Workload efficiency of professional football players: How does the ratio between external and internal load depend on the training load on the days before the match?

Johannes GRÜNBICHLER, BSc BSc
Matrikelnummer: 01115271
Innsbruck, April 2019

Masterarbeit
eingereicht an der Leopold-Franzens-Universität
Fakultät für Psychologie und Sportwissenschaft
Masterstudium Sportwissenschaft
zur Erlangung des akademischen Grades

Master of Science (MSc)

betreut von
Univ.-Prof. Dr. Federolf Peter
Priv.-Doz. Dr. Gatterer Hannes
Institut für Sportwissenschaft
Eidesstattliche Erklärung

Ich erkläre hiermit an Eides statt durch meine eigenhändige Unterschrift, dass ich die vorliegende Arbeit selbständig verfasst und keine anderen als die angegebenen Quellen und Hilfsmittel verwendet habe. Alle Stellen, die wörtlich oder inhaltlich den angegebenen Quellen entnommen wurden, sind als solche kenntlich gemacht.

Die vorliegende Arbeit wurde bisher in gleicher oder ähnlicher Form noch nicht als Magister-/Master-/Diplomarbeit/Dissertation eingereicht.

________________________________________  __________________________
Datum                                          Unterschrift
TABLE OF CONTENTS

Abstract.................................................................................................................................................. 4
1. Introduction........................................................................................................................................ 5
2. Methods........................................................................................................................................... 7
   2.1. Participants.................................................................................................................................. 7
   2.2. Experimental design .................................................................................................................. 7
   2.3. Measurements ............................................................................................................................ 8
   2.4. Statistical analyses ..................................................................................................................... 10
3. Results............................................................................................................................................... 12
   3.1. Multiple regression model ......................................................................................................... 12
   3.2. Descriptive statistics .................................................................................................................. 13
4. Discussion ......................................................................................................................................... 14
   4.1. Main results & interpretation .................................................................................................... 14
   4.2. Limitations .................................................................................................................................. 15
   4.3. Conclusion and practical applications ....................................................................................... 16
   4.4. Acknowledgements .................................................................................................................... 16
5. References ........................................................................................................................................ 17
6. Appendix.......................................................................................................................................... 20
ABSTRACT

**Purpose:** To assess the influence of the internal (heart rate data) and the external (time motion data) training loads of the previous days on the physiological efficiency of professional football players in a competitive match.

**Methods:** All data were collected during the competitive season 2017 / 2018. A total number of 44 training sessions and 16 competitive matches were tracked using 10-HZ global positioning system (GPS), 200 Hz accelerometer and heart-rate monitoring. Training loads were registered from day five (G-5) to day one (G-1) prior to each competitive match. Physical efficiency was defined as ratio between overall external physical performance and overall internal physiologic load, expressed by a single workload efficiency variable. All variables were z-transformed and then submitted to a multiple stepwise regression analysis to determine which load variables of the five previous days influence physiologic efficiency in a match.

**Results:** Training load variables of the previous days were able to explain 26.6% of the variance in workload efficiency. High sprinting distances on day four and three and high total distance one day before a game positively influenced the players' workload efficiency, whereas long training durations and high training load one day before a game showed adverse effects.

**Conclusions:** The present outcomes suggest that including sprint training (high sprinting distance) four and three days prior to a match may provide a positive stimulus for the subsequent workload efficiency in matches. The negative impact of long training duration and high training load one day before the game highlights the importance of a diligent planning of the immediate competition preparation phase. This study demonstrates how data from body-worn sensor technology can be evaluated to provide practical information for athletes and coaches on how to pace training load before a competitive match.

**KEYWORDS**
soccer; athlete performance; internal and external load; workload efficiency; wearable technology; GPS motion tracking systems
1. **INTRODUCTION**

With the rise of modern tracking systems, it is nowadays very common for professional football clubs to monitor players' load in training sessions and games (Akenhead & Nassis, 2016). Measures of training load or match load can be categorized as either internal or external. Internal loads are commonly defined as the relative biological (both physiological and psychological) stressors imposed on a player during training or match (Bourdon et al., 2017). In football, measures such as heart rate, blood lactate, and ratings of perceived exertion are commonly used to assess internal load (Akenhead & Nassis, 2016). On the other hand, external loads are objective measures of the work performed by the player and are assessed independently of internal loads (Bourdon et al., 2017). Time motion variables such as the total distance covered, the distance covered in different speed zones or the number of sprints, performed in a training session or in a match, are examples for external load measures in football (Akenhead & Nassis, 2016). Wearable sensor technology that combines motion tracking technology with heart rate monitors provides not only detailed information on the external work performed by players, but also on how they respond from a physiological perspective (i.e., internal load).

