Assessing physiological adaptations of professional soccer players using heart rate monitoring and data science

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Résumé

Professional soccer players face high physical demands across a season (Barnes et al., 2014). To ensure players' health (i.e., optimize physical performance and reduce injury risk), practitioners have developed monitoring strategies relying on external and/or internal indicators (Impellizeri et al., 2019). However, internal indicators have been neglected in favour of external indicators with the settlement of monitoring tools such as global positioning system units (GPS). Although the misuse of many internal indicators might be due to a technology not in adequacy with the environment of football, heart rate (HR), a surrogate measure of cardiorespiratory system, has raised some interest to monitor dose and response of training (Bellenger et al., 2016). Yet, there are several operational, technological and theoretical limitations hindering their daily use with elite athletes (Carling et al., 2018). To overcome these issues, recent sport science literature has shown interest in using machine learning models (Elstak et al., 2024) to create unobtrusive indicators, thus increasing the frequency of measurement alongside traditional metrics. A series of works were carried out with the aim of assessing physiological adaptations of professional soccer players using HR monitoring and data science. During multiple seasons, players' fitness was tracked using an indicator based on the difference between predicted and measured HR during specific football drills (ΔHR) (Diouron et al., 2025) as well as indicators regarding HR kinetics (i.e., acceleration and recovery of HR, Bellenger et al., 2016) and their difference with their predicted value to have a complete overview the player's cardiovascular system status.

Data were collected between July 2022 and May 2025, covering 3 soccer seasons, on 40 professional soccer players in France. Player's activity and HR were recorded using a 10 Hz GPS unit linked with a designed 1 Hz HR vest during training and game sessions. Individual predictive models of HR responses and HR kinetics were built using traditional machine learning methods (e.g., Random Forest, eXtreme Gradient Boosting, Kernal Ridge) and more recent deep learning models. HR prediction models were trained on a dataset that containing drills' external load data, hourly weather data, Borg CR-10 scale scores and cumulative load. Robustness of models was assessed through a resampling procedure, and hyperparameters were tuned using a grid search cross-validation method (CV=5). Root mean squared error, absolute and relative mean absolute error (MAE) and coefficient of determination were used to assess the prediction performance of the models. HR kinetics prediction models were built

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sciencesconf.org:acaps2025:649175

using raw data of players' activity (i.e., time series) and followed the same validation protocol as ΔHR. On the first season, a significant difference in ΔHR between months was found ($\chi^2 = 20$, $P < .05$). The face validity of ΔHR has been shown using the variation in the training load during a preseason. During the second season, preliminary results show better performance concerning HR prediction performance on the second season (MAE = 4.82). Additionally, preliminary results of HR kinetics predictive models showed good performance (i.e., < 3bpm) over short prediction windows (i.e.,

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