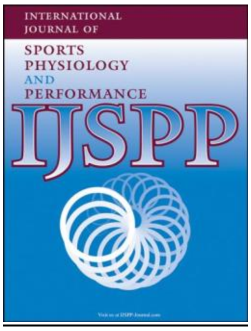

Title: ***Monitoring players' readiness using predicted heart rate responses to football drills.***

Submission type: Original investigation

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1. Abstract

Purpose: To examine the ability of multivariate models to predict the HR responses to some specific training drills from various GPS variables and to examine the usefulness of the difference in predicted vs actual HR responses as an index of fitness or readiness to perform.

Method: All data were collected during one season (2016-2017) with players' soccer activity recorded using 5-Hz GPS and internal load monitored using heart rate (HR). GPS and HR data were analysed during typical small-sided games and a 4-min standardized submaximal run (12 km/h). A multiple stepwise regression analysis was carried out to identify which combinations of GPS variables showed the largest correlations with HR responses at the individual level (HR_{ACT}, 149±46 GPS/HR pairs per player) and was further used to predict HR during individual drills (HR_{PRED}). HR predicted was then compared with actual HR to compute an index of fitness or readiness to perform (HR_{Δ},%). The validity of HR_{Δ} was examined while comparing changes in HR_{Δ} with the changes in HR responses to a submaximal run (HR_{RUN}, fitness criterion) and as a function of the different phases of the season (with fitness being expected to increase after the pre-season).

Results: HR_{PRED} was very largely correlated with HR_{ACT} (r=0.78±0.04). Within-player changes in HR_{Δ} were largely correlated with within-player changes in HR_{RUN} (r=0.66,0.50-0.82). HR_{Δ} very likely decreased from July to August (3.1±2.0 vs 0.8±2.2%) and most likely decreased further in September (-1.5±2.1%).

Conclusion: HR_{Δ} is a valid variable to monitor elite soccer players' fitness and allows fitness monitoring on a daily basis during normal practice, decreasing the need for formal testing.

Key words: Small-sided games, soccer, fitness monitoring, GPS

2. Introduction:

The monitoring of various training variables that may help to gain insight into players' training status is of major interest for most supporting staff in elite team sports. Today, a large range of variables can be used to monitor both external and internal load, and in turn, infer on players' fitness, fatigue and/or readiness to perform.[1] However, typical metrics such as distance covered in different speed zones or heart rate-related variables analyzed in isolation are often more influenced by contextual variables than players' training status *per se*.[2] As such, there is still a need for more robust monitoring variables and/or analyses[1] that could be used with confidence, irrespective of the daily training context.

To overcome the limitations inherent to the use of those latter variables, examining the dose-response relationship between work load and immediate physiological responses (or more simply generic models of work efficiency, i.e., output/cost relationships) may represent the first advances to assess training status from data collected routinely in elite players. The simplest way to assess players' locomotor work efficiency is likely to use ratios between typical internal and external load measures,[3] with the lower the ratio, the greater the efficiency. Recently, such ratios have been used in the context of elite soccer to assess either the overall acclimatization and fatigue trends during a training camp in a hot environment (very likely large increases in RPE/m.min^{-1} during the first two days in Asia (fatigue), trend of -0.4 RPE/m.min^{-1} decreased from D1 to D8 (acclimatization phase))[4], fitness changes following a two-week pre-season training period (changes in Total distance (TD)/ Heart rate (HR) were largely correlated with the velocity at lactate threshold (r=-0.69), a measure of aerobic fitness)[5] or running efficiency during official games (TD/HR was very likely slightly decreased during the second half vs the first half (~-4.4%)).[6] While these studies have suggested that internal-to-external load ratios could be used as a measure of fitness or readiness to perform, there remain several limitations to those studies. In these three studies, TD was used as the unique measure of external load. It is well-know that during soccer practice, overall running distance is a poor marker of locomotor demands.[7] As such, it is intuitive to think that the inclusion of other locomotor variables such as high-speed running, acceleration counts or mechanical load[2] into those analyses may provide better estimates of training status.[8] In the only study examining the relationships between those external training load variables and HR responses to training drills in professional rugby league players,[3] large-to-almost perfects relationships were reported between external-to-internal load ratios and measures of fitness or load. However, since several non-training related characteristics (e.g., playing experience, playing position or overall fitness level) likely affect the relationship between internal and external load at an individual level,[9] the relevance of any external load metrics to predict internal load is likely player-specific. Therefore, individual models including player-specific combinations of external-load variables (e.g., TD, HS, mechanical work) may be superior to team-average based models for the assessment of players' fitness when using data collected during training sessions.

The first aim of the present paper was to quantify in 10 elite soccer players the individual relationships (i.e., multivariate models) between various field-based external load measures (i.e., locomotor activity during small-sided games) tracked with global positioning system (GPS) and an objective measure of internal load (i.e., HR response to the same drills). The second aim was to examine the ability of each individual model to predict the HR responses to some specific training drills from various GPS variables. The third aim of the present study was then to examine the usefulness of the difference between predicted vs actual HR responses as an index of fitness or readiness to perform. If useful enough, this new metric would allow the assessment of players' fitness every time a small-sided game is performed, during normal practice, removing the need for formal testing sessions.

3. Methods:

Participants

Data were collected in 10 field players (26±5 years; 182±6 cm; 76±5 kg; max heart rate: 198±10 bpm (assessed during the 30-15 Intermittent Fitness Test)[10]) belonging to an elite French football team. During this period, none of the players suffered from an injury requesting to stop training for more than 1 week. These data arose from the daily monitoring in which player activities are routinely measured over the course of the season. Therefore, ethics committee clearance was not required.[11] The study conformed nevertheless to the recommendations of the Declaration of Helsinki.

