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Human Kinetics
ORIGINAL INVESTIGATION

Monitoring Players' Readiness Using Predicted Heart-Rate Responses to Soccer Drills

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Purpose: To examine the ability of multivariate models to predict the heart-rate (HR) responses to some specific training drills from various global positioning system (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 1 season (2016–17) with players' soccer activity recorded using 5-Hz GPS and internal load monitored using HR. GPS and HR data were analyzed during typical small-sided games and a 4-min standardized submaximal run (12 km·h^{-1}). A multiple stepwise regression analysis was used 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}). Then, HR predicted was 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 preseason). ***Results:*** HR_{PRED} was very largely correlated with HR_{ACT} ($r = .78$ [.04]). Within-player changes in HR_{Δ} were largely correlated with within-player changes in HR_{RUN} ($r = .66$, .50–.82). HR_{Δ} very likely decreased from July (3.1% [2.0%]) to August (0.8% [2.2%]) and most likely decreased further in September (−1.5% [2.1%]). ***Conclusions:*** 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.

Keywords: small-sided games, football, fitness monitoring, GPS

The monitoring of various training variables that may offer insight into players' training status is of major interest for most supporting staff in elite team sports. Currently, a large range of variables can be used to monitor both external and internal load, and in turn provide information on players' fitness, fatigue, and/or readiness to perform.[1] However, typical metrics such as distance covered in different speed zones or heart rate (HR)-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, regardless of the daily training context.

To overcome the limitations inherent in the use of those latter variables, examining the dose–response relationship between workload and immediate physiological responses (or more simply generic models of work efficiency, ie, 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 rating of perceived exertion [RPE]/m·min^{-1} during the first 2 d in Asia [fatigue], trend of −0.4 RPE/m·min^{-1} decreased from D1 to D8 [acclimatization phase]),[4] fitness changes following a 2-week preseason training period (changes in total distance [TD]/HR were largely correlated with the velocity at lactate threshold [$r = -.69$], 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 3 studies,[4–6] TD was used as the unique measure of external load. It is well known 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 (HS) running, acceleration counts, or mechanical load[2] in 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 perfect relationships were reported between external to internal load ratios and measures of fitness or load. However, since several non-training-related characteristics (eg, 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 (eg, TD, HS, mechanical work [MechW]) 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 this paper was to quantify the individual relationships (ie, multivariate models) between various field-based external load measures (ie, locomotor activity during small-sided games [SSG]) tracked with global positioning system (GPS) and an objective measure of internal load (ie, HR response to the same drills) in 10 elite soccer players. The second aim was to examine the ability of each individual model to predict the HR responses to[4–6] some specific training drills from various GPS variables. The third

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aim of this study was to examine the usefulness of the difference between predicted versus 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 an SSG is played during normal practice, removing the need for formal testing sessions.

Methods

Participants

Data were collected in 10 field players (26 [5] y; 182 [6] cm; 76 [5] kg; max HR: 198 [10] beats/min [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 for which they would request to stop training for more than 1 week. These data emerged 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] Nevertheless, the study conformed 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 1 season (2016–17), with player activity recorded using 5-Hz GPS and 100-Hz accelerometers (SPI-Pro, Team AMS R1 2016.8; GPSport, Canberra, Australia) and further analyzed using the Athletic Data Innovations analyzer (ADI; v5.4.1.514; Sydney, Australia)[2] to derive TD (m), HS 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 MechW (a.u.). Velocity load refers to the sum of distance covered weighted by the speed of displacement. fL refers to the sum of estimated ground reaction forces during all foot impacts assessed by the accelerometer-derived magnitude vector.[2] MechW is an overall measure of velocity changes and is computed using >2 ms^{-2} accelerations, decelerations, and changes of direction events.[12] On average, 9 (1) satellites were connected during each training session. Players consistently used the same unit to decrease measurement error.[13] HR was monitored using Polar H1 units (Polar Electro, Kempele, Finland) synchronized with GPS and further analyzed using the ADI analyzer to derive mean HR during each drill.

