MONITORING TRAINING STATUS WITH PLAYER-TRACKING TECHNOLOGY

STILL ON THE ROAD TO ROME

– *Written by Mathieu Lacome, Ben M. Simpson and Martin Buchheit, France*

PART 1: TRADITIONAL PRACTICES AND NEW CONCEPTS

The assessment of the various training aspects that may help to gain an insight into athletes' dose-response relationships to training has been the holy grail of coaches and sport scientists for decades[1]. The reasons for such interest lie in the need for individualised training to both improve performance and decrease injury risk. Given the high cost of injuries (~US$12.5 million annually per team in the top four football leagues[2]) and their strong association with team performance[3], the interest in both practical and analytical methods that may reduce injuries is warranted.

The last 15 years have seen an incredibly rapid development of (micro)technology in the field[4]. Player tracking has become one of the most important components of load monitoring in team sports[5]. Most professional teams use GPS or alternative tracking systems on a regular basis (e.g. Prozone®, TRACAB®, Inmotio®). Training load reports are now generated within moments following each training session and have become a key element in programming both team and indiviudal training sessions.

This manuscript is the first of a two-part article about training load monitoring in team sports. In this first part, we describe the current and ever-evolving challenges that practitioners face when monitoring their athletes' training load and health status. We then offer some thoughts on building a framework that may improve current models in an applied setting. The second part provides some guidance on how to improve data visualisation and increase coaching staff 'buy-in', which may, in turn, improve their ability to make informed decisions.

CURRENT PRACTICES AND ASSOCIATED CHALLENGES

Since the early 2000s there has been an exponential rise in research about training load monitoring[6-10], allowing sport scientists to base their analyses on strong foundations. While it is not the aim of this paper to build

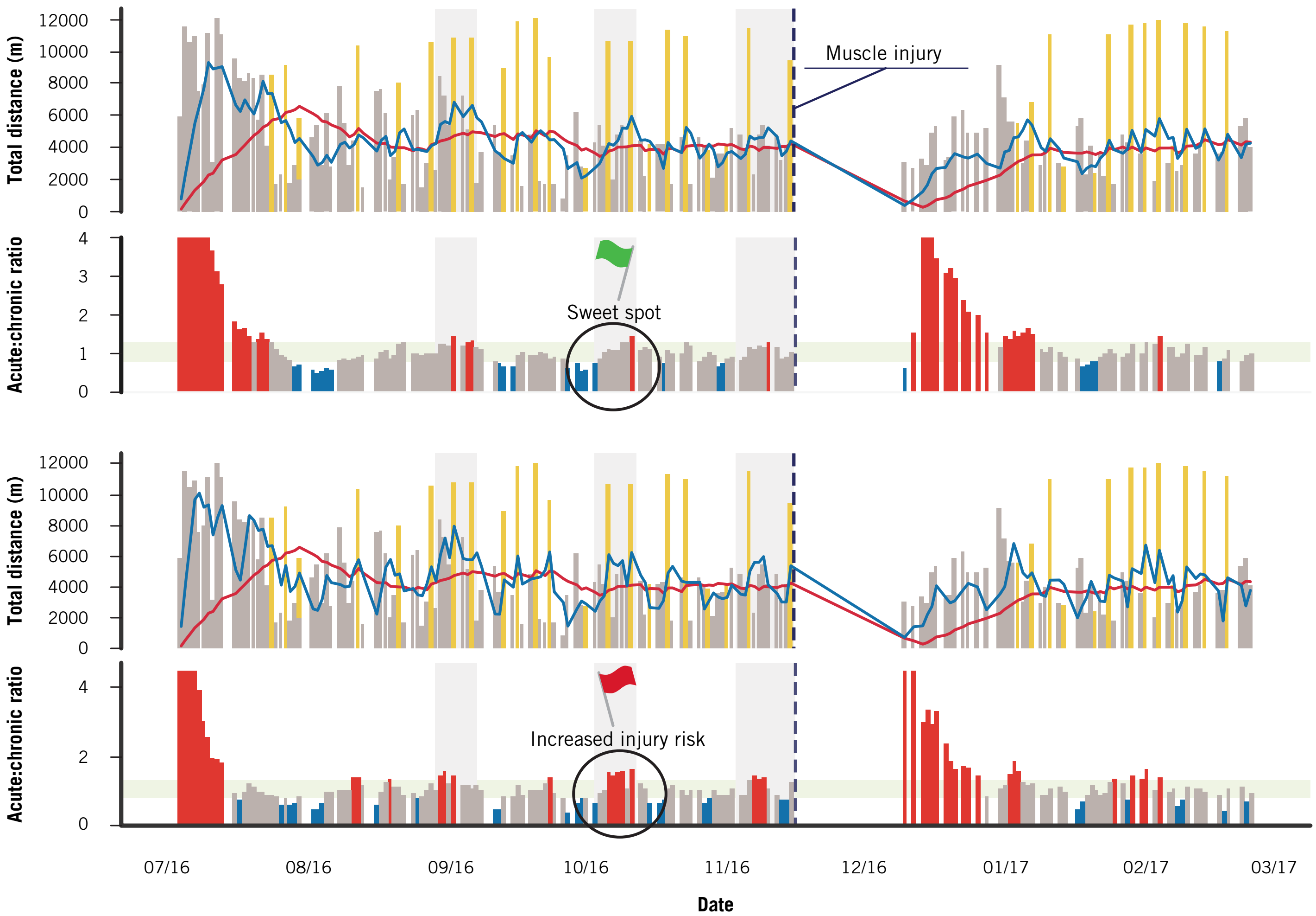


Figure 1: Change in total distance (m) for an elite football player over 7 months. Acute (blue line) and chronic (red line) loads are calculated using 7- and 28-day periods (upper panel) and 4- and 18-day periods (lower panel). Light grey zones represent international breaks when workloads are estimated based on data obtained from national team sports science support. Total distance graphs: grey bars=training sessions; yellow bars=matches. Acute:Chronic ratio graphs: bars are coloured blue and red, with blue representing unloading (acute<chronic load) and red representing loading periods (acute>chronic load), the green zone represents the theoretical sweet spot (0.8 to 1.5). Created in Tableau (v10.4).

a history of methods, refining current best practices is important to foresee the most relevant future directions.

GPS tracking with basic metrics

Results from a recent survey on the current practices of high-level football clubs to monitor training load showed that of 41 clubs surveyed, 40 collected heart rate and GPS data for every player during every field training session[11]. Among the top 10 variables used to quantify training load during practice, distance covered in different speed zones, accelerations, heart rate-related variables and accelerometer metrics (e.g. PlayerLoad™[12]) were the most frequently used. Referring to the Gray classification[5] (Level 1: typical distances covered in different velocity zones; Level 2: all events related to changes in velocity – accelerations, decelerations, and changes of directions; Level 3: all events derived from the inertial sensors/accelerometers), level 1 and 2 type of data are the most used in elite football. Since player activity patterns are more heavily influenced by contextual variables (e.g. rules, coaches' interventions, scoreline, drills used) than players' current fitness status[13], locomotor-related variables (level 1 and 2) may not be the most appropriate to directly monitor players' training status[5]. Additionally, given the diversity of soccer playing positions and/or player profiles that induce large between-player differences in locomotor activity, comparing locomotor performance between players is not very useful either. It therefore makes more sense to assess changes within individual players. One potential option, although limited, is the use of very standardised drills (such as D-1 game simulations, i.e. 9 vs 9+GKs[5] [D-1=1 day pre-game, D+1=1 day post-game, etc.]) to assess changes in individual players' movement strategies (relative to themselves) and gain insight into their training status. However, drill standardisation is not always feasible within the competitive context (e.g. some key players not available to train, congested fixtures minimising access to the drill of interest), which limits this first approach. To compensate for the limitations of level 1 or 2 variables in the absence of standardised drills, sport scientists generally examine a player's activity using two types of normalisation:

1. Comparing one player's data over multiples days, using historical data (i.e. intra-player trend).
2. Comparing a player's data to the rest of the team, with their locomotor activity systematically examined relative to the team or a group of players.