Methodology

Data collection:

All training data were collected during typical training sessions (AM or PM sessions, Heat index: 16°, range: 0-33°) during one season (2016-2017) with players' activity recorded using 5-Hz GPS and 100 Hz accelerometers (SPI-Pro, Team AMS R1 2016.8, GPSport, Canberra, Australia) and further analysed using the Athletic Data Innovations analyser (ADI, v5.4.1.514, Sydney, Australia) to derive total distance (TD, m), high-speed distance (HS, distance above 14.4 km.h-1, m), very-high speed distance (VHS, distance above 19.8 km.h-1, m), velocity and force load (vL and fL respectively, a.u) and mechanical work (MechW, a.u). Velocity load refers to the sum of distance covered weighted by the speed of displacement. Force load refers to the sum of estimated ground reaction forces during all foot impacts, assessed via the accelerometer-derived magnitude vector.[2] Mechanical work is an overall measure of velocity changes and is computed using $>2.ms^{-2}$ accelerations, decelerations and changes of direction events.[12] In average, 9±1 satellites were connected during each training session. Players used consistently the same unit to decrease measurement error.[13] Heart rate was monitored using Polar H1 units (Polar, Kempele, Finland), synchronized with GPS and further analyzed using the ADI analyzer to derive mean heart rate (HR) during each drill.

Heart rate and GPS data were analysed during typical small-sided games (SSGs) and a standardized submaximal run. The SSGs included for analyses were the following: 5v5, 6v6, 7v7, 8v8, 9v9 and 10v10 played as game simulations (with goal keepers) or possession drills; surface area per player: 117±65 m^2/player.[12] A standardized submaximal run (12 km/h paced with an acoustic reference, over a 50 ×100-m rectangle course) was performed 4±1 times throughout the pre-season and early in-season. The average HR during the last minute of the run was used for analysis.[14] All training sessions were performed on the same hybrid pitch (DESSO GrassMaster, Tarkett, Nanterre, France), with a mean pitch hardness value (measured with Clegg Impact soil tester – 2.5 kg) of 74±4 [range: 70-82]. Data were then normalised relative to the drill duration.

Analyses:

<u>*Model building*</u>

A mean of 149±46 [range: 84-230] observations per player (2±1 per session) were used to build individuals models. A multiple stepwise bidirectional regression analysis was carried out to identify which combinations of GPS-related variables (TD, HS, VHS, vL, fL, MechW) showed the largest correlations with HR responses.

Within-player models were created using R statistical software (R v3.4.1, R Foundation for Statistical Computing) using the *step* function of the *MASS package* (v7.3-47). Then, the relative importance of each GPS variables was calculated using the *calc.relimp* function from the *relaimpo* package (v2.2.-2). Predicted HR (HR_{PRED}) was subsequently calculated for each SSGs from the different GPS variables. Because of the likely effect of heat on HR responses, HR_{PRED} was further adjusted for changes in temperature (heat index, Weather tracker, Kestrel 4500 NV, Kestrel Weather instrument, Minneapolis, USA) as follow (Eq 1):

Eq 1: HR_{PRED} (%) = $HR_{PRED\ (unadjusted)}$ + 0.075*(Heat Index-Heat $Index_{MEAN}$) with Heat $Index_{MEAN}$ standing for the mean heat index over the period of interest (season 16/17).[15] Here are two examples of individual models (Eq 2 and Eq 3) aimed at predicting HR_{PRED}:

$$\text{Eq 2: P3: } HR_{PRED}\ (\%) = 51.52 + 1.47 \cdot fL + 0.44 \cdot VHS + 7.11 \cdot MechW + 0.075 \cdot (\text{Heat Index} - \text{Heat Index}_{MEAN})$$

$$\text{Eq 3: P10: } HR_{PRED}\ (\%) = 49.18 - 0.41 \cdot TD + 3.50 \cdot vL + 3.65 \cdot fL + 7.31 \cdot MechW + 0.075 \cdot (\text{Heat Index} - \text{Heat Index}_{MEAN})$$

The actual HR (HR_{ACT}) response was finally compared with HR_{PRED} for each SSG, and expressed as a percentage difference to compute HR_{Δ} (Eq 4), with the higher the difference, the lower the fitness (e.g. when $HR_{ACT} > HR_{PRED}$, HR_{Δ} values are positive, which suggests a lower fitness than usual).

$$\text{Eq 4: } HR_{\Delta}\ (\%) = HR_{ACT} - HR_{PRED}$$

It is worth mentioning that the training dataset used to build individual models was the same than the dataset used for HR prediction, possibly leading to overfitting. We are nevertheless confident in the results presented in this study since a comparison with similar models build using data from previous seasons (e.g., season 15/16, personal communication) yielded similar results.

Model validation

The validity of HR_{Δ} to predict players' fitness and readiness to perform was examined using 2 different approaches, i.e., while examining its change 1) in comparison with an objective (criterion) measure of fitness (i.e., HR responses to a submax run[14]) and 2) as a function of the different seasonal phases (pre-season (July), early in-season (August) and in-season (September)).

In fact, in young soccer players, individual decreases in HR responses to such a submaximal running test were associated with very likely improvements in aerobic fitness.[16] HR responses to this submaximal run (HR_{RUN}) were also adjusted for temperature as shown in Eq 1.

Relationships between within-player changes in HR_{RUN} and within-player changes in the mean HR_{Δ} recorded ±3 days before or after the HR_{RUN} were used to assess the concurrent validity of HR_{Δ} to estimate players' fitness. This period of 3 days corresponds to the average number of days between two games, representing our typical training microcycles.