Heart rate and GPS data were analyzed during typical 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 goalkeepers) or possession drills; surface area: 117 (65) m^2 per player.[12] A standardized submaximal run (12 km·h^{-1} paced with an acoustic reference, over a 50 × 100-m rectangle course) was performed 4 (1) times throughout the preseason and early inseason. 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; Turf-Tec International, Tallahassee, FL) of 74 (4) (range: 70–82). Data were then normalized relative to the drill duration.

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

Within-player models were created using R statistical software (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 variable was calculated using the *calc.relimp* function from the relaimpo package (v2.2.-2). Predicted HR (HR_{PRED}) was subsequently calculated for each SSG 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, MN) as follows (Equation 1):

$$HR_{PRED}\ (\%) = HR_{PRED\ (unadjusted)} + 0.075 \times (\text{heat index} - \text{heat index}_{mean}) \quad (1)$$

with heat index$_{mean}$ standing for the mean heat index over the period of interest (season 16/17).[15] Here are 2 examples of individual models (Equations 2 and 3) aimed at predicting HR_{PRED}:

$$\text{P3:}\ HR_{PRED}\ (\%) = 51.52 + 1.47 \times fL + 0.44 \times VHS + 7.11 \times MechW + 0.075 \times (\text{heat index} - \text{heat index}_{mean}) \quad (2)$$

$$\text{P10:}\ HR_{PRED}\ (\%) = 49.18 - 0.41 \times TD + 3.50 \times vL + 3.65 \times fL + 7.31 \times MechW + 0.075 \times (\text{heat index} - \text{heat index}_{mean}) \quad (3)$$

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

$$HR_{\Delta}\ (\%) = HR_{ACT} - HR_{PRED} \quad (4)$$

It is worth mentioning that the training data set used to build individual models was the same data set used for HR prediction, possibly leading to overfitting. Nevertheless, we are confident in the results presented in this study since a comparison with similar models built using data from previous seasons (eg, season 2015–16).

Model validation: The validity of HR_{Δ} to predict players' fitness and readiness to perform was examined using 2 different approaches, that is, while examining its change (1) in comparison with an objective (criterion) measure of fitness (ie, HR responses to a submax run[14]) and (2) as a function of the different seasonal phases (preseason [July], early inseason [August], and inseason [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 Equation 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 2 games, representing our typical training microcycles.

Second, we examined changes in HR_{Δ} throughout the preseason. In fact, there is generally a progressive increase in fitness from preseason to early inseason, 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] Therefore, it was 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 (preseason) to August (end of preseason, start of the season) and September (early inseason). The average HR_{Δ} over each month was used to assess the between-month 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 this study. Rather, we were 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.[2] 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 and figures are presented as means with SDs and 90% confidence limits/intervals (CL/CI). The typical error of estimate 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): ≤.1, trivial; >.1 to .3, small; >.3 to .5, moderate; >.5 to .7, large; >.7 to .9, very large; and >.9 to 1.0, almost perfect. Between-month changes in the HR_{Δ} were examined using standardized differences, based on Cohen d effect size principle. The scale was as follows: 25% to 75%, possible; 75% to 95%, likely; 95% to 99%, very likely; and >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 with the smallest worthwhile difference (SWD), which was set as 0.2 of the typical error of estimate.[20] When monitoring individuals, longitudinal changes are generally considered substantial when the probability for change is ≥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%).

Results

The average typical error of estimate for the 10 individual multiple regression analyses was 2.9% (0.3%) as for all SDs. (range: 2.5%–3.5%) with HR_{PRED} being very largely correlated with HR_{ACT} (r = .78 [.04] [range: .74–.84]) (Figure 1).

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

Figure 3 presents the MechW performed during the preseason and early inseason (upper panel) and corresponding HR_{Δ} and HR_{RUN} (lower panel) in 1 elite soccer player. Overall, HR_{Δ} was substantially greater than 0 (ie, $HR_{ACT} > HR_{PRED}$) during the first 15 days of training (average HR_{Δ} over the 15 d: +5.2% [3.3%]), with a substantial trend for a decrease in HR_{Δ} throughout this period (from D1 to D15, –0.5 $HR_{\Delta}\cdot d^{-1}$. HR_{Δ}). In addition, HR_{Δ} was substantially lower than 0 (ie, $HR_{ACT} < HR_{PRED}$) 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}.