Data analysis

Intra-player analyses

- Daily readiness: with this approach, practitioners monitor changes/trends in individual players' activity in relation to their own historical data, to track signs of acute fatigue. Comparing activity on a given day with the range of intensity/volume of activity that has been recorded for similar training days (e.g. mean drills response ± standard deviations for this particular player for a D+3 and D-2 session) allows for direct estimations of players' readiness to perform. However, since differences in the session content (e.g. coach added an extra finishing drill to the usual D-1 session) or context (i.e. playing a Champions League game vs playing the bottom team in the league the next day) may have a larger effect on players' locomotor activity than changes in their fitness status per se, definitive conclusions remain difficult to draw.
- Acute:chronic ratio: recently, the acute:chronic workload ratio (A/C) has been subject to growing interest as a way to monitor injury risk[14,15]. This model is not aimed at comparing specific session locomotor responses to each other, but rather at tracking the respective changes in the so-called acute (5 to 7 days) and chronic loads (21 to 28 days), using internal and/or external measures of load. Although promising, several limitations prevent elite football clubs from fully utilising this model[16]:

1. First, club sport scientists need to:
   - Collect enough data (at least 1 full year of training load and injury data) to build an in-house model for the club.
   - Find the best A/C ratio split (e.g. 7:28 vs 6:21 days) to fit their sport/club/culture context[17].
   - Calculate the optimal ratios for each variable (i.e. sRPE, high-speed running, mechanical work), since there are likely variable-specific sweet spots for decreased injury risk.
2. Second and perhaps most importantly, there must be a way to deal with the frequent periods of international duties of players at elite clubs. For the top clubs in Europe, during international breaks, 60 to 75% of the players are called up to their national teams (either senior or age-group). With little or no data provided to clubs by national teams, club staff would need 21 to 28 days after players return to compute A/C ratios, by which time there may already be another international break (Figure 1). With an international break every month from September to mid-November, the use of A/C ratios is compromised during the first part of the season. While data can be estimated[16], this requires a lot of work and whether it truly reflects players activity remains unclear. Figure 1 shows the data of an international player. During the first part of the season, the three international breaks require practitioners to estimate a significant amount of data (light grey areas), decreasing the confidence in the ratios calculated during this 3-month period. Also, the data can be interpreted differently depending on the windows used (7:28 vs 4:18, sweet spot vs increased injury risk) as seen in the data reported in this figure.
3. Finally, another limitation the authors have noted following 2 years using this method is the increasingly high number of false positives observed each day, especially using exponentially-

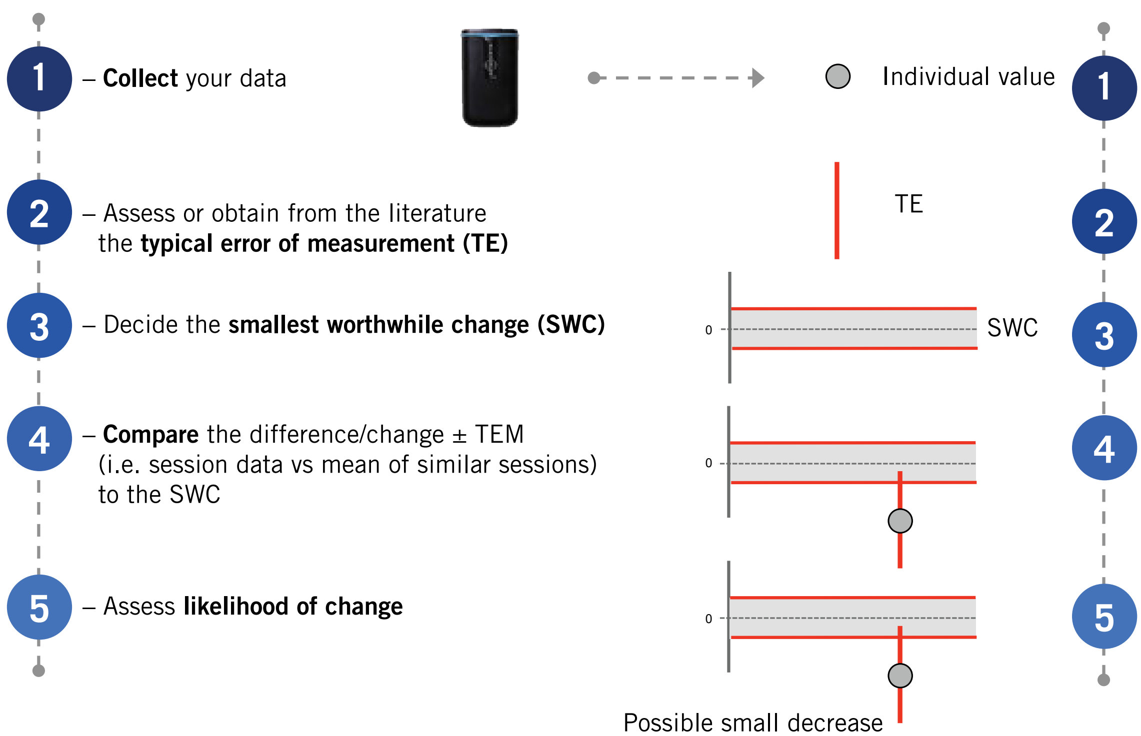


Figure 2: Statistical process to assess changes in monitoring variables in individual players.

weighted moving averages[15] (i.e. the ratio is very high but players remain injury-free). This directly discredits sports scientists trying to warn coaches and medical staff of the potential risk of injury to these players. Conversely, the fact that injuries may still occur 1 to 3 weeks[18] following a spike in load helps to offset this apparent error and to justify it as a reliable method for predicting injury. In fact, because of the recurrent spikes in load, once a player is injured it is often possible to find a spike retrospectively! (Figure 1).

These limitations require sport scientists to rely on other methods to analyse data and this is where normalisation of individual players' locomotor activity relative to the team or a group of players may offer new perspectives.

Between-player normalisation

Player activity normalisation relative to the mean/median of the team or a group of specific players (same profile, same position) is another way to look at the data (see equation below). The main draw of this approach is that it is less likely to be affected by possible changes in session content for a given day (e.g. D+3, D-2 load), since all players complete the same session. Additionally, it can also be used immediately upon return from international break, since the metric does not rely on load data. Once historical data are available (e.g. previous season), insights into players' fitness and/or early signs of fatigue can be gained while following the trends of these normalised data over several consecutive training days. Sport scientists can, in fact, use any variables (total distance, high-speed distance, accelerations, mechanical work-related variables/minute) to construct similar models. One possibility is the creation of a standardised value for each player, based on the mean or median value of a drill on a given day and known standard deviation of this drill (see equation). For example, following the examination of the variability of most of our drills at PSG (unpublished data), we have chosen to use only game simulations including goalkeepers, possession-based games, and some tactical and technical drills. Warm-ups were removed due to excessive between-player variability and overall low activity volumes. For our model, as the number of players is highly variable and generally less than 20 for the majority of the drills, data is normalised against the median value rather than the mean because it better represents the central tendency in a small population[19].

$$\textit{Individual player readiness} = \frac{\textit{drill locomotor value (TD)} - \textit{drill group median (TDmed)}}{\textit{standard deviation of the drill}}$$

However, there are still some limitations with this methodology, especially when:

1. Training with a small group of players (top-up sessions, positional-specific sessions), since the variability of the metrics likely increases with the decreased number of players.
2. A player is returning to play after an injury; as the player trains alone, no comparison can be made (Figure 5, panel Mech W Readiness).