Second, we examined changes in HR_{Δ} throughout the pre-season. In fact, there is generally a progressive increase in fitness from pre-season to early in-season, as evidenced by small-to-moderate increases in high-intensity running performance (Yo-Yo intermittent recovery level 2) and decreased HR responses to submaximal exercise tests (Yo-Yo IR1 test).[17,18] It was therefore hypothesized that if HR_{Δ} was to be a good indicator of players' fitness and readiness to perform, a progressive decrease would be expected from July (pre-season) to August (end of pre-season, start of the season) and September (early in-season). The average HR_{Δ} over each month was used to assess the between-months changes in HR_{Δ}. While we are well aware of the limitations of HR responses to inform on the actual metabolic cost (mostly oxidative) of exercise, especially during intermittent exercise,[19] it is important to note that assessing such an absolute oxidative contribution to exercise is not an objective of our study. We were rather simply making the assumption that changes in HR responses relative to some specific locomotor demands may be reflective of changes in fitness/readiness to perform. For that reason, we believe that the above-mentioned limitations of HR during intermittent exercise are not problematic.[3,5,6]

Statistical analysis

Data in the text, tables, and figures are presented as means with standard deviations (SD) and 90% confidence limits/intervals (CL/CI). The typical error of estimate (TEE) of the predictions as well as regression coefficient (r) was calculated for each player to assess the accuracy of the model.[20] The following criteria were adopted to interpret the magnitude of the correlation (r, 90% CI): ≤0.1, trivial; >0.1 to 0.3, small; >0.3 to 0.5, moderate; >0.5 to 0.7, large; >0.7 to 0.9, very large; and >0.9 to 1.0, almost perfect. Between-months changes in the HR_{Δ} were examined using standardized differences, based on Cohen's *d* effect size principle. The scale was as follows: 25−75%, possible; 75−95%, likely; 95−99%, very likely; >99%, almost certain. Threshold values for standardized differences were >0.2 (small), >0.6 (moderate), >1.2 (large) and very large (>2). If the 90% CI overlapped small positive and negative values, the magnitude was deemed unclear; otherwise, that magnitude was deemed to be the observed magnitude.[21] Probabilities were used to make a qualitative probabilistic mechanistic inference about the true differences in the changes, which were assessed in comparison to the smallest worthwhile difference (SWD) which was set as 0.2 of the TEE.[20] When monitoring individuals, longitudinal changes are generally considered substantial when the probabilities for changes are ≥75%, which occurs when the difference is greater than the sum of the SWD and the typical error of measurement[22] (TE; from reliability studies = ~3%).

4. *Results:*

The average TEE for the 10 individual multiple regression analyses was 2.9±0.3 % [range: 2.5-3.5 %] with HR_{PRED} being very largely correlated with HR_{ACT} (r=0.78±0.04 [range: 0.74-0.84]) (Figure 1).

Figure 2 showed that fL, MechW, vL, and TD shared the greatest part of the variance in the regression analysis (31±17, 24±8, 18±7 and 16±12% respectively).

Figure 3 presents the mechanical work performed during the pre-season and early in-season (upper panel) and corresponding HR_{Δ} and HR_{RUN} (lower panel) in one elite soccer player. Overall, HR_{Δ} was substantially greater than zero (i.e., HR_{ACT} > HR_{PRED}) during the first 15 days of training (average HR_{Δ} over the 15 days: +5.2±3.3%), with a substantial trend for a decrease in HR_{Δ} throughout this period (from D1 to D15, -0.5 HR_{Δ} / day. HR_{Δ}). Additionally, HR_{Δ} was substantially lower than zero (i.e., HR_{ACT} < HR_{PRED}) after day 75 (average HR_{Δ} from day 75 to day 150: -4.9±6.9%). Overall, except for 1 point (day 45), there was a good agreement between the changes in HR_{Δ} and HR_{RUN}.

Within-player changes in HR_{Δ} were largely correlated with within-player changes in HR_{RUN} (r, 90% CI=0.66, 0.50-0.82) (Figure 4).

HR_{Δ} very likely decreased from July to August (3.1±2.0 vs 0.8±2.2%; ES= -0.99±0.64; 0/3/97) and most likely decreased further in September (3.1±2.0 vs -1.5±2.1%; -1.96±0.95; 0/0/100). HR_{Δ} likely decreased from August to September (0.8±2.2 vs -1.5±2.1 %, -0.98±0.88, 2/5/95).

5. Discussion:

The aim of the present study was to quantify the relationships between various measures of external (GPS variables) and internal (HR) load measures in elite soccer players and assess if the differences between the HR predicted from GPS variables and that actually measured (i.e.,

HR_{Δ}) could be used to infer on players' fitness and readiness to perform. The key findings were the following: (1) HR responses during small-sided-games (HR_{ACT}) were largely related to locomotor activity (GPS variables) (Figure 1), with fL and MechW sharing the greatest part of the variance in the model (Figure 2), (2) within-player changes in HR_{Δ} were largely correlated with those in HR_{RUN} (Figure 4) and (3) HR_{Δ} decreased progressively from the pre-season to early in-season (Figure 5).

Model construction

Our results reported that the HRs predicted from GPS variables during SSGs were very largely correlated (r=0.78±0.04) with the HR responses actually measured (Figure 1). Furthermore, we observed that while fL and MechW were the greatest predictors of HR responses (31±17 and 24±8% respectively), TD and high-speed related variables explained less than 30% of the total variance (16±12%, 5±6 and 6±7% for TD, HS and VHS respectively). More specifically, for a player-equation based on fL, VHS and MechW (Eq 2), a 20% increase in either MechW or VHS would be expected to lead to a 2.4% or 0.5% increase in HR response respectively. Interestingly, while a majority of studies have focused on the relationships between relative distance (m.min-1) or locomotor-related measures (high-speed and total distance) and HR,[23] our results demonstrated that HR during football-specific training drills is more related to the mechanical demands of the task (acceleration, decelerations, and changes of direction). Our results confirmed the major importance of mechanical work and force load when estimating internal load[2] and the necessity of taking into account these two variables when assessing load and in turn, planning training.

