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Research Article

# Tracking Individual Differences in the Training Response of Professional Soccer Players

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## Abstract

The present study aimed to develop a model that partioned sources of variability in the external-internal training load relationship and examined individual differences in the training response of professional soccer players. External and internal training load was recorded daily in fourteen professional soccer player across an eight week pre-season period. The within-player and between-player effects of external training load on internal training load as well as the between-player, between-session and within-player variability were estimated with a linear mixed model. There were curvilinear effects of external training load on internal training load with very to most likely large to very large substantial linear slopes (34% to 72%, effect size: 1.3 to 3.0) and likely small to moderate substantial quadratic slopes (-7% to -11%, effect size: -0.3 to -0.6). The between-player effects were less pronounced with possibly trivial to likely small substantial linear slopes (2% to 7%, effect size: 0.1 to 0.4) and unclear to possibly substantial quadratic slopes (0.8% to 6%, effect size: 0.04 to 0.26). Individual responses were unclear to likely moderate substantial (2% to 4%, effect size: 0.04 to 0.19). The between-session variability was most likely large to very large (18% to 41%, effect size: 0.95 to 1.4), whilst within-player variability ranged ~16 - 22%. The modeled effects were used to derive an "expected" internal load whilst the sources of variability were combined to derive uncertainty limits of the "expected" response and project these against boundaries of practical importance to derive individual training responses for a given session. Practitioners may develop theoretical models to derive practical monitoring systems aiding in the day-to-day decision making process.

***Keywords:*** *Linear Mixed Model; Monitoring Process; Variability; Training Framework; Individual Response*

## Abbreviations

TL: Training Load; GPS: Global Positioning System; MEMS: Micro Electromechanical Sensor; bTRIMP: Banister Training Impulse; TD: Total Distance; VHSR: Very High Speed Running Distance; SD: Standard Deviation; ES: Effect Size; CI: Confidence Interval; SWC: Smallest Worthwhile Change

## Introduction

In modern soccer where teams and/or individual players may well surpass 60+ official games, the foundations of in-season success are determined by a thoroughly-planned and well-executed pre-season that prepares players for an impending in-season phase [1,2]. To this end the optimization of fitness and the potentiation of biomotor abilities are considered central to the preparation of athletes for the frequent and substantial physical demands of in-season competition [3]. Current thought in the training process dictates monitoring of internal and external training load (TL) as a means to prevent increased levels of fatigue, higher risk of illness and injury [4,5].

External training load represents the actual physical work performed during the training session or match (e.g. total distance, high-intensity distance, accelerations etc.), whilst internal training load represents the associated biochemical (physical and physiological) and biomechanical stress responses [6]. Both acute and chronic changes in the training outcome (i.e. transient fatigue, increase in fitness or mal-adaptation and overtraining) are effectively the result of an athlete's cumulative internal load over a given time frame (i.e. training session, microcyle, training block, mesocycle, etc.) [4-6]. Whilst the relationship between external and internal TL, which effectively represents the dose-response nature of the training stimulus [5, 6], has been examined thoroughly in several studies [7-9], there are very few data regarding the individual internal TL responses to external TL in professional soccer players [10]. In addition, what is even more challenging for the practitioner is the timely identification of important trends in a player's data and/or deviations from "typical" patterns [11,12].

To this end practitioners must unravel and model all potential sources of variability in the external-internal training load relationship [13,14]. The first source of variability is the individual slopes in external-internal training load relationship which represent how "more" or "less" than the "expected", a given player's difference in internal load varies for a given change in the "dose" of external load [10]. In addition, only recently it has been acknowledged that external TL can exert within- as well as between-player main effects on internal TL; thus external TL is actually two variables instead of one [15]. The within-player effect represents the impact of a player's day-to-day variation around his average TL levels (i.e. a player having higher or lower daily external TL compared to his individual average external TL across a training phase) whilst the between-player effect represents the impact of the player-to-player variation in average external TL across a training phase (i.e. pre-season; some players have higher average pre-season external TL than others) [10,15]. In addition, the inability to reproduce the same external daily TL over repeated training days is perhaps the major source of internal TL variability [10,14]. The remaining residual variability after controlling for the above sources represents within-player variability in a typical training day and can be conceptualized as the player-training day interaction [16]. Therefore, partitioning sources of variation in the external-internal training load response will enable practitioners to overlay the actual over the "expected" (along with its uncertainty limits) and decide whether a given player's response (internal load) for a given external training load on any a given training session lies within "normal" ranges [12].