Importance of using the right statistics

The main aim of this paper is not to describe in detail all statistical methods available but to highlight the current best practices to assess changes in monitoring variables in individual players. For more information about the use of statistics in sports sciences, the reader is referred to the recent papers by Buchheit et al[20,21]. Figure 2 presents a practical framework for using statistics in applied sport science. In short, data analysis should start by

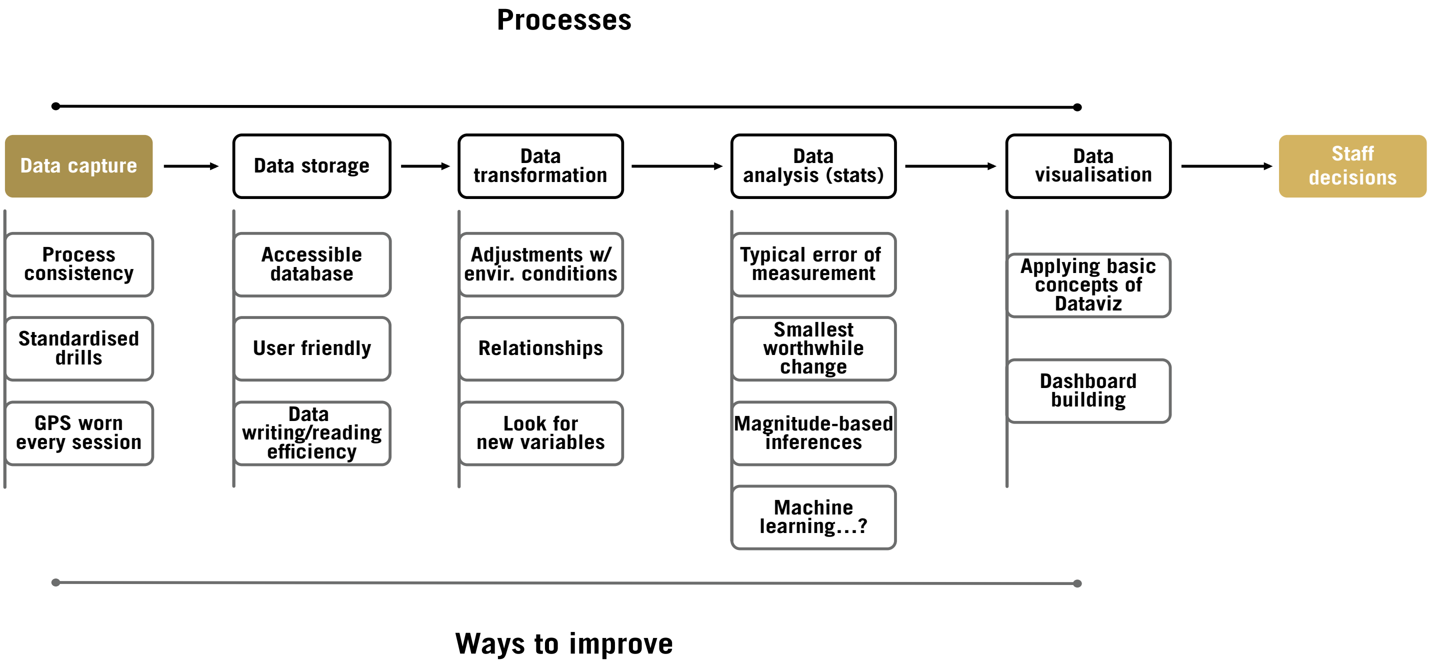


Figure 3: Framework for continual optimisation of training load monitoring models.

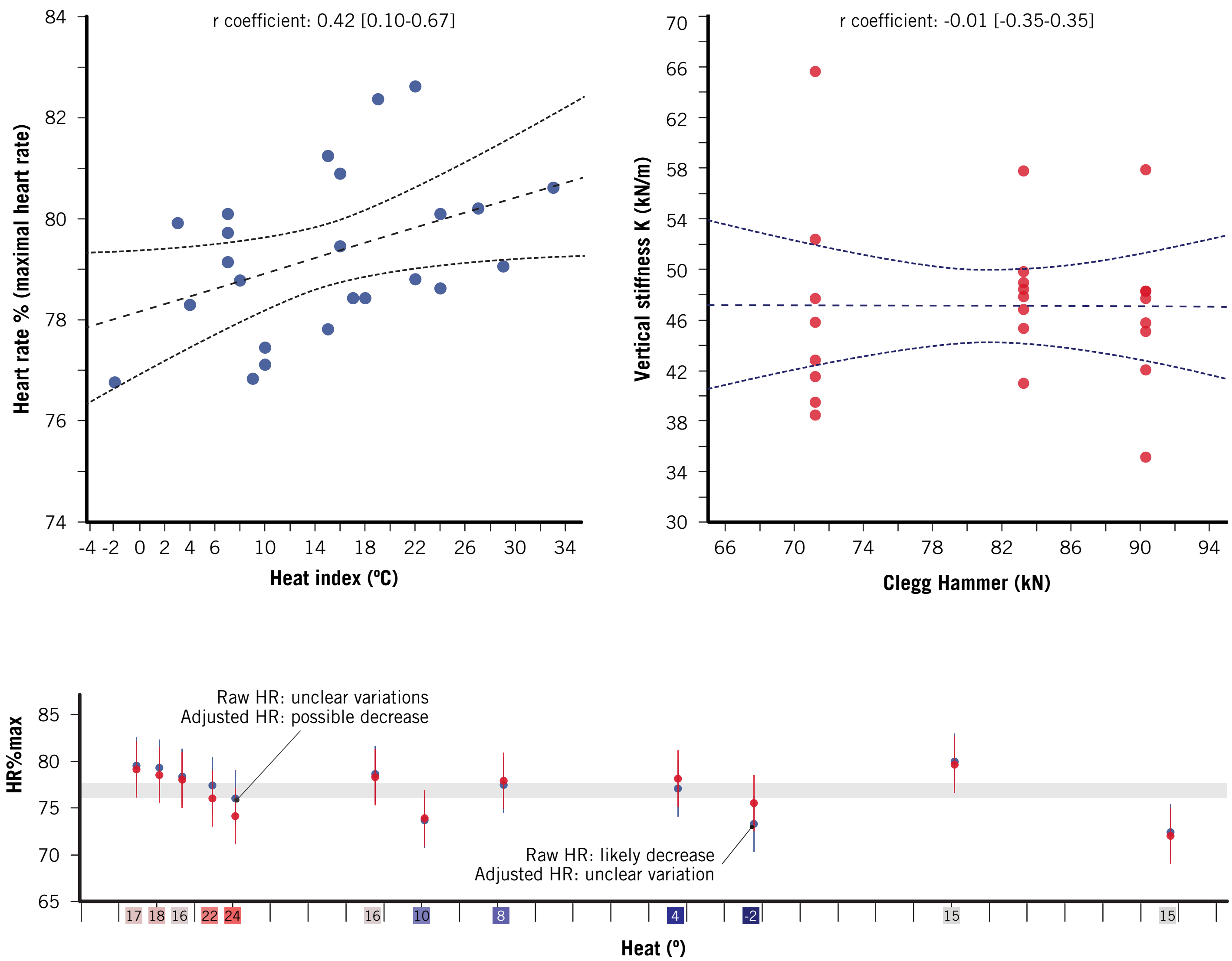


Figure 4: Upper panel: relationships between heart rate (HR) response during a 4-minute submaximal monitoring run and heat index (index that combines air temperature and relative humidity in an attempt to determine the human-perceived equivalent temperature in °C) (left) and relationships between leg stiffness (K) and pitch hardness measured with a Clegg Hammer (kN) (right). Regression coefficients (r) are presented as mean [±90% confidence limits]. Lower panel: intra-player changes in HR response (unadjusted (blue) and adjusted based on heat index (red)) to the 4-minute submaximal monitoring run (grey area represents the season mean ±1%). During the 5th run, the unadjusted HR value suggests unclear variation in fitness while the adjusted HR based on the heat index (+24°C) suggests a possible improvement (decreased HR). During the 10th run, the temperature was -2°C; unadjusted data suggest likely increased fitness while the variation may in fact be unclear when considering adjusted HR. Created with Tableau 10.2.

assessing the typical error of measurement (TE) of each metric (or obtaining it from the literature) and defining the smallest worthwhile change (SWC, i.e. what is the smallest meaningful change). Once these two important variables are defined, magnitude-based inferences can be used to compare the change/difference in the variable of interest (±TE) with the SWC and, in turn, provide the staff with meaningful results expressed either in plain wording (e.g. possible small decrease) or simply used to highlight the right numbers.