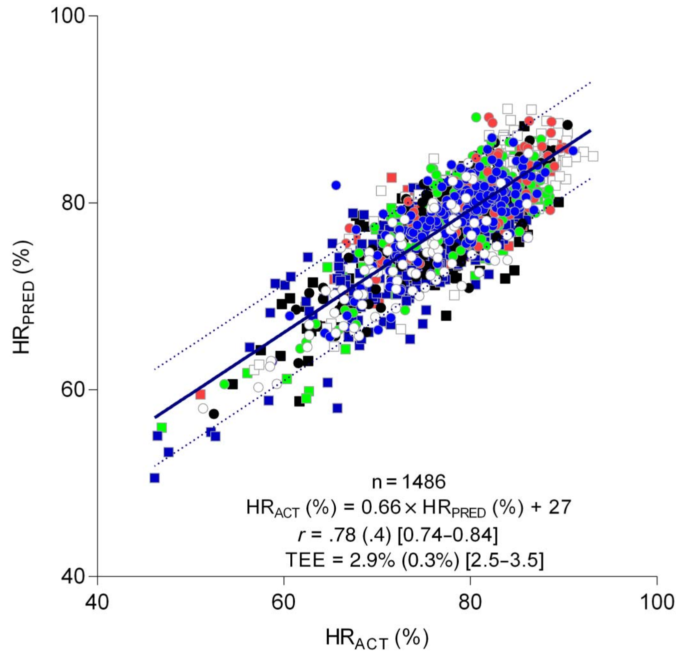

Figure 1 — Relationship between predicted HR from GPS data and actual HR. Data are presented as mean (SD) [range]. Solid and dashed lines: linear fit with 90% CI. Shades and shapes are set for each player. CI indicates confidence interval; GPS, global positioning system; HR, heart rate; HR_{ACT}, actual HR; HR_{PRED}, predicted HR; SEE, standard error of the estimate.

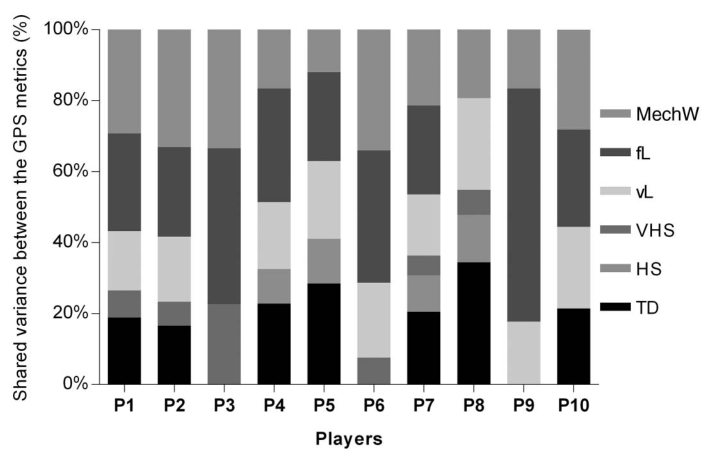

Figure 2 — Relative contribution of the GPS variables to HR responses during SSG (multiple regression analysis models for each individual player). fL indicates force load (a.u.$\cdot$min^{-1}); GPS, global positioning system; HR, heart rate; HS, distance >14.4 km$\cdot$h^{-1} (m$\cdot$min^{-1}); MechW, mechanical work (a.u.$\cdot$min^{-1}); P1 to P10, players 1 to 10; SSG, small-sided games; TD, total distance (m$\cdot$min^{-1}); VHS, distance >19.8 km$\cdot$h (m$\cdot$min^{-1}); vL, velocity load (a.u.$\cdot$min^{-1}).