## Purpose of the Study

The purpose of the present study was to present a model examining individual differences in the training response in professional soccer players. To that end we modeled and quantified the within-player and the between-player effects of external load on internal training load across a pre-season in professional soccer players and partioned sources of variability in the training responses into individual differences, between session variability and within-player (residual) variability. Based on the modeled sources of variability we derived a framework for examining individual differences in the training response.

## Materials and Methods

### Participants

A total of fourteen male players from one professional soccer team (age: 25.2 ± 3.1 years, height: 1.81 ± 0.05m, body mass: 74.0 ± 6.8 kg), participating in the top national league, volunteered to participate in the study. Players had to remain free from injury during the observation period and were also required to have completed ≥85% of the pre-season training sessions. All players had participated in similar types of research in the past and were familiar with the procedures, discomforts, and possible risks of the present study. Players were informed about the experimental procedures and signed a written informed consent form. The experimental protocol complied according to the Declaration of Helsinki for research with human subjects. Ethical approval was granted by the local Institutional Review Board.

### Study design

We designed the study to compare measures of internal and external load during the pre-season period, from early June to September (8 weeks). A total of 605 individual player training observations from 46 training sessions were included, with a median of 41 observations per player (range 39 - 46). The training sessions were all on-field sessions and were performed on the same football pitch covered with natural turf.

### Internal and external load monitoring

The study used a longitudinal observational research design in which TL data were collected during an 8-week preseason. Heart rate and player-tracking data were recorded on all 46 sessions via a short-range telemetry system (Polar Team Pro, Polar Electro Oy, Kempele, Finland) that integrated a heart rate monitor, a global positioning system (GPS) sampling at 10 HZ and a micro electromechanical sensor (MEMS) (accelerometer, gyroscope, magnetometer) sampling at 200 Hz. Heart and GPS data were downloaded onto a portable PC and analyzed using dedicated software (Polar Team Pro Software) and an electronic spreadsheet (Excel, Microsoft Corporation). Internal TL was measured using the training impulse proposed by Banister (bTRIMP) using previously described procedures [17] and external TL was quantified using total distance (TD) and very high speed running distance (VHSR).

### Statistical analysis

Our analysis expanded on a previous linear model examining within- and between-player effects of external TL on internal TL [10]. The data were analyzed using a quadratic mixed-effects model (the MIXED routine in SPSS software, version 25; IBM, Armonk, USA). The quadratic model allowed for a curvilinear effect of external TL on internal TL; thus bTRIMP was treated as the outcome variable and log-transformed to reduce bias due to non-uniformity of errors and TD and VHSR were treated as predictor variables in separate models. All effects were back-transformed to percent effects. Fixed effects in each model were the intercept, the within-player predictor, the square of the within-player predictor, the between-player predictor and the square of the between-player predictor, which collectively evaluated the mean quadratic of the within-player and between-player effects [18-20]. The within-player predictor was obtained by standardizing the external load variable to 1 standard deviation (SD) of the mean of each player; it evaluates the magnitude of a change from a typical to a typical high daily load for a given player [10,15]. To obtain the between-player predictor the individual player's mean external load was standardized to 1 SD of the average of all players' mean; it gauges the systematic variation of the within-player predictor for players with typical low, to average, to typical high mean training load [15,18-20]. The model was specified with random intercept for player and random intercept for session, as well as random slope for player × within-player effect (with an "unstructured" covariance structure; the between-player effect cannot have random effect) [15]. We allowed for negative variances to estimate realistic confidence limits for the variances and the SD derived. The random effects are presented as SD's (in percentage) and represent pure between-player variability, between-session variability, individual response to 1 SD of the within-player effect (individual variation from the fixed within-player effect) and residual variability.

The magnitudes of the effects are presented as standardized effect sizes (ES) (the effects divided by the square root of the sum of the pure between-player and residual variances), where < 0.2, 0.2 to 0.6, 0.6 to 1.2, 1.2 to 2.0, and > 2.0 are regarded as trivial, small, moderate, large, and very large effects, respectively. For interpreting random effects, which are SDs, these thresholds were halved [16]. Nonclinical, magnitude-based inferences were used, where an effect was deemed unclear if the 90% confidence interval (CI) included small positive and negative effects; the effect was otherwise deemed clear. Qualitative assessment of chances of clear outcomes was as follows: > 25% to 75%, possibly; > 75% to 95%, likely; > 95% to 99%, most likely [16].