While group-responses are helpful to understand the overall relationships between internal and external load, substantial between-players variations in this relationship were reported in this study (Figure 2). Indeed, while MechW shared the greatest part of the variance at a group level (24%), at individual level MechW accounted for 12 to 34% of the variance of HR_{ACT}. On the other side, while TD only accounted for 16% of the variance at the team level, individual values ranged from 0 to 34%. As such, it is important for each player to be treated individually when building models examining the training response. Indeed, factors such as fitness,[5] neuromuscular capacity, playing position or playing experience[9] can modify the way external load is related to internal load. This result has several implications for training plannification and further highlights the need for practitioners to assess and monitor training loads at the individual level. For example, given the very large between-player differences in the locomotor/HR responses relationships (Figure 2), it is likely that players' HR would respond differently to different types of drills. There may be players for whom high levels of HR may be better reached through increased MechW.min^{-1} (as with SSGs including a low number of players over small spaces), while for others, through increased in HS running (larger number of players and more running space, or run-based interval training).

Case study example.

To interpret clear individual changes in HR_{Δ}, it is necessary to know the minimum difference that maters, i.e., that can be assessed with a probability of at least 75% (SWD+TE[22]). In the present study, the SWD for the different individual models ranged from 0.5 to 0.7%. Considering that the TE of HR during training bouts is about 3%,[14] changes of at least ~4% (SWD ~1% + TE 3%) were required to ensure that changes in HR_{Δ} were real at the individual level. It is, however, worth noting that this required 4% difference can be decreased with repeated measurements, improving the sensitivity of the monitoring. In fact, since the TE is inversely related to the number of measurements performed (TE decreases as a factor of $\sqrt{n}$ measures),[24] practitioners can decrease the 3% value by pooling multiple drills performed in the same session or pooling multiple sessions. In Figure 4, TE was adjusted on the number of distinct SSGs performed during each session (between 1 to 4). Based on these data, we were able to easily assess changes in HR_{Δ} and HR_{RUN} during pre-season and early in-season. In this case study, HR_{Δ} clearly decreased during the 15 first days of the pre-season, likely reflecting the expected fitness improvement. Also, it is noteworthy that changes in HR_{Δ} were concomitant with those in HR_{RUN}, expect at 1 time-point (i.e., day 45) where the change in HR_{RUN} was unclear while that in HR_{Δ} was clearly above 0. While data are lacking to explain this unique dissociation between HR_{Δ} and HR_{RUN}, acute change in hydration status and plasma/fluids shifts can sometimes cause large changes in HR from a day to another independently of fitness.[25]

Association between HR_{Δ} and HR_{RUN}

Our results reported that within-player changes in HR_{Δ} were moderately correlated with within-player changes in HR_{RUN} (used as a criterion measure of fitness, r=0.66, 0.50-0.82, Figure 4), confirming the potential of HR_{Δ} to inform practitioners on changes in player's fitness through the season when only looking at HR responses to SSGs. However, while the fact that the correlation was not perfect could be seen as a limitation of the usefulness of HR_{Δ}, it is in contrast, in fact, a very good point, i.e., it suggests that HR_{Δ} may reflect something slightly different than HR_{RUN}. We belive that the four quadrans defined by the 2 axes in Figure 4 could be used to infer on players specific needs in terms of conditioning. It is generally believed that fitness (as many other physical capacities) can be regarded from two different angles, a general component mostly related to cardiopulmonary performance during generic types of exercise bouts (i.e, straight-line running such as during the submaximal run), vs. a soccer-specific fitness with a greater neuromuscular component, which relates to the ability to perform and repeat specific types of locomotor actions such as repeated accelerations, decelerations, changes of directions (as during SGGs).[26] Following these lines, and while still hypothetical given the low number of players examined and the limited time window analyzed (i.e., 1 season), it could be hypothesized that while HR_{RUN} may be used as an index of generic fitness, HR_{Δ} could be more used as a measure of soccer-specific fitness. In fact, when it comes to pre-season conditioning,[26] players generally transition from unfit (top right quadran, both HR_{Δ} and HR_{RUN} lower than usual) to generally fit (mid pre-season, top left quadran, HR_{RUN} improved but not HR_{Δ}), before becoming specifically fit at the end of the pre-season (bottom left quadran, both HR_{Δ} and HR_{RUN} improved). Interestingly and in line with our proposal, it is noteworthy that there was no players reported in the bottom-right hand corner, suggesting that generic fitness is needed to build football-specific fitness. Analysed in light of HR_{RUN} performance, HR_{Δ} could provide key information for practitioners to better understand when a player needs more generic running conditioning (e.g. during early pre-season or after an injury) vs. more soccer-specific training (e.g. high mechanical work tolerance, specific strength training, actions with the ball more generally in-season).

Changes in HR_{Δ} from the pre-season to early in-season

Interestingly, we also observed a progressive decrease in HR_{Δ} from July to August and then September (Figure 5). Since players fitness generally moderately increases from the pre-season to early in-season (moderate increases in YoYo IR2 performance in elite football players; ES=~0.80),[17] the corresponding large change in HR_{Δ} (ES=1.96±0.95) confirms again its sensitivity to changes in fitness. The monitoring of HR_{Δ} on a regular basis could probably allow practitioners to assess whether players are gaining fitness (or not) throughout the pre-season and early in-season, while external or internal load measures used separately cannot. This new model might provide practitioners with a simple tool to better understand the dose-response relationship between training load and fitness, and allow the monitoring of players' fitness at a higher frequency, i.e., every time a SSG is performed (almost daily) and most importantly, during normal practice (no formal testing needed!).

Limitations.