Long-term seasonal monitoring of training loads enables athletes and coaching staff to better plan and adapt the training load in order to avoid excessive fatigue and overtraining, to augment the training stimulus, to reduce injury occurrences, and to increase players physical fitness level (Akubat, 2014). This procedure can also be applied in the short-term training process (i.e. weekly preparation for a competitive match). Excessive training loads during the week, for instance may induce fatigue, whereas too low training loads may induce detraining effects both negatively affecting the following match performance. Although this is a well-known concept, there are few objective criteria for optimizing training intensity in the days before a match. Consequently, professional soccer teams still adopt training strategies that predominantly evolved from practical experience. The question arises, how to organize training sessions during the week in an optimal way and how to adequately monitor these sessions to bring the physical performance to an optimal level for the following competitive match.

Defining criteria for the physical performance in matches is difficult. Professional soccer players are characterized by a high physical fitness, as evaluated by laboratory tests, yet these lab-based parameters do not necessarily determine match performance. Additionally, many factors, such as match importance, score line, home or away games, opposition standard, recovery
days, tactics and players’ conscious or subconscious pacing strategies (Paul et al., 2015; Bradley & Noakes 2013) may influence physical match performance and determine match outcome. Nonetheless, in many studies match performance was quantified by solely measuring absolute external loads, such as the distances covered in different speed zones or the number of high-intensity movements (Rampinini et al., 2007; Castagna et al., 2010; di Salvo et al., 2013; Rebelo et al., 2014; Silva et al., 2014; Fessi et al., 2016). Yet, evaluating players' physical performance in games by solely analysing external load variables, and ignoring internal load (e.g., heart rate responses, perceived exertion) would be far too reductionist and there is a need for a combined variable that represents players overall workload in games (Carling, 2013).

A possible way to deal with this issue, is to express physical performance and strain as a relative variable. This relative performance variable puts the external performance or load in proportion to the respective internal load (Carling, 2013), and thus may give a more comprehensive view on the players load and performance level. In this regard, Suarez-Arrones et al. (2015) proposed a basic “efficiency index” for professional football players in competitive games that puts the individual player’s relative total distance (m/min) in proportion to the average percentage of the maximal heart rate (% HR$_{max}$). As the total distance alone cannot represent the real overall external load of a player, also other external load variables (including distances in different speed zones, accelerations, decelerations and other mechanical load variables), in conjunction with the internal load parameters, are needed to predict a player’s current physical performance and strain (Lacome et al., 2018a).

Thus, the aims of the current study were, first, to refine earlier concepts of physiologic efficiency based on measures for overall internal and external training load that are provided by body-worn sensor technology; second, to monitor the individual physiologic efficiency as well as internal and external training and match loads in a professional soccer team; and third, to analyse how physiologic efficiency during a match was influenced by the training loads during the five days before the match.
2. Methods

2.1. Participants

Healthy male (n = 14; age, 22.6 ± 4.3 yrs; height, 181.5 ± 5.7 cm; weight, 75.7 ± 5.8 kg) professional football players of an Austrian Second League team took part in the study. Players from different field positions were investigated: central defenders (n = 2), wide defenders and midfielders (n = 4), central midfielders (n = 4), and attackers (n = 4). The tracking of training and match load is a standard procedure in the analyzed football club, thus this study did not cause any additional effort to the players and coaching staff and did not interfere with training and match routines in any way. The players approved the use of training and match data for the purpose of the present study by written consent. The study was carried out in conformity with the ethical standards of the declaration of Helsinki and has been approved by the Institutional Review Board of the Department of Sport Science of the University of Innsbruck.