OPTIMISING THE MODEL

Every practitioner working in elite sport continually looks for improvements in the way they collect, analyse and report data to the coaching staff (Figure 3). To move forward, sport scientists could use a simple, yet effective framework for continual improvement looking at:

1. Adjustment of previously used variables based on contextual variables to decrease noise.
2. Relationships between existing variables.
3. Integration of new and useful variables to try to gain insight into players' fitness, readiness to perform and/or fatigue (Figure 3).

Adjusting the metrics based on environmental conditions

For outdoor sports, weather and environmental conditions may add noise to measurements and act as additional confounding factors, which should be accounted for when interpreting the data. The following examples show how better insights can be gained using simple statistics.

Monitoring submaximal heart rate (HR) is common today in elite team sports clubs[16,22]. Many clubs use 4- to 5-minute steady state (~12 to 14 km/h) running-based monitoring on a weekly/monthly basis[11] as an index of cardiovascular fitness. Since HR is closely related to oxygen uptake during continuous exercise, HR during exercise (when expressed as a percentage of maximal HR) provides a good marker of a player's relative exercise intensity; the lower the HR, the fitter the player[23,24]. However, to accordingly assess players training status, practitioners must know both the error of the measurement (3%[25]) and the magnitude of the changes in HR that matters (Figure 2). Using simple linear relationships between training-induced changes in HR and high-intensity running performance, we previously suggested[25] that changes in submaximal heart rate as small as 1% were likely associated with a small but substantial improvement in high-intensity running performance (i.e. SWC (1% for incremental test or 0.2× between-athletes SD for the 30-15 Intermittent Fitness Test[5]).

However, because of the likely effect of heat on HR responses, adjustments must be made to ensure that the confounding influence of heat on HR is ruled out. One option is to perform the monitoring inside, where the environment can be controlled[26]. However, in the likelihood of limited available indoor space for running-based monitoring, testing players on exercise bikes is an alternative[27], albeit far less engaging for running-based team sport players. On the field, football teams are more inclined to use running-based monitoring, meaning the temperature effect on HR for the given conditions must be known.

Preliminary data collected at PSG have shown that a 10°C increase in temperature leads roughly to a 1% increase in HR% during a 4-minute monitoring run (Figure 4). There can be large temperature variations between summer training camps in hot conditions (temperature >35°C) and the cold winter in France (temperature <0°C). Such variation can lead to changes of up to +/-2% in HR%, which are higher than the SWC and thus meaningful. To avoid misinterpretation (i.e. players are assessed as unfit while the shift in HR% is due to hot temperature), it is necessary to adjust the HR values recorded based on outside temperature (Figure 4, lower panel).

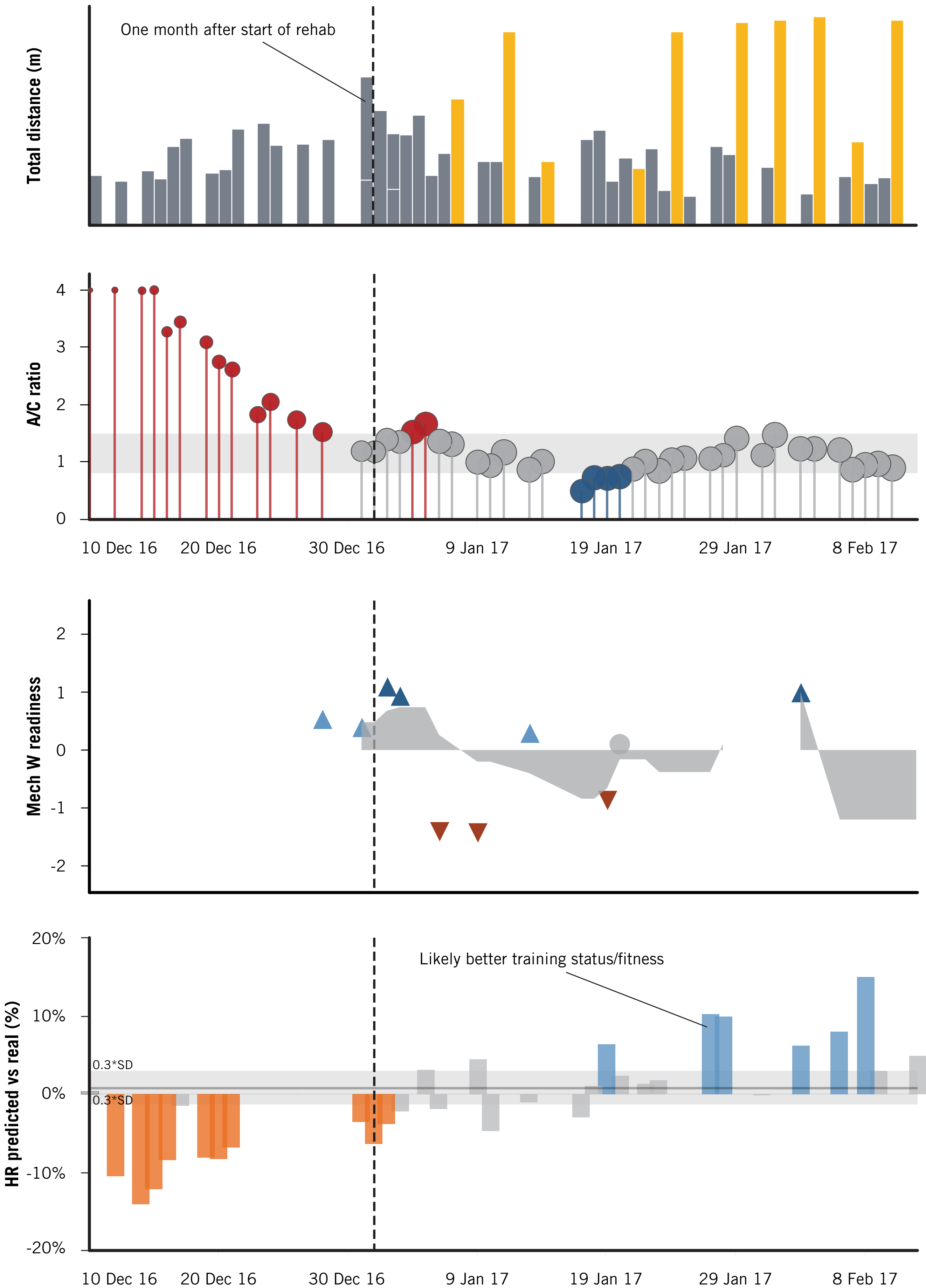
Other changes in environmental conditions could have an impact on recorded metrics. Understanding the influence (or lack of) of the various contextual variables that can affect training load metrics is of great importance. With the recent utilisation of advanced metrics (described later in this paper, level 3 metrics), sport scientists can record contact time, flight time and/or leg stiffness (K)[28,29] during running, which suggests that understanding the player-pitch interaction is of interest. Yet little is known on how pitch surface (hardness, shear strength) can influence these metrics. While preliminary internal studies have shown that slight variation in pitch stiffness as measured with the Clegg hammer (~70 to 85 kN) has no clear influence on metrics related to neuromuscular efficiency during running (K) (Figure 4), future research should examine potential factors that could influence accelerometer data. It is our responsibility as sport scientists to identify every contextual variable that could increase the noise of the model and, in turn, decrease the ability of staff to detect meaningful changes in players' fitness or fatigue and/or to lead inaccurate interpretations.