First, the present monitoring approach can't be used with players with only limited historical data (e.g., for new signings some time to build the models is needed (≥ 60 data points,[27] ~ 6-8 weeks). Second, players need to be compliant with wearing heart rate belt during training, which is not always without complications. Third, erroneous heart-rate is common during team sport training (e.g., due to shocks and contacts), which can result in erroneous HR interpretations if care is not applied to correct each individual files, potentially biasing the fitness estimates. We also agree that timing of the SSG both during the session and the week may affect the actual relationships between locomotor activity and HR responses (i.e., for the same external work, HR may be higher during SGGs performed at the end of a session as a consequence of a possible cardiac drift,[28] or lower the day following a heavy session as a consequence of a likely plasma volume expansion.[29] This could not be accounted for in the present study and have likely decreased the magnitude of the associations between GPS variable and HR responses. We nevertheless believe that the monitoring of trends in HR_{Δ} changes (rather than day-to-day, isolated changes) should partially overcome this limitation. It is also worth noting that GPS with a greater sampling frequency may allow the collection of more reliable data,[30] which in final may increase the strength of the relationships observed between GPS variables and HR responses. The models presented in the present study may become more robust in the future with the use of more advanced technology.

6. **Practical applications**

(1) Mechanical work and force load are the greatest predictors of the HR responses to SSGs, highlighting the importance of taking into account these two GPS/accelerometers-derived variables when assessing load and planning training
(2) HR_{Δ}, computed from both external (GPS) and internal (HR) load variables can be used to track players' fitness through the pre-season and early in-season. A moderate ~4% decrease in HR_{Δ} (similar to a ~5% decrease in HR_{RUN}) (Figure 4) is likely indicative of ~4% increase in maximal aerobic speed (0.5 km.h^{-1}).[16]
(3) This approach allows a monitoring on a daily basis during normal practice, eliminating the need for formal fitness testing.
(4) Used together, HR_{RUN} and HR_{Δ} can be used to define players conditioning needs (e.g., generic vs. soccer-specific-fitness).

7. Conclusions

In this paper, we saw large and player-dependent associations between the HR responses to SSGs and some of the locomotor/mechanical demands of those SSGs as assessed via GPS and accelerometers. We then demonstrated that HR_{Δ} (i.e, the difference between the predicted and actual HR responses to SSGs) can be confidently used to track players' fitness throughout the season while using data collected during game-play only. While further larger scale studies are needed to confirm our preliminary results, these findings open new opportunities for practitioners willing to monitor players' fitness on a regular basis, decreasing the need for formal testing.

8. References:

1. Halson SL. Monitoring training load to understand fatigue in athletes. *Sports medicine (Auckland, NZ).* 2014;44 Suppl 2:S139-147.
2. Buchheit M, Simpson BM. Player-Tracking Technology: Half-Full or Half-Empty Glass? *International journal of sports physiology and performance.* 2017;12(Suppl 2):S235-s241.
3. Delaney JA, Duthie GM, Thornton HR, Pyne DB. Quantifying the relationship between internal and external work in team sports: development of a novel training efficiency index. *Science and Medicine in Football.* 2018:1-8.
4. Buchheit M, Cholley Y, Lambert P. Psychometric and Physiological Responses to a Preseason Competitive Camp in the Heat With a 6-Hour Time Difference in Elite Soccer Players. *International journal of sports physiology and performance.* 2016;11(2):176-181.
5. Akubat I, Barrett S, Abt G. Integrating the internal and external training loads in soccer. *International journal of sports physiology and performance.* 2014;9(3):457-462.
6. Torreno N, Munguia-Izquierdo D, Coutts A, de Villarreal ES, Asian-Clemente J, Suarez-Arrones L. Relationship Between External and Internal Loads of Professional Soccer Players During Full Matches in Official Games Using Global Positioning Systems and Heart-Rate Technology. *International journal of sports physiology and performance.* 2016;11(7):940-946.
7. Buchheit M, Lacome M, Cholley Y, Simpson BM. Neuromuscular Responses to Conditioned Soccer Sessions Assessed Via GPS-Embedded Accelerometers: Insights Into Tactical Periodization. *International journal of sports physiology and performance.* 2017:1-21.
8. Bartlett JD, O'Connor F, Pitchford N, Torres-Ronda L, Robertson SJ. Relationships Between Internal and External Training Load in Team-Sport Athletes: Evidence for an Individualized Approach. *International journal of sports physiology and performance.* 2017;12(2):230-234.
9. Gallo T, Cormack S, Gabbett T, Williams M, Lorenzen C. Characteristics impacting on session rating of perceived exertion training load in Australian footballers. *Journal of sports sciences.* 2015;33(5):467-475.
10. Buchheit M, Al Haddad H, Millet GP, Lepretre PM, Newton M, Ahmaidi S. Cardiorespiratory and cardiac autonomic responses to 30-15 intermittent fitness test in team sport players. *Journal of strength and conditioning research.* 2009;23(1):93-100.
11. Winter EM, Maughan RJ. Requirements for ethics approvals. *Journal of sports sciences.* 2009;27(10):985.
12. Lacome M, Simpson BM, Cholley Y, Lambert P, Buchheit M. Small-Sided Games in Elite Soccer: Does One Size Fits All? *International journal of sports physiology and performance.* 2017:1-24.
13. Buchheit M, Al Haddad H, Simpson BM, et al. Monitoring accelerations with GPS in football: time to slow down? *International journal of sports physiology and performance.* 2014;9(3):442-445.
14. Buchheit M. Monitoring training status with HR measures: do all roads lead to Rome? *Frontiers in physiology.* 2014;5:73.
15. Lacome M, Simpson B, Buchheit M. Monitoring training status with player-tracking technology: Still on the road to Rome. *Aspetar - Sports Medicine Journal.* 2018 (in press).