To evaluate the response at the individual player level we plotted the difference between the observed and "expected" internal TL for each player on a given training session. The "expected" internal TL represented the prediction made by the fixed effects of the model. Each player's difference was surrounded by ± 90% confidence intervals computed as 1.65 x residual variability [12,15,16]. Given that there would be a large number of independent comparisons, we evaluated differences of at least moderate magnitude (determined as 0.6 x sum of residual plus between player variability) that both CI limits resided outside the relevant boundaries [14].

## Results

Box-plots (mean ± inter-quartile range) for internal load are presented in figure 1 for player average and figure 2 for session average.

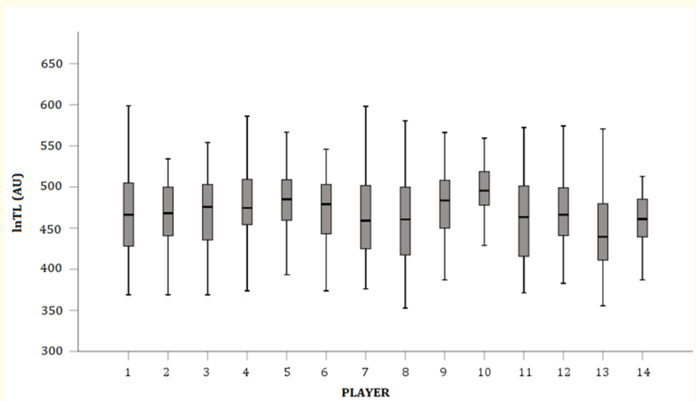


***Figure 1:*** *Mean ± inter-quartile range for player internal training load across pre-season. lnTL = log transformed bTRIMP, AU = arbitrary units.*

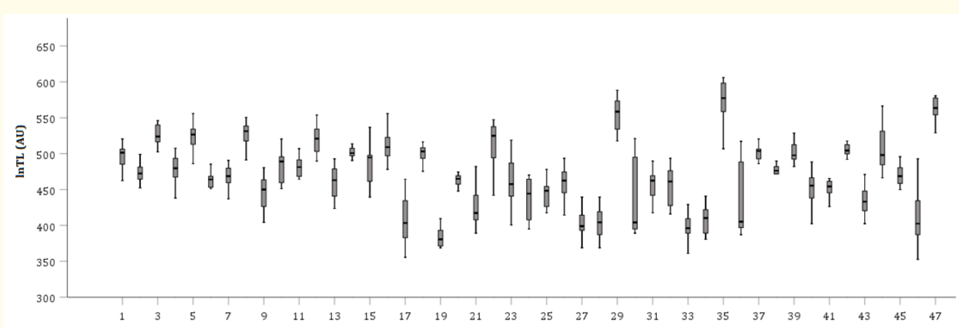


***Figure 2:*** *Mean ± inter-quartile range for session internal training load across pre-season. lnTL = log transformed bTRIMP, AU = Arbitrary units.*

TD had a very large positive linear within-player effect (most likely substantial) and a moderate negative quadratic within-player effect (very likely substantial) on bTRIMP (Table 1). The linear between-player effect on bTRIMP for TD was small (likely substantial) but the quadratic between-player effect was unclear (Table 1). Collectively the mean quadratic effect of the within-player effect of TD on bTRIMP had a decelerating positive function (Figure 3). VHSR had a large positive linear within-player effect (most likely substantial) and a small negative quadratic within-player effect (very likely substantial) on bTRIMP (Table 2). Both the linear between-player effect and the quadratic between-player effect of VHSR on bTRIMP were less pronounced (possibly trivial and possibly substantial respectively) (Table 2). Collectively the mean quadratic effect of the within-player effect of VHSR on bTRIMP had also a decelerating positive function (Figure 4).

| | +1 SD | % change | 90%CI (% change) | ES |
|---|---|---|---|---|
| Within-player effect | 54.5 | 72.5 | 66.2;79.1 | 3.00*** |
| Between-player effect | 6.9 | 7.1 | 1.8;12.7 | 0.38* |
| Quadratic within-player effect | -11.0 | -10.4 | -12.1;-8.7 | -0.61** |
| Quadratic between-player effect | 0.8 | 0.8 | -4.8;6.9 | 0.04 |