Building relationships between existing variables

In football clubs around the world, compound metrics created by combining two or more variables are used, requiring appropriate internal validation. For example, the ratio between velocity load (or metres/min) and force load (or PlayerLoad™) can provide a representation of the amount of 'force' or 'ground impulses' required per unit of displacement. This metric can be used to assess neuromuscular/running efficiency (the greater the ratio, the better the efficiency) during standardised drills such as box-to-box runs or small-sided games[29,30] (see next section). While this metric still requires proper validation, the concept in itself and the preliminary results are promising.

To assess locomotor/work efficiency and, in turn, infer potential fatigue and readiness to perform outside the laboratory, sport scientists may use internal-to-external load ratios. In other words, simple internal-to-

Since player activity patterns are more heavily influenced by contextual variables than players' current fitness status, locomotor-related variables may not be the most appropriate to directly monitor players' training status


One month after start of rehab
Total distance (m)
A/C ratio
4
3
2
1
0
10 Dec 16
20 Dec 16
30 Dec 16
9 Jan 17
19 Jan 17
29 Jan 17
8 Feb 17
Mech W readiness
2
1
0
-1
-2
Likely better training status/fitness
HR predicted vs real (%)
20%
10%
0%
-10%
-20%
0.3*SD
0.3*SD
10 Dec 16
20 Dec 16
30 Dec 16
9 Jan 17
19 Jan 17
29 Jan 17
8 Feb 17

external load ratios can provide insights into players' training status and may be helpful when deciding whether to alter their training load. Using existing metrics to build relationships between internal and external training load variables is a simple way to assess internal load relative to external load as a cost/output relationship[31]. For example, an increase in internal load relative to a standardised external load (e.g. monitoring run) may infer player fatigue or decreased fitness, while a reduced internal load (e.g. a lower heart rate or perception of effort) during a standardised external load likely indicates that a player is gaining fitness and coping well with training[32]. Buchheit et al[33] used a ratio between RPE and relative total distance (RPE:m/min) to assess the overall acclimatisation and fatigue trends during a training camp in a hot environment preceded by long-haul flight. In addition, Akubat et al[34] observed that the ratio between total distance (TD) and iTRIMP (individualised training impulse, a compound measure based on HR[35]) – TD:iTRIMP – during a standardised football-specific exercise was related to measures of fitness (velocity at onset of blood lactate accumulation – vOBLA, velocity at lactate threshold – vLT), suggesting that such a ratio could be used as a measure of readiness to perform or running efficiency during official games[36].

As recently shown in Australian rules football, measures of internal load (RPE) are related to various external load metrics, while being highly individual[37]. As such, individual relationships between internal- and external-load-related metrics could be assessed during a pre-determined period to later be used as a prediction model. Then, external load metrics (e.g. GPS) could be used as independent variables to predict the dependent variable internal load (e.g. HR) after sessions. Predicted HR responses could, therefore, be compared to the real HR responses and a HR_{real}:$HR_{predicted}$ ratio could, in theory, inform whether the athlete is gaining fitness and coping well with training or becoming fatigued (Figure 5, panel predicted vs real (%)). To sum up the pros and cons of the different methods, Figure 5 presents total distance covered by a player over 2 months, from the start of his rehabilitation post-injury to his full return to play. The different panels present (from top to bottom), total distance covered, and three different options for monitoring injury risk or potential signs of fatigue: acute:chronic ratios, readiness index, and internal:external relationships with $HR_{predicted}$ vs HR_{real} comparisons.

Possibility for new variables

With the ever-evolving advances in technology, a new batch of GPS devices will be soon available on the market (GPSport Evo, Statsport APEX, Catapult G5, to name a few) incorporating improved GPS chips (≥15 Hz) and accelerometers (≥400 Hz). Sport scientists will encounter new challenges and opportunities in terms of athlete monitoring. Level 3 (accelerometer) data will be easily available and likely more accurate than in the past.

As previously described[5], innovative and promising variables will be available for every session and in turn, fatigue monitoring could become much easier and more precise.

- **Force load (fL)[5]:** with the Athletic Data Innovation analyser (ADI), force load refers to the sum of estimated ground reaction forces during all foot impacts, assessed via the accelerometer-derived magnitude vector. fL reflects only locomotor-related impacts and provides better estimates of overall footwork and impulses than total distance or PlayerLoad™[12], especially when the session includes static movements and low displacement (e.g. rondos, free kicks).
    - During a standardised drill, an average velocity (vL) to force load ratio (vL:fL) can be used to assess neuromuscular/running efficiency (the greater the ratio, the better the efficiency). Recently, the vL:fL ratio during box-to-box runs was shown to decrease following football-specific endurance and speed sessions, suggesting a loss of efficiency in horizontal force application capability (likely due to the fatiguing effect of large amounts of high-speed running or training volume on posterior chain function)[29]. Also, moderate-to-large increases in vL:fL were observed 2 days after the end of an intense training camp in the heat, suggesting an increase in neuromuscular efficiency, which likely related to a rebound in players' neuromuscular freshness[30].
    - fL can be compared between right and left legs during any locomotive actions (e.g. specifically while accelerating vs running at high speed, which is likely related to the use and potential weaknesses of different muscle groups)[28].
- **Stride characteristics (contact and flight time calculated from accelerometer data):** from these two variables, it is possible to calculate vertical stiffness

Figure 5 (previous page): Training load (total distance, TD, metres), acute:chronic ratio (A/C ratio), readiness index (based on mechanical work, Mech W readiness) and heart rate (HR) response expressed as a percentage of predicted HR (predicted vs real (%)) in a typical player returning to training following injury. Grey vertical dashed line shows the date of return to training with the whole group. Panel TD (m): grey bars=training sessions; yellow bars=matches. A/C ratio panel: size of the circle relates to chronic load (m); red circle=A/C>1.5; blue circle=A/C<0.8. Light blue area represents the theoretical sweet spot (0.8-1.5). A/C ratio>1.5 during the rehabilitation phase is due to preceding prolonged period without training. Mech W Readiness panel: each triangle represents standardised mechanical readiness for one training session (see equation in main text); blue triangle=Mech W readiness>0.2; Red triangle=Mech W readiness<0.2. Grey zone=rolling average over the last three sessions. HR predicted vs real (%) panel: differences between GPS-based predicted HR and real session mean HR; orange bar=predicted<real – means poorer-than-usual fitness. Blue bar=predicted>real – means better-than-usual fitness. Grey area=in the absence of a clear value to define the smallest worthwhile change, the grey area was defined as 0.2× between-player standard deviation. Following a prolonged period without training, A/C ratio progressively returned to a zone of reduced risk. At the same time, the difference between predicted and observed HR increased, which likely means that the player gained fitness. Created with Tableau 10.2.