16. Buchheit M, Simpson MB, Al Haddad H, Bourdon PC, Mendez-Villanueva A. Monitoring changes in physical performance with heart rate measures in young soccer players. *Eur J Appl Physiol.* 2012;112(2):711-723.
17. Mohr M, Krustrup P. Yo-Yo intermittent recovery test performances within an entire football league during a full season. *Journal of sports sciences.* 2014;32(4):315-327.
18. Bangsbo J, Iaia FM, Krustrup P. The Yo-Yo intermittent recovery test : a useful tool for evaluation of physical performance in intermittent sports. *Sports medicine (Auckland, NZ).* 2008;38(1):37-51.
19. Buchheit M, Laursen PB. High-intensity interval training, solutions to the programming puzzle: Part I: cardiopulmonary emphasis. *Sports medicine (Auckland, NZ).* 2013;43(5):313-338.
20. Buchheit M, Cholley Y, Nagel M, Poulos N. The Effect of Body Mass on Eccentric Knee-Flexor Strength Assessed With an Instrumented Nordic Hamstring Device (Nordbord) in Football Players. *International journal of sports physiology and performance.* 2016;11(6):721-726.
21. Hopkins WG, Marshall SW, Batterham AM, Hanin J. Progressive statistics for studies in sports medicine and exercise science. *Med Sci Sports Exerc.* 2009;41(1):3-13.
22. Hopkins WG. How to interpret changes in an athletic performance test. *Sport Science.* 2015.
23. McLaren SJ, Macpherson TW, Coutts AJ, Hurst C, Spears IR, Weston M. The Relationships Between Internal and External Measures of Training Load and Intensity in Team Sports: A Meta-Analysis. *Sports medicine (Auckland, NZ).* 2018;48(3):641-658.
24. Haugen T, Buchheit M. Sprint Running Performance Monitoring: Methodological and Practical Considerations. *Sports medicine (Auckland, NZ).* 2016;46(5):641-656.
25. Buchheit M, Laursen PB, Al Haddad H, Ahmaidi S. Exercise-induced plasma volume expansion and post-exercise parasympathetic reactivation. *Eur J Appl Physiol.* 2009;105(3):471-481.
26. Verheijen R. *The Original Guide to Football Periodisation. Part 1.*: World Football Academy; 2014.
27. VanVoorhis CW, Morgan BL. Understanding power and rules of thumb for determining sample sizes. *Tutorials in Quantitative Methods for Psychology.* 2007;3(2):43-50.
28. Wingo JE, Ganio MS, Cureton KJ. Cardiovascular drift during heat stress: implications for exercise prescription. *Exerc Sport Sci Rev.* 2012;40(2):88-94.
29. Buchheit M, Racinais S, Bilsborough JC, et al. Monitoring fitness, fatigue and running performance during a pre-season training camp in elite football players. *Journal of science and medicine in sport.* 2013;16(6):550-555.
30. Scott MT, Scott TJ, Kelly VG. The Validity and Reliability of Global Positioning Systems in Team Sport: A Brief Review. *Journal of strength and conditioning research.* 2016;30(5):1470-1490.

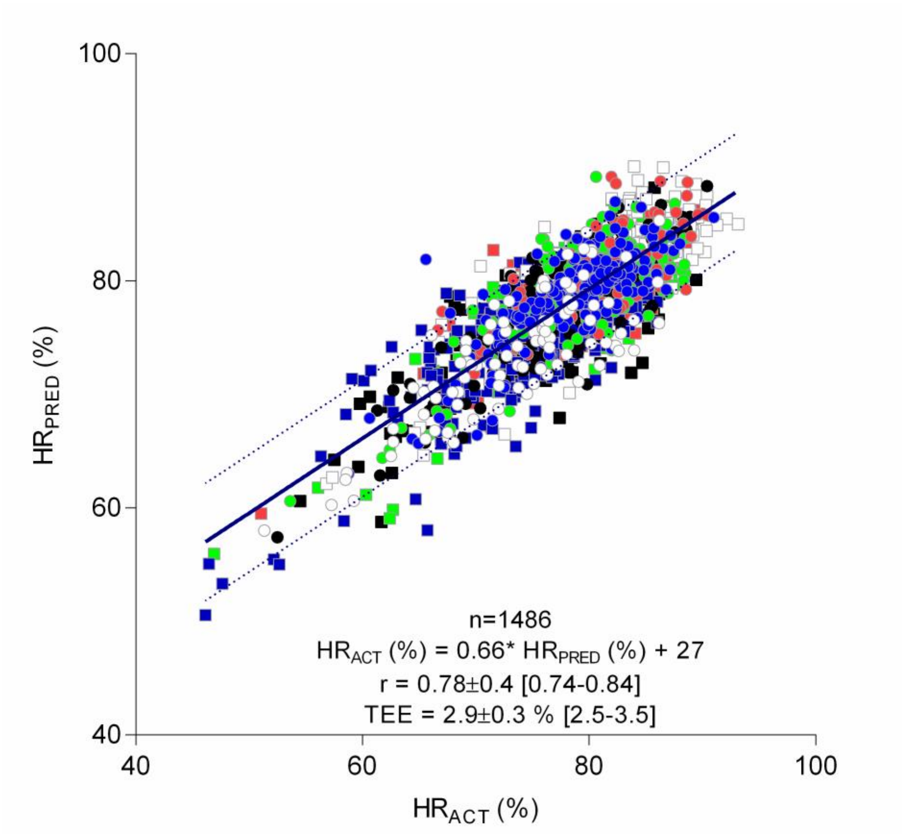

Figure 1 Relationship between predicted HR from GPS data and actual HR.

Data are presented as mean±standard deviation [range]. Blue ligne and dashed lines: Linear fit with 90% confidence intervals. TEE: Standard error of the estimate. HR_{PRED}: Predicted heart rate. HR_{ACT}: Actual heart rate. Colors and shapes are set for each player.