2.2. Experimental design

Training and match load data were collected over a 13-week period during the competitive season 2017 / 2018 from March 2018 until June 2018. A total number of 44 training sessions and 16 competitive matches were tracked on both home and away grounds. This resulted in 514 individual training and 180 match observations (including data from substituted players). All training sessions were on-field training sessions where the whole team participated as well as training sessions for the non-playing squad on the day following a competitive match. Individual recovery and strength training sessions in the club’s gym were not included in the data collection. All on-field training sessions consisted of a warm-up and either technical and tactical drills or on-field conditioning drills such as speed training or HIT drills in combination with technical and tactical training.

A typical in-season one-week micro-cycle consisted of four training days before a competitive match, followed by a regeneration training or non-starter training one day after the match and a day off two days after the match. In this part of the season, the observed team often played two competitive matches in one week, which led to various types of micro-cycles with different numbers of training days between matches (Table 1). Consequently, as a typical week was difficult to define, load analyses always included a five-day period before a competitive match – either it was a training session, another competitive game or a day off. For this reason, training
and game loads were classified into five categories based on the number of days before a game day (i.e., Game day minus one day = “G-1”).

<table>
<thead>
<tr>
<th></th>
<th>Game day</th>
<th>G-1</th>
<th>G-2</th>
<th>G-3</th>
<th>G-4</th>
<th>G-5</th>
</tr>
</thead>
<tbody>
<tr>
<td>training sessions</td>
<td>0 (0%)</td>
<td>15 (94%)</td>
<td>9 (56%)</td>
<td>6 (38%)</td>
<td>10 (63%)</td>
<td>7 (44%)</td>
</tr>
<tr>
<td>regeneration</td>
<td>0 (0%)</td>
<td>1 (6%)</td>
<td>7 (44%)</td>
<td>6 (38%)</td>
<td>1 (6%)</td>
<td>9 (56%)</td>
</tr>
<tr>
<td>competitive games</td>
<td>16 (100)</td>
<td>0 (0%)</td>
<td>0 (0%)</td>
<td>4 (24%)</td>
<td>5 (31%)</td>
<td>0 (0%)</td>
</tr>
</tbody>
</table>

Data are expressed as total number and ratio (%) of total sessions on the respective loading day. G-1: game day minus one day, G-2: game day minus two days, G-3: game day minus three days, G-4: game day minus four days, G-5: game day minus five days.

### 2.3. Measurements

#### Data Collection

The players’ external and internal loads in training sessions and competitive matches were measured with the Polar Team Pro System (Polar Electro Oy, Kempele, Finland). Polar Team Pro provides portable 10 Hz global positioning (GPS) and 200 Hz movement sensors as well as heart rate sensors to track players’ distance, speed, acceleration and heart rate data. Heart rate measurement was enabled by wearing specially designed underwear shirts (Polar Electro Oy, Kempele, Finland) with integrated electrodes that directly touch the skin. In addition, these shirts contain neck pockets where the portal GPS and movement sensors were placed to provide a clear satellite signal. To avoid possible inter-unit errors (Buchheit et al., 2014), players wore the same shirt and sensors in every training and match.

As reported by Giersch et al. (2018) validity and reliability of Polar Team Pro concerning measurement of distance and speed in linear (coefficient of variation < 2.69%) and complex (changes in velocity and direction, accelerations, decelerations and stoppings) movements (coefficient of variation < 1.76%) is comparable to other GPS tracking systems (Castellano et al. 2011; Hoppe et al. 2018; Rampinini et al. 2015), currently used by top-level football clubs. Polar Team Pro therefore represents an adequate tracking system for agility-based sports like football.
Data analysis and approach

After each training or match, GPS and heart rate data were downloaded and processed with the respective Polar Team Pro Software (Polar Electro Oy, Kempele, Finland) to a spreadsheet programme (Microsoft Office Excel 2018, Microsoft Corporation, Redmond, USA). For competitive matches, the pre-game warm-up was excluded from the analyses. Incomplete or erroneous recordings were excluded from the analyses.

Variables selected for describing the external training or match load were duration (Dur [min]), total distance (TD [m]), equivalent distance (ED [m]), high speed (> 14.4 km/h) running distance (HSD [m]), very high speed (> 19.8 km/h) running distance (VHSD [m]), sprinting (> 25.2 km/h) distance (SPD [m]) as well as the number of medium (2.00 - 2.99 m/s²) and high (> 3.0 m/s²) accelerations (Acc_m, Acc_h [#]) and the number of medium (-2.00 - -2.99 m/s²) and high (< -3.0 m/s²) decelerations (Dec_m, Dec_h [#]).