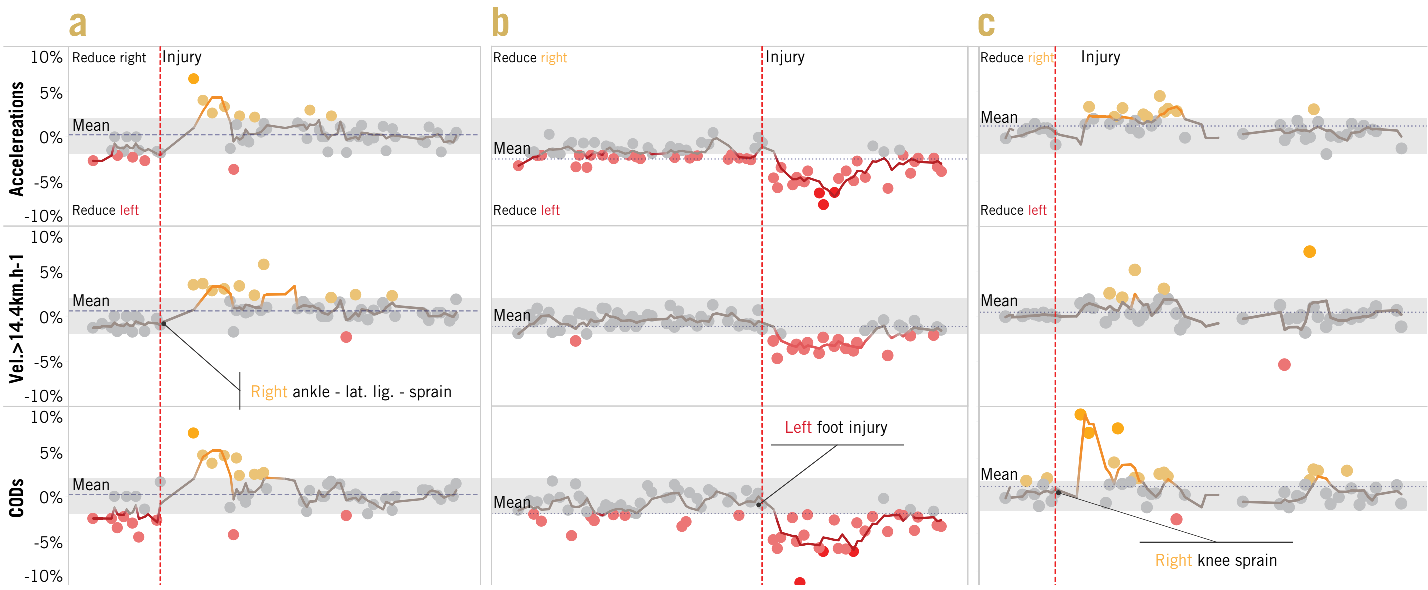


Figure 6: Examples of force load symmetries in three players before their injury and during the return to play period following (a) inferior tibiofibular ligament sprain – right ankle, (b) left foot sprain and (c) medial collateral ligament sprain – right knee. The symmetry is calculated from the force load of all foot impacts during (from top to bottom): accelerations, running phase above 14.4 km/h and changes of directions. Orange circles=right-leg force deficit >2%; red circles=left-leg force deficit >2%; red dashed lines=injury date. Created in Tableau Software 10.2.

> *Every practitioner working in elite sport continually looks for improvements in the way they collect, analyse and report data to the coaching staff*

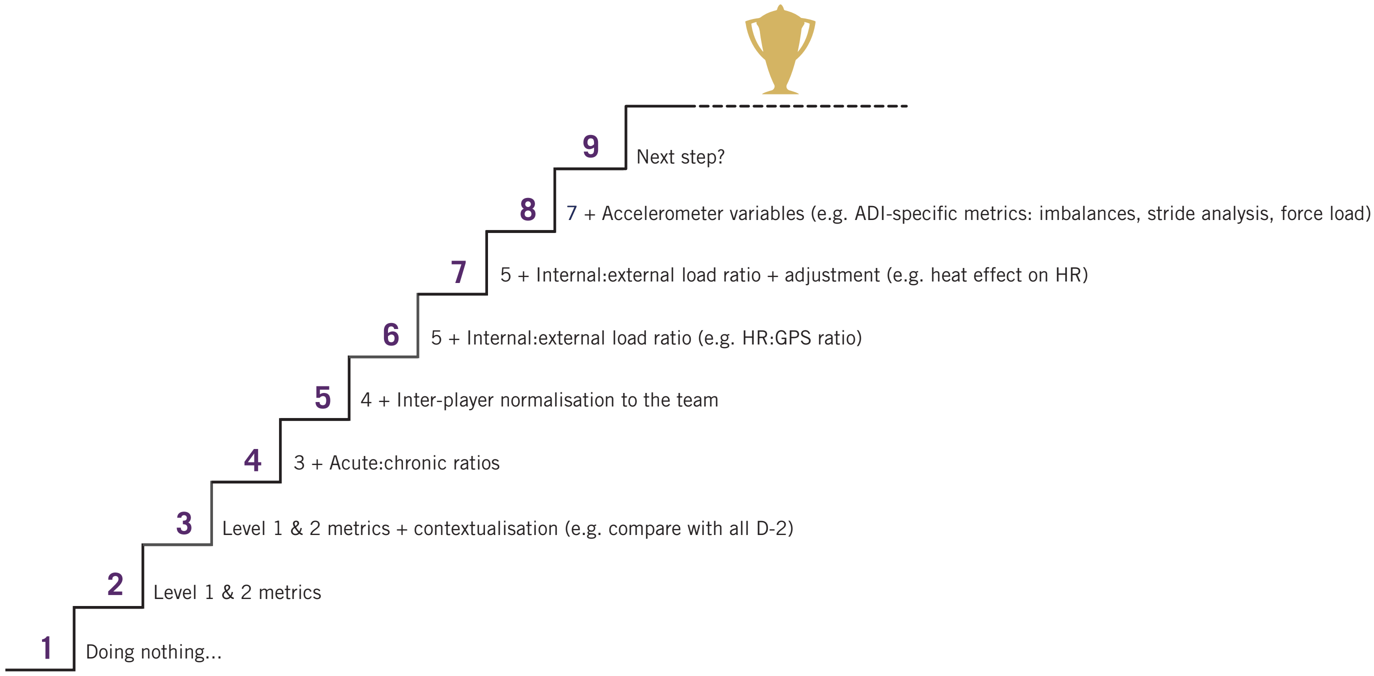


Figure 7: The road to Rome – a summary of the different training load monitoring practices.

(K), which has been shown to decrease substantially with neuromuscular fatigue[38]. While the typical error for K is slightly greater when calculated in the field (i.e. box-to-box runs) compared with standardised runs on an indoor treadmill (11±4.5% vs 6±1.5%[28,29]), it remains relatively small. The constant monitoring of stride characteristics during standardised running bouts in the field provides new perspectives for monitoring of neuromuscular status in ecological conditions.

Figure 6 shows how such variables can be used in practice. Panel A shows the symmetry calculated from the fL of all foot impacts when either running above 14.4 km/h, changing direction (CODs) or accelerating (>2 m/s/s) for all the sessions of a player suffering from a tibiofibular inferior ligament sprain (right ankle). Following his injury, there was a clear force deficit on the left side, which progressively returned to baseline as the return-to-play programme advanced. With these novel metrics, especially given that force-load imbalances can be locomotor-phase-specific (i.e. CODs vs accelerations vs high-speed running), detailed patterns can be identified for specific injuries. For example, in panel C, a player with a medial collateral (MCL) sprain in the right knee presented much greater strength-imbalances during CODs phases than during high-speed running and/or accelerations, which is likely due to the specificity of the strain associated with this injury (the MCL is mainly involved in protecting the knee against lateral force and less involved in anteroposterior movements). The diagnosis of strength imbalances is thus locomotion-dependent allowing sport scientists to complement/confirm the doctor or physio's manual testing. This in turn allows the provision of a fully functional diagnosis of the sprain or imbalance.