***Table 1:*** *The within-player and between-player effects of TD on bTRIMP.*

*#=Possibly, *=Likely, **=Very likely, ***=Most likely; unclear effects do not have a superscript.*

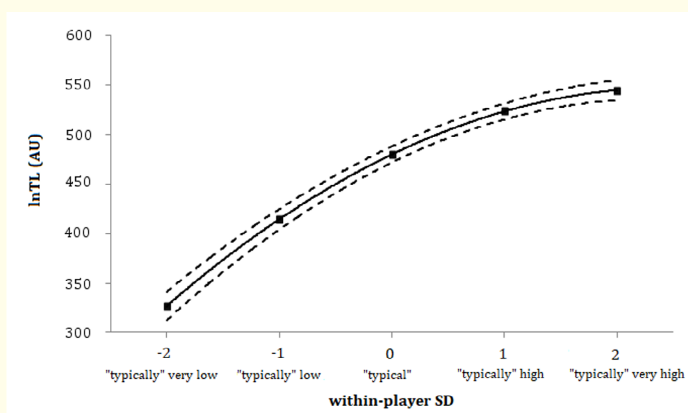


***Figure 3:*** *The within-player effect of TD on bTRIMP conditioned on the between-player effect set to zero (i.e. a player with "typical" average pre-season TD). The dotted lines represent 90% CI in bTRIMP. The within-player SD indicates how far away is the daily TD from individual average TD (thus within-player SD=0 indicates a session where the player accumulated TD equal to his pre-season average). lnTL = log transformed bTRIMP, AU = Arbitrary units.*

| | +1 SD | % change | 90%CI (%) | ES |
|---|---|---|---|---|
| Within-player effect | 29.9 | 34.9 | 28.7;41.4 | 1.32*** |
| Between-player effect | 2.0 | 2.0 | -4.1;8.4 | 0.10# |
| Quadratic within-player effect | -6.9 | -6.7 | -8.3;-5.0 | -0.30* |
| Quadratic between-player effect | 6.0 | 6.2 | -0.3;13.0 | 0.26# |

***Table 2:*** *The within-player and between player effects of VHSR on bTRIMP.*

*#=Possibly, *=Likely, **=Very likely, ***=Most likely; unclear effects do not have a superscript.*

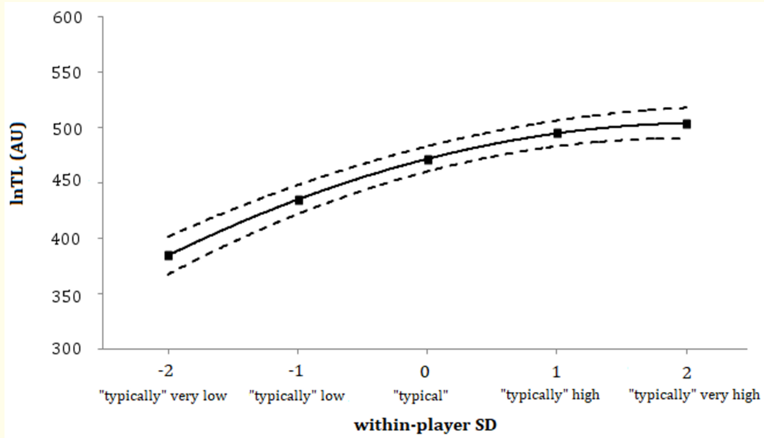


***Figure 4:*** *The within-player effect of VHSR on bTRIMP conditioned on the between-player effect set to zero (i.e. a player with "typical" average pre-season VHSR). The dotted lines represent 90% CI in bTRIMP. The within-player SD indicates how far away is the daily VHSR from individual average VHSR (thus within-player SD=0 indicates a session where the player accumulated VHSR equal to his pre-season average). lnTL = log transformed bTRIMP, AU = Arbitrary units.*

Individual responses in bTRIMP were moderate (likely substantial) to TD and between-session variability was large (most likely substantial) (Table 3). Additionally, bTRIMP showed a within-player CV of 16.0% (90% CI, 15.1 to 16.8) to TD in a typical training day. Individual responses in bTRIMP were unclear to VHSR and between-session variability was very large (most likely substantial) (Table 3). Finally, bTRIMP showed a within-player CV of 21.6% (90% CI, 20.4 to 22.8) to VHSR in a typical training day.