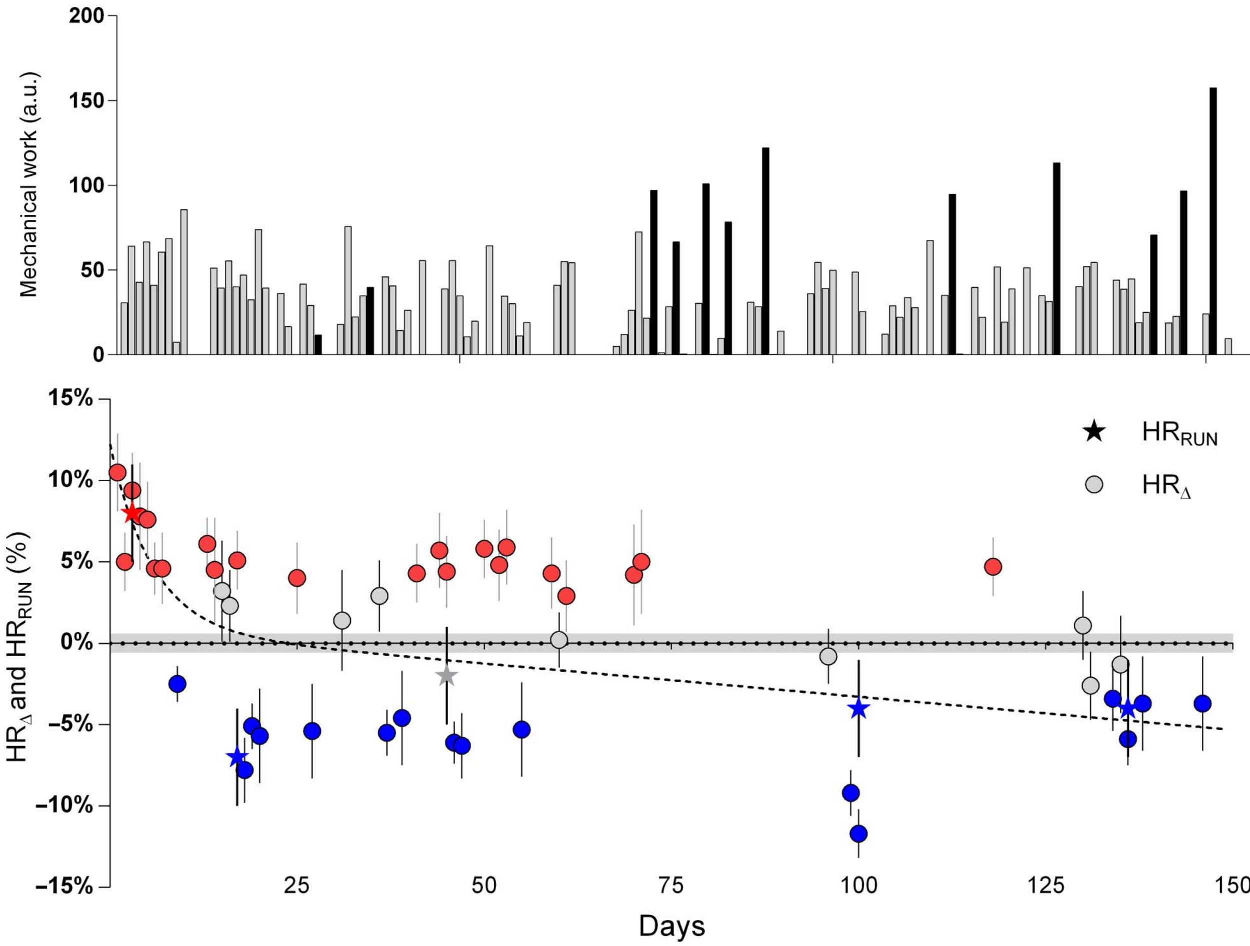

Figure 3 — Changes in MechW (a.u., upper panel), HR$_\Delta$, and HR$_{RUN}$ (lower panel) during preseason and early inseason in 1 representative elite soccer player. This player was chosen over the 9 others for different reasons, including the fact that he did not suffer from any major injuries, which allowed researchers to obtain data continuously throughout the entire year. Upper panel—gray bar, training session; black bar, match. Lower panel—dark gray circles/stars, 75% of substantial increase in HR$_\Delta$ and HR$_{RUN}$; black point, 75% of substantial decrease in HR$_\Delta$ and HR$_{RUN}$; light gray point, unclear changes in HR$_\Delta$ and HR$_{RUN}$. Gray area stands for trivial changes. Each data point is provided with its TE (when multiple SSGs values were combined, the data points represent the mean and the TE is adjusted for the number of measures [see Methods section]). HR indicates heart rate; HR$_{RUN}$, HR responses to a submaximal run; MechW, mechanical work; SSG, small-sided games; TE, typical error.