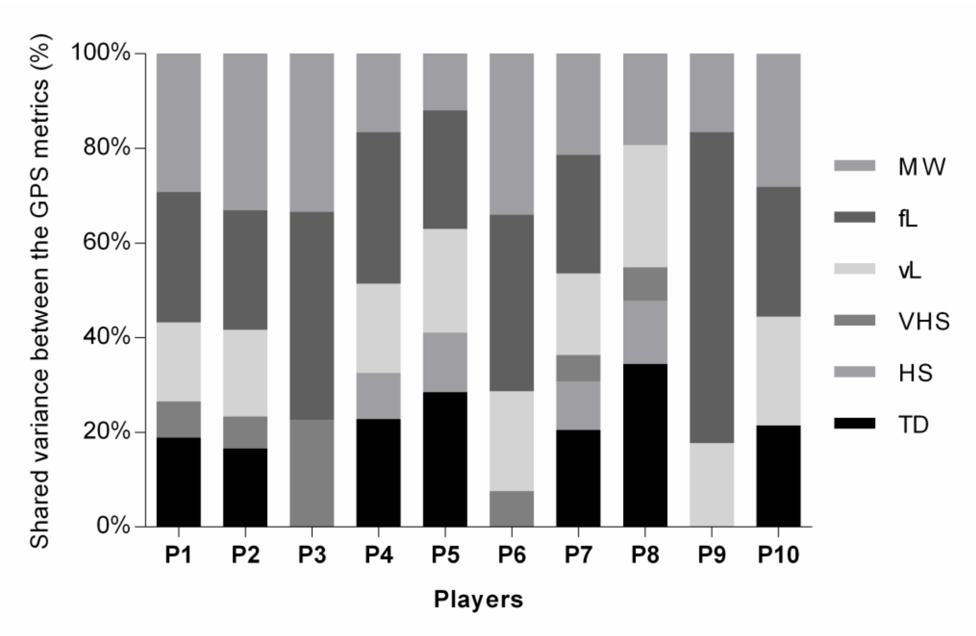

Figure 2: Relative contribution of the global positioning system variables to heart rate responses during small-sided games (multiple regression analysis models for each individual player).

TD: Total distance ($m.min^{-1}$), HS: Distance>14.4 km.h ($m.min^{-1}$), VHS: Distance>19.8 km.h -$m.min^{-1}$), vL: Velocity load ($a.u.min^{-1}$), fL: Force load ($a.u.min^{-1}$); MW: Mechanical work ($a.u.min^{-1}$). P1 to P10: Player 1 to 10

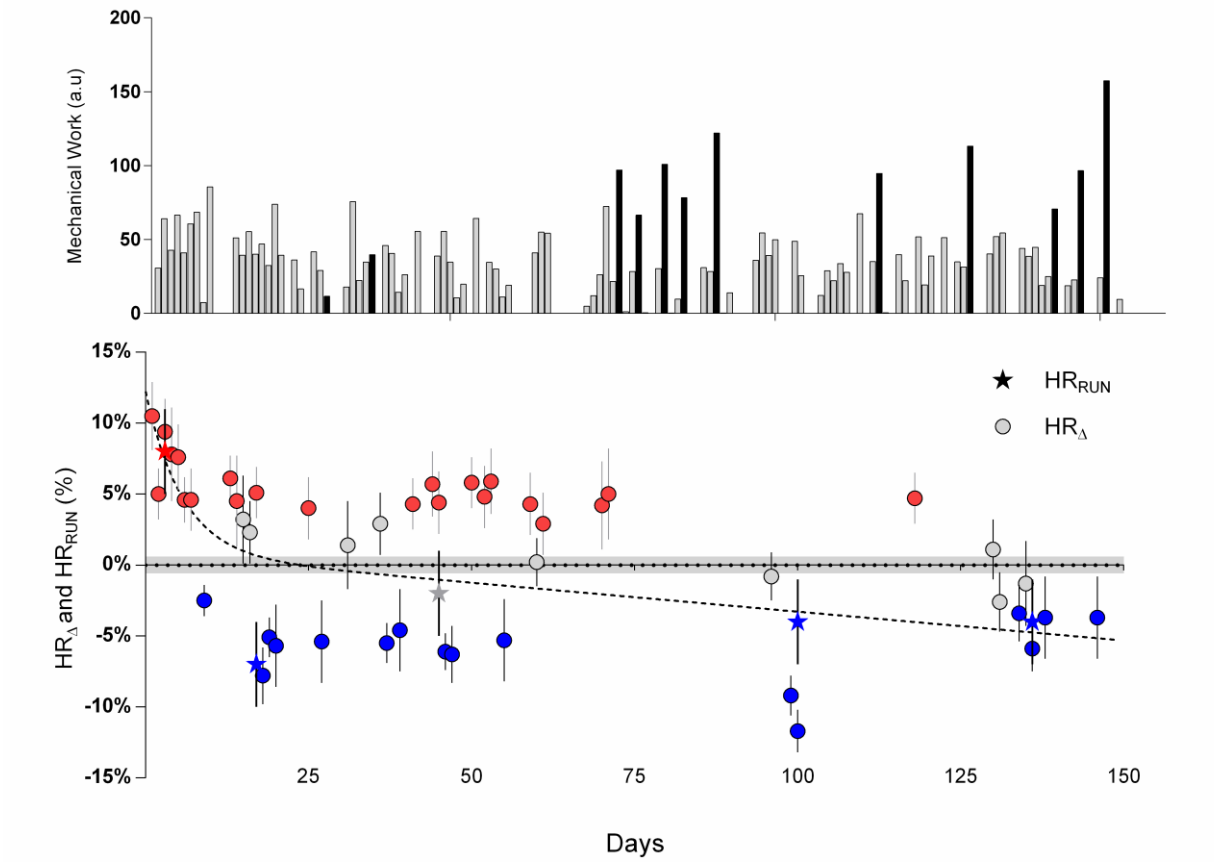

Figure 3: Changes in Mechanical Work (a.u, upper panel), HR_{Δ} and HR_{RUN} (lower panel) during pre-season and early in season in one representative elite soccer player. This player was chosen over the 9 others for different reasons, including the fact that he didn't suffer from any major injuries, which allowed to get some data continuously throughout the entire year.