ED was calculated from the sessions’ raw data, by applying the equations provided by Osgnach et al. (2010) and Di Prampero et al. (2015), through performing an integrated metabolic power calculation using the time course of accelerations and speed. ED is then calculated by dividing the total energy expenditure of the session through the product of an adjustable terrain factor and energy cost of constant running on flat terrain. ED represents the distance that a player would have covered theoretically at a steady pace on grass using the total energy spent over the match or training (Osgnach et al., 2010; Di Prampero et al. 2015). The more high-intensity actions – such as accelerations and high speed running – a player performs, the more his ED will differ from his actual total distance. ED thus represents an overview variable of the overall external workload a player has performed.

Variables selected for describing the internal training or match load were duration (Dur [min]), Polar Training Load (PTL [arbitrary units]) and a modified training impulse (TM [arbitrary units]) specially designed for football players by Stagno et al. (2007). PTL is a metrically scaled, predefined variable of the Polar Team Pro Software which includes the session’s duration and heart rate data, the individual player’s training history, a sport specific factor as well as the individual player’s aerobic capacity (VO₂max and anaerobic threshold). TM was calculated from the raw data and represents the time spent in certain heart rate zones multiplied by weighting factors (Stagno et al., 2007). TM therefore represents an overview variable of a player’s overall internal workload.
To create a variable that reflects the workload efficiency in a match, the external variable ED was set in relationship to TM (ED/TM = “EDT”). As Lacome et al. (2018b) reported, analyzing and comparing the heart rate responses in proportion to the external load of specific football drills, represents a viable tool to describe changes in a player’s workload efficiency, indicating changes in the player’s fitness level.

The following example should illustrate the potential of a workload efficiency index to indicate on a player’s current fitness level: Player XY achieves an ED of 12,000 m in Game 1. His internal load TM in Game 1 was 280 au. In Game 2, Player XY achieved an ED of 13,500 m with the same amount of TM. One can conclude that in Game 2, Player XY was physically more efficient than in Game 1, as he achieved more ED with the same amount of internal load. Therefore, one can assume that his fitness level was higher in Game 2 than in Game 1.

2.4. Statistical analyses

Multiple regression model
As external and internal load variables are highly athlete-specific and different in magnitude, all variables were expressed in z-scores to make changes comparable. Z-scores of the respective variables were computed using each individual player’s mean and standard deviation calculated over all match and training days. A hierarchical multiple regression analysis was used to assess if and how external and internal load variables of the previous five days significantly predicted the players’ match performance. Preliminary analyses were performed to ensure there was no violation of the assumption of normality, linearity, multicollinearity and homoscedasticity. Missing values were replaced with mean. With the whole team as sample, EDT was therefore set as dependent variable, all other load variables from G-1, G-2, G-3, G-4 and G-5 as independent predictor variables (Table 2).
Table 2. Predictor variables integrated in the multiple regression analysis

<table>
<thead>
<tr>
<th>dependent variable</th>
<th>independent predictor variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>EDT</td>
<td>G-1, G-1, G-1, G-1, G-1</td>
</tr>
<tr>
<td>Dur_</td>
<td>G-2, G-2, G-2, G-2, G-2</td>
</tr>
<tr>
<td>TD_</td>
<td>G-3, G-3, G-3, G-3, G-3</td>
</tr>
<tr>
<td>SPD_</td>
<td>G-4, G-4, G-4, G-4, G-4</td>
</tr>
<tr>
<td>HSD_</td>
<td>G-5, G-5, G-5, G-5, G-5</td>
</tr>
<tr>
<td>VHSD_</td>
<td>Acc_m, Acc_h, Acc_m, Acc_h,</td>
</tr>
<tr>
<td>Acc_m</td>
<td>Dec_m, Dec_h, Dec_m, Dec_h,</td>
</tr>
<tr>
<td>Acc_h</td>
<td>ED, PTL, TM, ED, PTL, TM,</td>
</tr>
<tr>
<td>Dec_m</td>
<td></td>
</tr>
<tr>
<td>Dec_h</td>
<td></td>
</tr>
</tbody>
</table>
| G-1: game day minus one day, G-2: game day minus two days, G-3: game day minus three days, G-4: game day minus four days, G-5: game day minus five days, Dur: duration, TD: total distance, SPD: sprinting distance, HSD: high speed distance, VHSD: very high speed distance, Acc_m: number of medium accelerations, Acc_h: number of high accelerations, Dec_m: number of medium decelerations, Dec_h: number of high deceleration, ED: equivalent distance, PTL: Polar Training Load, TM: modified training impulse.