Within-player changes during HR$_\Delta$ were largely correlated with within-player changes during HR$_{RUN}$ (r, 90% CI = .66, .50–.82) (Figure 4).

HR$_\Delta$ very likely decreased from July (3.1% [2.0%]) to August (0.8% [2.2%]; ES = –0.99 [0.64]; 0/3/97) and most likely decreased further in September (–1.5% [2.1%]; –1.96 [0.95]; 0/0/100). HR$_\Delta$ likely decreased from August to September (0.8% [2.2%] vs –1.5% [2.1%], –0.98 [0.88], 2/5/95).

Discussion

The aim of this 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 (ie, HR$_\Delta$) could be used to predict players' fitness and readiness to perform. The key findings were the following: (1) HR responses during SSGs (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$_\Delta$ were largely correlated with those in HR$_{RUN}$ (Figure 4); and (3) HR$_\Delta$ decreased progressively from the preseason to early inseason (Figure 5).

Model Construction

Our results reported that the HRs predicted from GPS variables during SSGs were very largely correlated (r = .78 [.04]) with the HR responses actually measured (Figure 1). Furthermore, we observed that fL and MechW were the greatest predictors of HR responses (31% [17%] and 24% [8%], respectively), whereas TD- and HS-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 (Equation 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 (HS and TD) and HR,[23] the results of this study demonstrated that