| Model | Between-player variability | | Within-player variability | | Between-day variability | | | Individual responses | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | CV, % | 90%CI | CV, % | 90%CI | CV, % | 90%CI | ES | CV, % | 90%CI | ES |
| TD | 11.1 | 5.8;14.7 | 16.0 | 15.1;16.8 | 18.3 | 14.2;21.7 | 0.95*** | 4.0 | 1.5;5.5 | 0.19* |
| VHSR | 12.1 | 5.9;6.3 | 21.6 | 20.4;22.8 | 41.3 | 31.8;49.8 | 1.39*** | 1.5 | -2.3;3.2 | 0.04 |

***Table 3:*** *Random effects describing the variability in bTRIMP that is not explained by the respective quadratic models.*

*#=Possibly, *=Likely, **=Very likely, ***=Most likely; unclear effects do not have a superscript; thresholds for random effects are: > 0.1, small; > 0.3, moderate; > 0.6, large; > 1.2, very large; > 2.0 extremely large. Between-player and within-player variability are combined to determine smallest worthwhile change (SWC) and do not have effect sizes.*

Methods for interpreting individual player training responses within a given session are presented in figure 5 (TD) and figure 6 (VHSR). Based on our thresholds for practical importance (determined as 0.6 x sum of residual plus between player variability - represented by the horizontal grey lines) and the differences ± 90%CI uncertainty limits (determined as 1.65 x residual variability), a given individual response was deemed as "unusual" if the point estimate lied outside the area of practical importance and neither of the boundaries in the uncertainty crossed these values. For example, none of the players presented an "unusual" response based on TD (Figure 5), whilst one player presented an "unusual" training based on VHSR (Figure 6 - denoted PLAYER 11 by *). Furthermore the "unusual" response could further be broken down into "over response" if the difference was positive and "under response" if the difference was negative. For the player denoted in figure 6 the actual internal TL was lower than the "expected" after accounting for the models fixed effects (plus the day-to-day uncertainty in the response). Thus the actual response experienced by the player in question was lower than the anticipated. On the contrary a positive difference would have implied that the actual response experienced by the player in question was higher than the "expected".

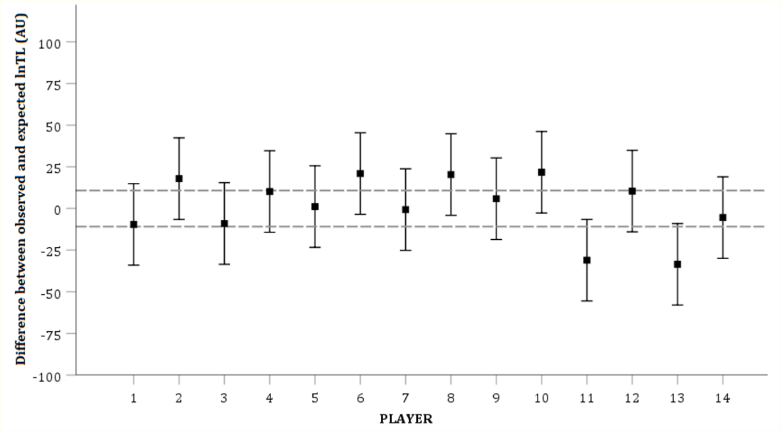


***Figure 5:*** *Difference between the observed and "expected" bTRIMP derived from the TD model for a given session. The dotted lines represent a moderate effect relative to the observed between-player effect (sum of between-player and within-player variability). Error bars (± 90%CI) represent the session-to-session uncertainty in the "expected" difference after accounting for the individual-differences and between-session variability. Players that have their difference and both their error bars lie outside the dotted lines present an "unusual" individual response.*