Descriptive statistics

For descriptive statistics, mean, standard deviation (SD) and/or 95% confidence interval (CI) of all internal and external load variables were computed for each loading day. Statistical procedures were completed on SPSS V.24.0 (SPSS, Chicago, Illinois, USA) for Windows. Statistical significance was established at $p \leq 0.05$. 
3. RESULTS

3.1. Multiple regression model

In the first step of the hierarchical multiple regression (summary in Table 3), only SPD_G-3 was entered and explained 12.3% of the variance in EDT. Variables SPD_G-4, HSD_G-3, PTL_G-1 and TD_G-1 were then entered stepwise to explain 23.8% of the variance in EDT after Step 5. In the final model, HSD_G-3 was removed and Dur_G-1 was entered.

<table>
<thead>
<tr>
<th>Model</th>
<th>R</th>
<th>R²</th>
<th>adjusted R²</th>
<th>standard error of estimate</th>
<th>Durbin-Watson-Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>.357&lt;sup&gt;a&lt;/sup&gt;</td>
<td>.128</td>
<td>.123</td>
<td>.901</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>.422&lt;sup&gt;b&lt;/sup&gt;</td>
<td>.178</td>
<td>.169</td>
<td>.878</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>.455&lt;sup&gt;c&lt;/sup&gt;</td>
<td>.207</td>
<td>.194</td>
<td>.864</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>.474&lt;sup&gt;d&lt;/sup&gt;</td>
<td>.225</td>
<td>.207</td>
<td>.857</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>.513&lt;sup&gt;e&lt;/sup&gt;</td>
<td>.263</td>
<td>.242</td>
<td>.838</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>.505&lt;sup&gt;f&lt;/sup&gt;</td>
<td>.255</td>
<td>.238</td>
<td>.840</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>.535&lt;sup&gt;g&lt;/sup&gt;</td>
<td>.286</td>
<td>.266</td>
<td>.825</td>
<td>2.089</td>
</tr>
</tbody>
</table>

a. predictor variables: (constant), SPD_G-3
b. predictor variables: (constant), SPD_G-3, SPD_G-4
c. predictor variables: (constant), SPD_G-3, SPD_G-4, HSD_G-3
d. predictor variables: (constant), SPD_G-3, SPD_G-4, HSD_G-3, PTL_G-1
e. predictor variables: (constant), SPD_G-3, SPD_G-4, HSD_G-3, PTL_G-1, TD_G-1
f. predictor variables: (constant), SPD_G-3, SPD_G-4, PTL_G-1, TD_G-1
g. predictor variables: (constant), SPD_G-3, SPD_G-4, PTL_G-1, TD_G-1, Dur_G-1

R: multiple correlation coefficient, R²: coefficient of determination

The result of the final model indicated that five predictor variables explained 26.6% of the variance (corrected R² of .266, F (5, 174) = 13.9512, p < .000).

It was found that SPD_G-3 (β = .477, p < .001), TD_G-1 (β = .380, p < .001), SPD_G4 (β = .312, p < .001), PTL_G-1 (β = -.259, p = .001) and Dur_G-1 (β = -.216, p = .007) significantly predicted EDT.

Players’ predicted match physiologic efficiency EDT expressed in z-scores was equal to:

\[.001 \text{ (constant)} + .477 \text{ (SPD_G-3)} + .380 \text{ (TD_G-1)} + .312 \text{ (SPD_G-4)} -.259 \text{ (PTL_G-1)} -.216 \text{ (Dur_G-1)}\]
3.2. Descriptive statistics

Descriptive statistics of the non-normalized data in Table 4 revealed that mean internal and external load increased from G-5 over G-4 with a peak on G-3. Internal and external load are subsequently lower on G-2 and decrease to lowest scores on G-1.