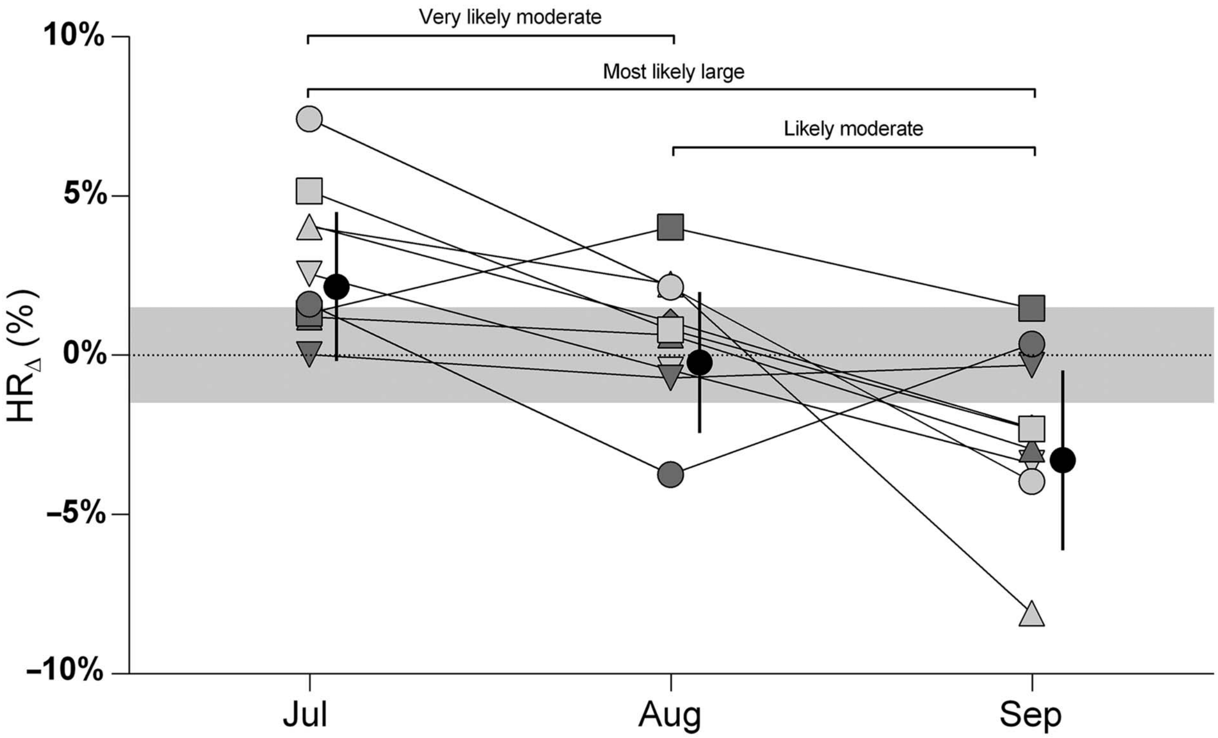

Figure 4 — Between-months changes in the differences between actual and predicted HR. GPS indicates global positioning system; HR, heart rate; HR_Δ, difference between the HR predicted from the GPS variables and the actual HR. Data point shades and shapes are set for each player.

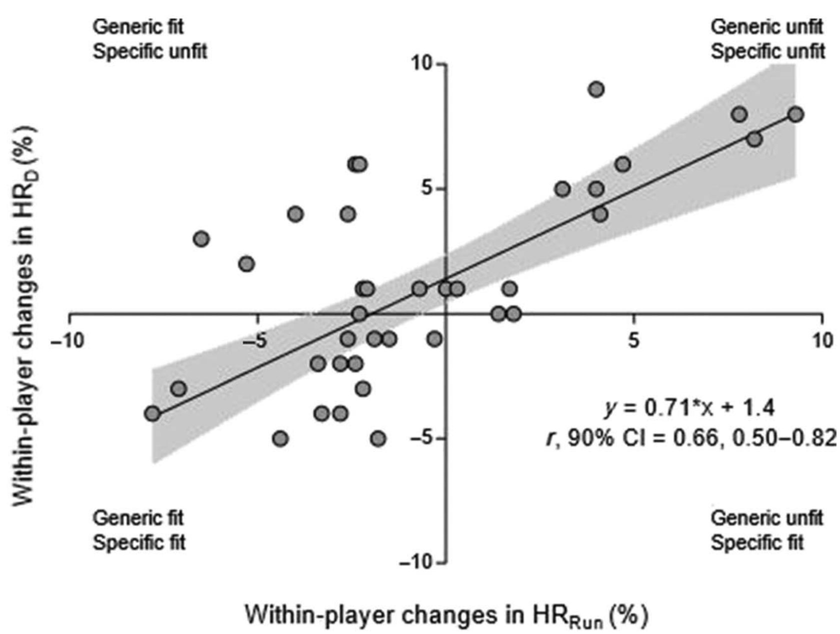

Figure 5 — Relationship between within-player changes in HR_Δ and HR_{RUN} in elite soccer players. HR_{RUN}: HR during the last minute of the 4-minute standardized submaximal running protocol. HR_Δ: difference between predicted HR from the GPS variables and the actual HR response. *y* and *x* axes cut the figure into 4 quadrants. Players in the upper right quadrant present both greater HR_Δ and HR_{RUN} values, suggesting that they lack both generic and specific fitness. In the bottom left quadrant, 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 quadrant 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 quadrant, which would imply an unexpected (less probable) scenario: players unfit at the general level but showing specific fitness. GPS indicates global positioning system; HR, heart rate; HR_{RUN}, HR responses to a submaximal run.