Upper panel: grey bar: training session; black bar: match.

Lower panel: Red point:75% of substantial increase in HR_{Δ} and HR_{RUN}. Blue point:75% of substantial decrease in HR_{Δ} and HR_{RUN}. Grey point: unclear changes in HR_{Δ} and HR_{RUN}. Grey area stands for trivial changes. Each data point is provided with its typical error (when multiple small-sided games values were combined, the data points represent the mean and the typical error is adjusted for the number of measures (see methods).

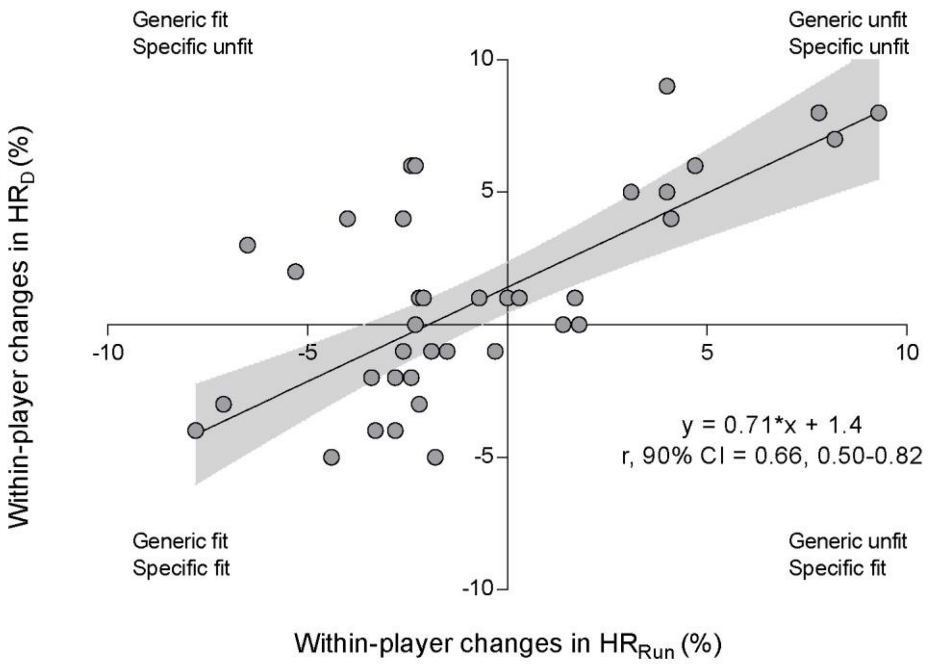

Figure 4: Relationship between within-player changes in HR_{Δ} and HR_{RUN} in elite soccer players.

HR_{RUN} : Heart rate during the last 1-min of the 4-min standardised submaximal running protocol. HR_{Δ}: difference between predicted HR from the GPS variables and the actual HR response. Y and X axes cut out the figure into 4 quadrans. Players in the upper-right quadran present both greater HR_{Δ} and HR_{RUN} values, suggesting that they lack both generic and specific fitness. In the bottom-left quadran, players present both lower HR_{Δ} and HR_{RUN} values, suggesting that these players gained both generic and specific fitness. Finally, some players in the upper-left quadran report greater HR_{Δ} values but lower HR_{RUN} values, suggestive of generic fitness but a lack of specific fitness. Note that there are no data point in the lower-right quadran, which would imply an unexpected (less probable) scenario: players unfit at the general level but showing specific fitness.

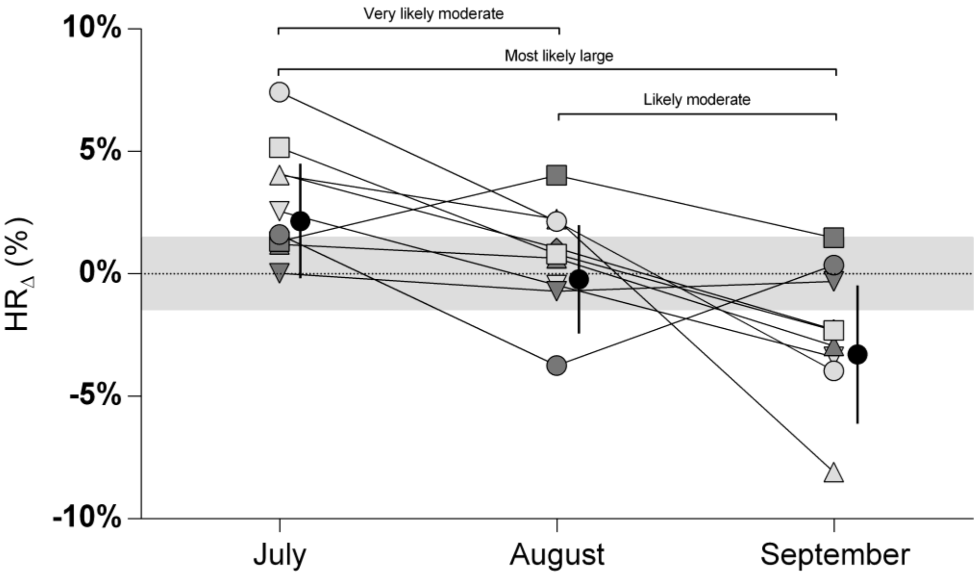

Figure 5: Between-month changes in the differences between actual and predicted heart-rate.

HR_{Δ}: difference between the HR predicted from the GPS variables and the actual HR. *Data points colors and shapes are set for each player.*