Table 4. Descriptive statistic of internal and external load variables separated by game and loading day

| variable | Game | G-1 | | | G-2 | | | G-3 | | | G-4 | | | G-5 | |
|----------|------|-----|---|---|-----|---|---|-----|---|---|-----|---|---|-----|
|          | Mean (SD) | 95% CI | Mean (SD) | 95% CI | Mean (SD) | 95% CI | Mean (SD) | 95% CI | Mean (SD) | 95% CI | Mean (SD) | 95% CI | Mean (SD) | 95% CI |
| EDT (au) | 47.3 (7.3) | 46.3 | 48.4 | 31.1 | 96.9 | 92.2 | 28.5 | 79.5 | 87.2 | 54.5 | 91.1 | 86.6 | 91.6 | 88.2 | 80.2 | 77.5 |
| Dur [min] | 3985.3 (2933.1) | 8552.9 | 4193.8 | 4089.4 | 4889.0 | 4705.3 | 7555.5 | 6756.7 | 5974.1 | 5528.0 | 4195.9 | 4044.3 | | | |
| HSD [m] | 11098.7 (3618.6) | 10537.5 | 5036.4 | 4904.4 | 5888.9 | 5645.0 | 8707.3 | 8109.7 | 7268.3 | 6713.1 | 4984.6 | 4794.0 | | | |
| SPD [m] | 581.9 (299.8) | 537.9 | 81.6 | 69.7 | 177.2 | 146.4 | 387.7 | 332.5 | 274.8 | 227.9 | 108.2 | 84.7 | | | |
| Acc_m [m] | 11.7 (9.2) | 10.4 | 6.2 | 5.7 | 7.7 | 6.4 | 10.2 | 8.8 | 9.0 | 7.8 | 5.3 | 4.5 | | | |
| Acc_h [m] | 20.9 (15.5) | 10.4 | 5.2 | 4.7 | 7.8 | 6.5 | 15.2 | 13.4 | 11.4 | 9.8 | 4.6 | 3.9 | | | |
| PTL [au] | 262.2 (90.4) | 247.9 | 84.3 | 79.1 | 101.6 | 93.8 | 187.6 | 171.1 | 157.0 | 142.1 | 82.4 | 75.4 | | | |
| TM [au] | 240.2 (86.8) | 227.5 | 54.9 | 50.5 | 69.4 | 62.3 | 159.1 | 142.5 | 124.5 | 109.7 | 54.6 | 48.1 | | | |

G-1: game day minus one day, G-2: game day minus two days, G-3: game day minus three days, G-4: game day minus four days, G-5: game day minus five days, Dur: duration, TD: total distance, SPD: sprinting distance, HSD: high speed distance, VHSD: very high speed distance, Acc_m: number of medium accelerations, Acc_h: number of high accelerations, Dec_m: number of medium decelerations, Dec_h: number of high deceleration, ED: equivalent distance, PTL: Polar Training Load, TM: modified training impulse, au: arbitrary units.
4. **DISCUSSION**

4.1. **Main results & interpretation**

The present study investigated the training practice of a professional soccer team and related the weekly training load to workload efficiency in matches. In regard to the training load, data show that the team adopts a weekly periodization with the highest sprinting distance four and three days before a game and the lowest overall loads on G-5 and one day before game (Table 4). Such load distribution and periodization strategies are in accordance with reports from the literature (Anderson et al., 2016; Stevens et al., 2017). The new findings of this study is, that training loads recorded during the days before a match are able to predict workload efficiency in matches, yet only to a limited extend (26.6% of the variance can be explained).

In detail, if either SPD_G-3, TD_G-1, SPD_G-4, PTL_G-1 or Dur_G-1 each rise by 1 * standard deviation (SD) (assuming all other variables in the model are held constant), EDT rises by 0.477 * SD, by 0.380 * SD and by 0.312 * SD above mean, or is reduced by 0.259 * SD and by 0.216 * SD below mean, respectively. The performed sprinting distance four and three days before a game and the total distance one day before a game seem beneficial to players’ workload efficiency in the upcoming game. High training loads and long training sessions one day before a game on the other hand will negatively influence players’ workload efficiency.