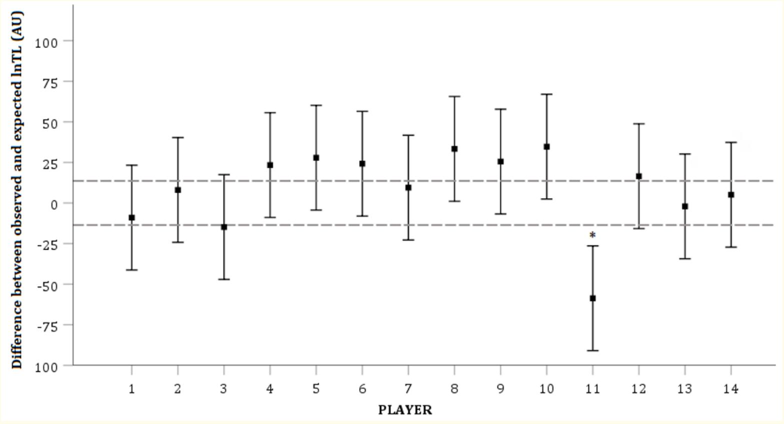


***Figure 6:*** *Difference between the observed and "expected" bTRIMP derived from the VHSR model for the same session with figure 5. The dotted lines represent a moderate effect relative to the observed between-player effect (sum of between-player and within-player variability). Error bars (± 90%CI) represent the session-to-session uncertainty in the "expected" difference after accounting for the individual-differences and between-session variability. Players that have their difference and both their error bars lay outside the dotted lines present an "unusual" individual response.*

## Discussion

The present study modeled the effect of TD and VHSR on bTRIMP during pre-season training sessions in professional soccer players, using an individualized approach. We found that both TD and VHSR had substantial non-linear within-player effect (large to very large linear slope and small to moderate negative quadratic slope) on bTRIMP. Between-player effects were linear and likely small for TD but less pronounced for VHSR. Individual responses in the linear within-player effect of the quadratic model were moderate for TD but unclear for VHSR. Despite adjusting for either TD or VHSR, there was still large to very large between training sessions variability. Finally, within-player variability was higher for VHSR compared to TD. By combining the above sources of variability we were able to create a quick "scan" for any given training session and identify players with an "unusual" difference between their observed and predicted responses for the selected session.

Our results indicate that bTRIMP could differentiate between 1SD of the within-player training effect for either TD or VHSR, which corresponds to the difference between a training day where the player is at his average TD or VHSR and a training day where the player has a "typically high" TD or VHSR (i.e. average+1SD). In this regard the within-player effect individualized the impact of the training load imposed since for every player both the "average" and the "SD" represent their corresponding individual values of the preseason. Our results are in agreement with a previous study that demonstrated large/very large ES of TD and VHSR on sRPE-TL [10]. Furthermore our study extends previous findings [10] since our quadratic models indicated a substantial non-linear relationship between within-player external TL and bTRIMP (Figure 3 and 4). In fact, curvilinear (quadratic) relationships have been demonstrated for the effect of training load on match performance [18,20], variability of musculoskeletal screening scores [19] and neuromuscular performance and hormonal concentrations [20]. The decelerating positive function identified for both TD and VHSR (positive linear and negative quadratic slope) indicates that as daily external TL increases from very low, to typical, to very high, the rate of increase in bTRIMP decreases (Figure 3 and 4).

The between-player effect quantifies the expected difference in bTRIMP between players with a "typical" and "typically high" average TD or VHSR across the preseason. Players who completed more TD on average across the pre-season report ~7% higher daily bTRIMP, whilst players who completed more VHSR on average across the pre-season report ~2% higher daily bTRIMP. Previously the between-player effect was shown to be moderate (~17 - 19%) for both TD and VHSR [10]. Although this particular study evaluated 2SD of the between-players effects, our results are still of lower magnitude, especially for VHSR. However, the unexplained between-player variability (conditioned specifically on a session that players are at their individual "typical" daily external TL) [15] that could not be explained by the external load variables was around 11 - 12%, somewhat less than the 13 - 16% previously reported [10]. Potential reasons for these differences maybe (i) that our study was conducted during pre-season and every player had a somewhat tightly controlled overall pre-season external TL, thus the accumulated average internal TL was quite similar for all players across the pre-season (Figure 1) and (ii) the aforementioned study monitored only 10 sessions per player that were spanned throughout a 32 week in-season period, thus between-player differences were expected to be more pronounced [10].

As per the individual responses in bTRIMP to TD and VHSR, we observed moderate and unclear variability respectively (Table 3). In practice this means that, due to the individual responses, the average 72.5% increase in bTRIMP AU per 1SD increase in within-player TD (Figure 3) will correspond to 61.8 - 84.0% increase for 90% of the sample [15]. As for VHSR, the average 34.9% increase in bTRIMP AU per 1SD increase in within-player VHSR (Figure 4) will correspond to 31.5 - 38.3% increase for 90% of the sample. The individual responses are considered an interaction of external load by individual player characteristics [5]. These characteristics may include player experience status, position and physical fitness [21]. After considering the individual responses, the between-session variability represents variability in bTRIMP due to every session is different. As expected the between-session variability in bTRIMP was much higher for VHSR than TD [10]. In pre-season many sessions can actually have very low levels of VHSR, thus between-session variation in bTRIMP is not reflected in between-session variation in VHSR. Even after accounting for daily variation of TD from individual "typical" values there is some 18%

