic fitness. This is similar to previous research in soccer but is different to that of Rugby Union where Taylor et al. identified a curvi-linear response to TL and changes in aerobic fitness[17]. The authors suggest that because external TL was similar for forwards and backs, the response caused some players to improve and others to potentially overtrain to demonstrate the theorized hormesis popular in training theory. Similar data exist with Manzi et al. who have identified curvi-linear relationships with iTRIMP and autonomic nervous system responses in endurance athletes[55]. Therefore, when modelling TL measures with training outcomes, it is important to consider linear and non-linear approaches. Moreover, TL measures derived from GPS/MEMS provide limited explanation to the change in aerobic fitness during the pre-season period. Practitioners should be mindful of TL measures that have been previously validated against measures with no dose-response relationships with aerobic fitness. TL measures should take an individualised approach to monitoring and incorporate individualised physiological data into the TL calculation such as iTRIMP. Practitioners should also be aware that whilst this method appears to demonstrate the strongest relationship, it does require repetitive lactate testing under laboratory conditions. Practitioners must weigh up the value of the information provided against the time and resource required to obtain the information.

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