HR during soccer-specific training drills is more related to the mechanical demands of the task (acceleration, decelerations, and changes of direction). The results of this study confirmed the major importance of MechW and fL when estimating internal load[2] and the necessity of considering these 2 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-player variations in this relationship were reported in this study (Figure 2). Indeed, whereas 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}. By contrast, TD only accounted for 16% of the variance at the team level, whereas 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 internal load is related to external load. This result has several implications for training planning 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 response 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), whereas for others, this would be achieved through increases 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 matters, that is, that which can be assessed with a probability of at least 75% (SWD + TE[22]). In this 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. However, it is 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 and 4). Based on these data, we were able to easily assess changes in HR_Δ and HR_{RUN} during preseason and early inseason. In this case study, HR_Δ clearly decreased during the 15 first days of the preseason, likely reflecting the expected fitness improvement. In addition, it is noteworthy that changes in HR_Δ were concomitant with those in HR_{RUN}, except at 1 time point (ie, day 45) where the change in HR_{RUN} was unclear, whereas that in HR_Δ was clearly above 0. While data are lacking to explain this unique dissociation between the changes in HR_Δ and HR_{RUN}, acute change in hydration status and plasma/fluid shifts can sometimes cause large changes in HR from one day to another independent 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, $r = .66$ [.50–.82], Figure 4), confirming the potential of HR_Δ to inform practitioners on changes in player 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 a very good point. This suggests that HR_Δ may reflect something slightly different than HR_{RUN}. We believe that the 4 quadrants defined by the 2 axes in Figure 4 could be used to understand players' specific needs in terms of conditioning. It is generally believed that fitness (as many other physical capacities) can be regarded from 2 different angles: a general component mostly related to cardiopulmonary performance during generic types of exercise bouts (ie, straight-line running such as during the submaximal run), versus a soccer-specific fitness with a greater neuromuscular component that relates to the ability to perform and repeat specific types of locomotor actions such as repeated accelerations, decelerations, and changes of direction (as during SSGs).[26] Following these lines, and while still hypothetical given the low number of players examined and the limited time window analyzed (ie, 1 season), it could be hypothesized that whereas 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 preseason conditioning,[26] players generally transition from unfit (top right quadrant, both HR_Δ and HR_{RUN} greater than usual) to generally fit (mid preseason, top left quadrant, HR_{RUN} improved but not HR_Δ), before becoming specifically fit at the end of the preseason (bottom left quadrant, both HR_Δ and HR_{RUN} improved). Interestingly and in line with our proposal, it is noteworthy that there were no players reported in the bottom right-hand corner, suggesting that generic fitness is needed to build soccer-specific fitness. Analyzed 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 (eg, during early preseason or after an injury) versus more soccer-specific training (eg, high MechW tolerance, specific strength training, actions with the ball more generally inseason).

Changes in HR_Δ From the Preseason to Early Inseason

Interestingly, we also observed a progressive decrease in HR_Δ from July to August and then September (Figure 5). Since players' fitness generally increases from the preseason to early inseason (eg, moderate increases in Yo-Yo IR2 performance in elite soccer 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 preseason and early inseason, whereas 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, that is, every time an SSG is played (almost daily) and, most importantly, during normal practice (no formal testing needed).

Limitations

First, the present monitoring approach cannot be used with players with only limited historical data (eg, for new signings some time to build the models is needed [≥60 data points,[27] ~6–8 wk]). Second, players need to be compliant with wearing an HR belt during training, which is not always without complication. Third, erroneous HR is common during team sport training due to shocks and contacts, which can result in erroneous HR interpretations if care is not applied to correct each file, 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 (ie, for the same external work). HR may be higher during SSGs played 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 this study and has likely decreased the magnitude of the associations between GPS variable and HR responses. Nevertheless, we 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 may increase the strength of the relationships observed between GPS variables and HR responses. The models presented in this study may become more robust in the future with the use of more advanced technology.

Practical Applications

- MechW and fL are the greatest predictors of the HR responses to SSGs, highlighting the importance of considering these 2 GPS/accelerometers-derived variables when assessing load and planning training.
- HR_{Δ} computed from both external (GPS) and internal (HR) load variables can be used to track players' fitness through the preseason and early inseason. 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 ($0.5\ km{\cdot}h^{-1}$).[16]
- This approach allows monitoring on a daily basis during normal practice, eliminating the need for formal fitness testing.
- HR_{RUN} and HR_{Δ} can be used together to define players' conditioning needs (eg, generic vs soccer-specific fitness).

Conclusions

In this study, we have observed large and player-dependent associations between the HR responses to SSGs and some of the locomotor/mechanical demands of those SSGs as assessed using GPS and accelerometers. We then demonstrated that HR_{Δ} (ie, the difference between the predicted and actual HR responses to SSGs) can be confidently used to track changes in 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.

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