From a training science perspective, the finding of a negative effect of high PTL and long training duration performed one day before the match is not surprising. The high training load and training duration may induce fatigue (Thorpe et al., 2017), which negatively impacts performance (Rowell et al., 2018). On the other hand, covering long overall running distance one day before the game, seemingly performed at a low intensity apparently has positive effect on EDT. Low intensity running in this sense could be seen as a recovery strategy (Rey et al., 2018) and thus might have a performance beneficial effect the next day when the game is played. Next of covering longer regenerative runs one day before the game, data indicate that a certain weekly high-intensity load, preferentially sprint training performed 3 to 4 days before the game, is necessary to keep the players fit and induce workload efficiency improvements on the match day. In this context, it must also be considered that the number of games on loading days G-4 and G-3 was 31% and 24%, respectively. As high intensity bouts, like sprints, in football are typically characterized by relatively short recovery times (Bradley et al., 2010), it could be
assumed, that the sprinting distance on those days was mainly covered in a type of sprint interval loads. In this perspective, Sloth et al. (2013) report, that there is strong evidence for an improved aerobic performance and VO\textsubscript{2max} that go hand in hand with an increased oxidative potential of the muscle following sprint interval training. According to Buchheit (2014), an increase in high-speed distance (above 14.4 km/h) was positively correlated to an increase in heart rate variability and therefore indicating an improvement in aerobic fitness in football players.

As this study applies a novel approach for physical match performance by creating a new workload efficiency variable, our results are not directly comparable to other current studies on this topic. However, there is a similar trend with the findings of Rampinini et al. (2007), who found significant correlations between the performance of repeated-sprint-tests with the total distance and high speed distance performed in competitive matches. In line with this, Silva et al. (2014) state, that players with greater results in sprinting tests (time after 5 m and 30 m) show lower performance decrements the last minutes of a game and reach higher sprinting performances.

### 4.2. Limitations

In this study, physical game performance was expressed with heart rate data (TM) relative to an overall external performance (ED) to conclude on the individual player’s workload efficiency. This relative variable makes it possible to cancel out numerous confounding factors like tactical influences. However, in this context, it must be considered that - besides by a player’s fitness level - heart rate could also be influenced by internal factors such as psychological stress, hydration levels and caffeine intake as well as external factors like air temperature and humidity (Carling, 2013; Paul et al., 2015). Regarding the external load measurements with GPS devices, it must be acknowledged that the validity of accelerations and distance into speed zones is acceleration and speed dependent; that is, their validity decreases as the acceleration and speed increases (Buchheit & Simpson, 2017).

Furthermore, this study provided a team average based model to assess the influence of training load variables on players’ workload efficiency. Due to non-training related factors like playing position, player’s age, experience, and overall fitness level, the way and magnitude of how
external load variables influence the individual’s physical efficiency can be player-specific (Lacombe et al., 2018a). In actual coaching, one should therefore aim at designing individual models to provide more detailed information for the coaching staff. In the current thesis, this is not included to protect the players’ sensitive data. Lastly, it has to be stated that this study is of an observational nature and the results as well as training recommendations can only be applied for the analysed team. Thus, the author cannot state whether manipulating training load as suggested from this study, really will improve workload efficiency in matches.

4.3. Conclusion and practical applications

This study demonstrates how data from body-worn sensor technology can be evaluated to provide practical information for athletes and coaches on how to pace training load before a competitive match. Present findings suggest, that for an optimal pre-game preparation, coaches should plan sprint training session during the week (3-4 days before the game) if no game is performed on those days. Non-starters and players from the reserve squad should be exposed to additional training to reach an appropriate sprinting load. Additionally, excessive training loads and long sessions one day before the game should be avoided. Low intensity running the day before the game, however, can be included.

4.4. Acknowledgements

The author thanks the technical staff and the football players of the professional team who participated in this study. No sources of funding were used to assist in the preparation of this manuscript.
5. REFERENCES


Certificate of good standing, 18/2019

This document certifies that the

Board for Ethical Questions in Science of the University of Innsbruck

has reviewed the project

"Physiological efficiency of professional football players: How does the ratio between external and internal load depend on the training load on the days before the match?"

of

Univ.-Prof. Dr. Peter Federolf
Priv.-Doz. Dr. Hannes Gatterer
Johannes Grünbichler

It is hereby certified that this project is in correspondence with the requirements of the ethical principles and the guidelines of good scientific practice of the University of Innsbruck.

Univ.-Prof. Dr. Ulrike Tanzer
Vicerector for Research
Universität Innsbruck

Universität Innsbruck, Christoph-Probst-Platz, Innrain 52, 6020 Innsbruck, Austria