CONCLUSION

The role of sport scientists is beginning to be well understood in elite clubs and the peak of inflated expectations has now passed. While many roads lead to Rome, we believe that sport scientists should have a clear vision of the framework required to develop/optimise/improve the models used to analyse training loads. This will help them gain better insight into players' fitness, readiness to perform and fatigue, and improve the quality and efficiency of their support to coaching staff. But, as we will see in the second part of this manuscript, this is only halfway to Rome and good data visualisation should help practitioners improve coaching staff 'buy-in' and, therefore, staff ability to make informed decisions.

References available at www.aspetar.com/journal

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PART 2: INCREASING COACH 'BUY-IN' WITH GOOD DATA VISUALISATION

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As we have seen in part 1, we believe that practitioners with a clear vision of the framework to develop and improve the models used to analyse training loads will be able to gain better insight into players' fitness, readiness to perform and fatigue.

However, as human beings, the amount of information we receive every day has risen drastically in recent years, while the time allocated to analyses has decreased. This is particularly true for football coaches. As such, data needs to be provided to decision-makers in an easily accessible and engaging format. While optimised models are important in themselves, they are useless if the information does not make it to the people who make the decisions[1]. In this second part, we will provide some guidance on how to improve data visualisation and increase coaching staff 'buy-in', which may, in turn, improve their ability to make informed decisions.

DATA VISUALISATION

In most elite sports/football clubs, the sport science department supports the coaching staff/performance manager, but it is the coach(es) who dictates the training programme and, therefore, a large part of the training load[2]. Effective communication to increase coach buy-in is now one of the more (if not the most!) important soft skills to develop for sport scientists working in an elite set-up[3]. Today, coaches and

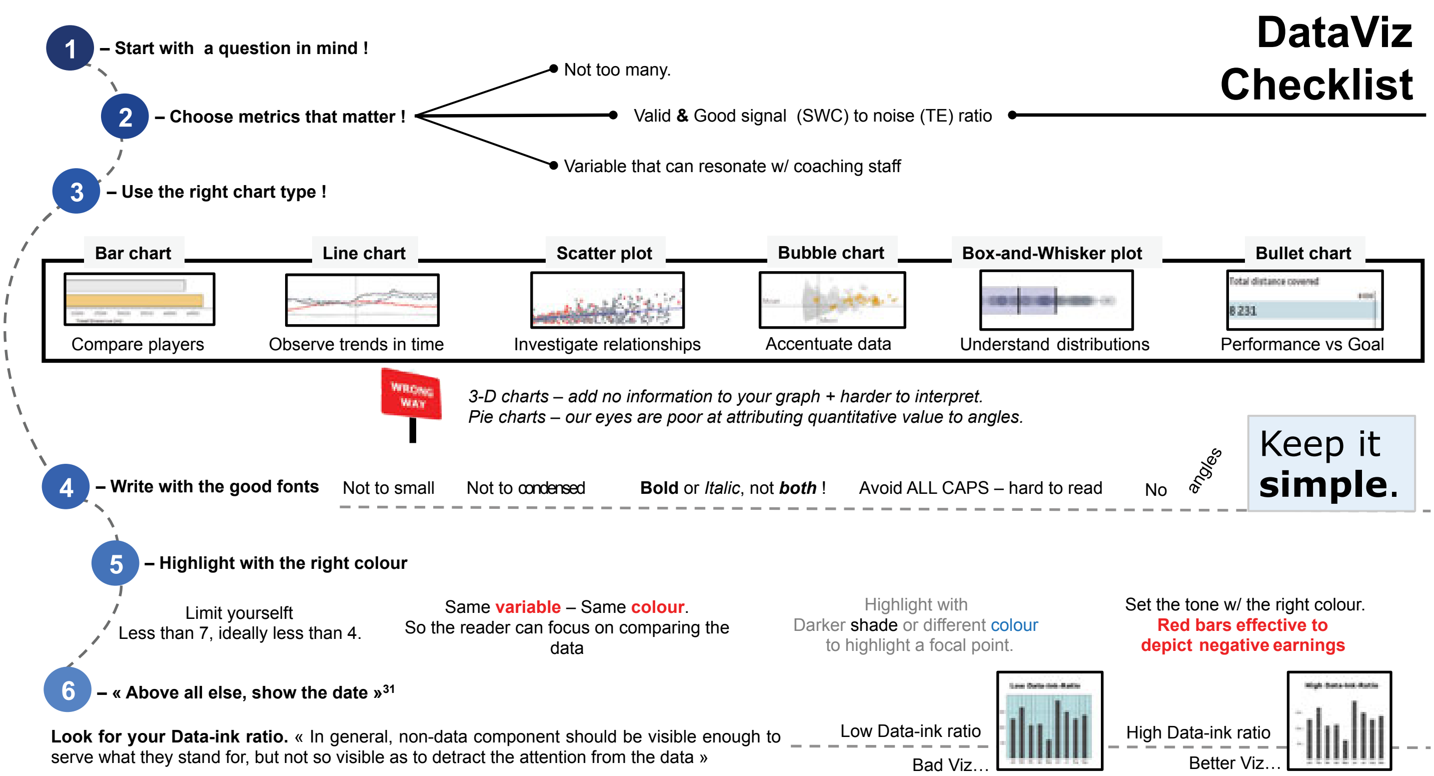

Figure 1: DataViz CheckList – inspired by Tuft[4] and Hardin et al[5].

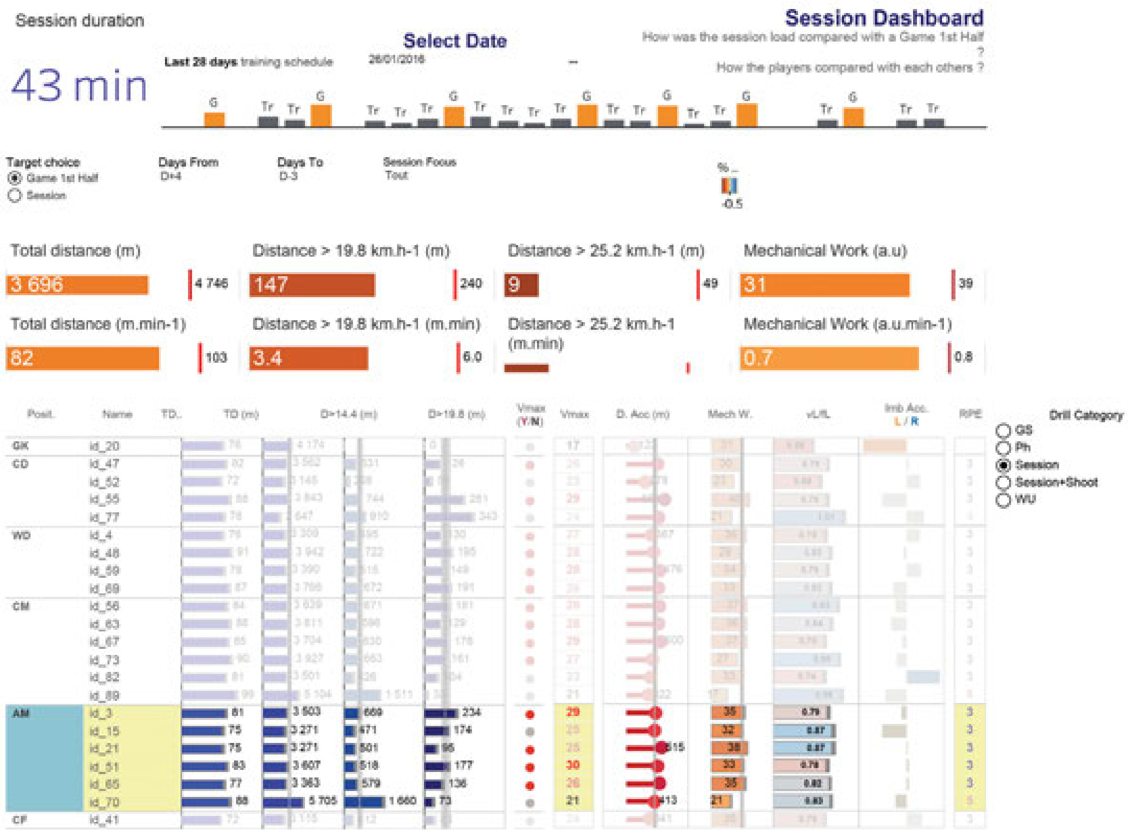

Figure 2: Example of a session dashboard presenting session training load.