variability in the day-to-day mean session bTRIMP, highlighting the mediating role of factors such as training mode and training drills have on internal TL [6]. It should be noted that training sessions in soccer appear rather non-specific; that is they tend to combine on all aspects of performance (technical, tactical, physical, mental), therefore the magnitude of between-session variability seems reasonable. Following principles of training periodization [2] it might be that some sessions might be more similar compared to other, thus future studies could examine whether the effect of predictors such microcycle of training block could reduce the between-session variability.

The above random effects (individual responses and between-session variability) mainly serve to analyze "between-cluster" effects, such as between-player and between-session differences. What is not explained is reflected in the remaining within-player (residual) variability (Table 3). Our estimates of within-player variability range ~16-22% which is lower to what has been previously reported for TD and VHSR [10]. In practical terms our estimates of variability denote how much more (or less) the bTRIMP of a given player might be after we consider his external load daily variation from his individual "typical" levels and also account for mean differences between sessions [15]. Although its magnitude is considered to be constant [10,13,14], this may not be the case; in fact "how off" a player might be from his "expected" response on a session-to-session basis across a pre-season may be dependent on a multitude of factors such as daily nutritional status, recovery state, fitness or fatigue accumulation. Mixed modeling procedures may take into consideration characteristics and/or factors that may influence within-player variability [15].

It should be acknowledged that machine learning techniques have provided quite lower estimates of within-player variability [22,23]. However, machine learning modeling approaches are considered "black boxes" and whilst they may provide better prediction, their interpretability in terms of modification in the daily practice may be questionable [24]. On the contrary the simplicity of our model is straightforward. The practical value of the above model is that it may enable practitioners to assess how similar external TL might affect a given player on sequential training sessions or how individual player variation on daily external TL affects internal TL individual responses on a given session [11,12]. Whilst most practitioners tend to rely on monitoring only external TL [25], the current thought of practice is that combining external and internal TL monitoring and establishing their relationship may provide a "snapshot" of player and team fitness [5,26]. Our model established the relationship between external TL and bTRIMP, thus an "expected" bTRIMP can be derived based on the fixed effects of our model [15]. The random effects adjust the "expected" response due to player and session characteristics and the remaining within-player variability determines the uncertainty in the possible range of the "expected" bTRIMP due to physiological variation and factors not accounted for by our model [12-16]. By projecting the "expected" over the observed bTRIMP we derive a difference between the actual and modeled bTRIMP [12]. Whether this difference has practical implications will effectively be determined by smallest worthwhile change (SWC) [16] and the uncertainty of the observed vs. "expected" difference in bTRIMP [12]. By combining individual player information from both models the practitioner can have a clearer "snapshot" [26] (Figure 5 and 6). In addition, in our approach we used boundaries for moderate differences between the observed and "expected difference [12]. Another option would be to create boundaries for small, moderate and large differences and assign a different "flag" to each magnitude [26]. For example, small differences, which would be more likely to occur, would be flagged as "green light", moderate are "amber light" and large as "red light" [26]. We propose that these classifications would further enhance the feedback derived for coaches, supporting staff and stakeholders [27-29].

## Limitation of the Study

Some limitations must be acknowledged when attempting to draw generalized conclusions from the present study. Currently there is no agreement upon a gold standard measure of training load (be it external or internal) in soccer. It is possible that other practitioners may prefer different variants of TRIMP as indicators of internal TL or different indicators of internal TL altogether. In addition to TD and VHSR a multitude of external TL variables have been considered by sports scientists. Finally, the current sample represents one professional club and different training approaches between clubs and even more between leagues may warrant caution in adoption of the current model and monitoring approach.

## Conclusion

In conclusion the present study developed a simple linear mixed model that estimated bTRIMP as a function of daily variation of external TL from individual "typical" levels as well as partioned uncertainty of the "expected" response into between-player and between-session sources. Accordingly, these estimates were used to derive a practical framework that provided feedback on the training response of individual players on any given session. Implementing both the theoretical and practical proposed frameworks may provide sports medicine/science practitioners additional confidence in the day-to-day decision making process.

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