Upper panel: training schedule during the last 28 days. Grey bars=training sessions; orange bars=games. Middle panel: bullet chart reporting key session metrics (white number) compared with target (similar session or mean game 1st half) values (red bar and black number). Lower panel: grey line and zone=mean ± 95%CI. White tooltip=player name, position variable value of the bar selected and ranking in the selected group. Data for AM positional group, darker and brighter=data highlighted by the practitioner. Created in Tableau 10.2.

performance managers are required to dedicate time to players' demands, media requests and sponsors – highlighting the importance of time-efficient practices when preparing and debriefing sessions and/or the training plan. As a result, it is not feasible for most decision-makers to spend more than 3 to 5 minutes reading reports. Feedback, therefore, has to be accurate, straight-to-the-point and delivered in a timely manner.

With the rise of data visualisation tools (e.g. Tableau Software®, Microsoft Power BI®, Qlik® to cite a few), data scientists are now able to display data in a more effective and engaging way for coaches. The road to better reports likely passes first though the basic concepts of powerful and engaging data visualisation (dataviz) and second, the building of interactive dashboards, which help to tell a story. With these advances, the future of athlete monitoring may echo louder into the coaching sphere and potentially aide their decisions.

Concepts of good dataviz

The checklist presented in Figure 1 summarises the different aspects of powerful dataviz.

Build interactive dashboards to tell a story

A dashboard is a visual display of the most important information, consolidated and arranged on one single screen/sheet, which allows the overall picture to be examined at a glance[6]. Dashboards depict indicators using graphics over text, which generally resonates better for busy staff not used to scientific data[7].

For this reason, it may be the time to move away from 'multipage-data' reports (on paper) to 'single-page engaging, question-based' dashboards (on a tablet or computer screen). While these dashboards are meant to be easy to read, they also offer users the ability to explore the data at a glance with more interaction. With a dashboard, the coaching staff can interact with the data by filtering or highlighting content (Figure 2).

Filtering

Filters allow the performance manager to analyse data from different angles or to dive into a more detailed level of analysis. To avoid confusion, it is always important to guide the user through the filtering process using suggestive sub-heading verbs such as 'Select', 'Click' or 'Choose'. Several examples of filter options are provided in the dashboard presented (Figure 2):

- The coach/performance manager can **select the date** of interest if he needs to look at another session.
- In the lower panel, if they are interested in looking deeper, the dashboard offers the flexibility to **choose a drill category** and then get full details of that drill.
- When the coach needs to compare the session relative to a game, they can change the **target choice** from 'similar session' to 'game 1st half' (top left-hand corner).
- Lastly, if the coach wants to observe a particular player, a dashboard offers this possibility. By **clicking on the player name** (or positional group) they can get the data in the middle-panel bullet charts and upper-panel training load history to filter relative to this player (or positional group).

Highlighting

Highlighting can quickly show relationships between values in specific areas or categories, even across multiple views. One key advantage of highlighting is that it preserves the context of the

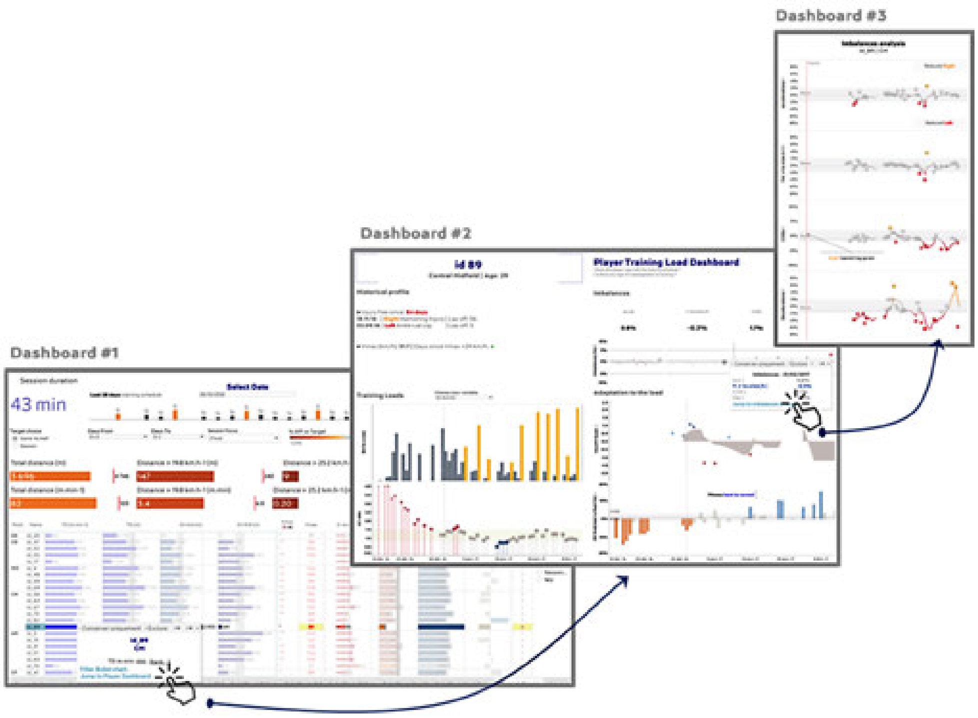

Figure 3: Multiple dashboards connected into a story board provide an engaging story for the coaching staff. For example, the performance manager can decide to highlight the session data of a player returning from injury (Dashboard #1). Further, for that specific player, he can gain insight into his individual training load data (Dashboard #2) to access key training load and fitness metrics not provided in Dashboard #1. Finally, the story ends with a specific display of the left-right force load imbalances of that particular player (Dashboard #3).

rest of the points (unlike filtering)[8]. For example, by clicking on a specific player or positional group, the dashboard allows the performance manager to quickly highlight the data of this specific group in the lower panel (Figure 2).

Everyone loves stories, with dashboards and persuasive dataviz, large amounts of data can be turned into an engaging story (Figure 3). By telling the coaching staff a story instead of reporting masses of data, sport scientists will increase coach buy-in. More importantly, stories motivate action. Dataviz and storytelling are likely key aspects in sport scientists' quest to have a clear impact on the training plan in team sports.

CONCLUSION

In this two-part manuscript, we have tried to facilitate the journey of practitioners on the 'road to Rome'. We believe that by mastering the following key elements, sport scientists may improve the quality and efficiency of their support to coaching staff, which should help them to be 'part of the conversation' with decisions-makers:

1. A clear vision of the framework required to develop/optimise/improve the models used to analyse training loads, in order to gain better insight into players' daily fitness, readiness to perform and fatigue.
2. An engaging way to display data to the coaching staff/performance manager that is attractive, efficient and increases interactivity of and 'buy-in' to the use of data.

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