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Influence of Prematch Perceived Wellness on High-Intensity Locomotor Activities of Professional Soccer Players During in-Season Matches

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Purpose: The aim of this study was to determine the influence of prematch perceived wellness on high-intensity locomotor activities of professional soccer players during in-season matches. ***Methods:*** Twenty male soccer players (26.74 [3.27] y; 179.77 [6.06] cm; 76.72 [9.33] kg), members of a professional soccer team, participated in this longitudinal study. Data collection was conducted during the competitive period of 1 season and involved the 34 league official matches. Perceived wellness was assessed individually 3 hours before each match using a 5-point Likert questionnaire, and external loads during matches were monitored using global navigation satellite system devices. Each wellness item (ie, fatigue, delayed-onset muscle soreness [DOMS], sleep, and stress) was considered as an individual wellness component and analyzed as raw score, team z score, and individualized z score. Different random forest regression models and linear mixed models were carried out for statistical analysis. ***Results:*** Individualized z scores should be considered the most important variables to estimate the proportion of external-load variation during match play, but the proportion of the variance that may be explained from the prematch perceived wellness suggests a limited capacity in relation to external-load measures. Only individualized z scores of DOMS showed significant effects on sprint running distance (>24.0 $km \cdot h^{-1}$) and number of sprints (>24.0 $km \cdot h^{-1}$) during matches ($P < .05$). ***Conclusions:*** Sprint performance of professional soccer players during in-season matches may be slightly influenced by the players' day-to-day variation of prematch perceived DOMS.

Keywords: delayed-onset muscle soreness, external load, sprint

Training load represents the input variable that is manipulated to elicit the desired training response and can be described as either external or internal.[1] External load refers to the physical work prescribed in the training plan, and internal load incorporates all the psychophysiological responses occurring during the exercise.[1] Irrespective of how it is quantified, training load monitoring allows coaches and performance staff to analyze whether an athlete is correctly adapting to the training program, or showing signs of fatigue that could increase the risk of nonfunctional overreaching, injury, and illness.[2] Particularly, some psychometric tools such as perceived wellness questionnaires are considered one of the most relevant monitoring tools among sport practitioners,[2] and their application is now common place within team sport environments. These questionnaires may help to obtain information related to a player's health, wellness status, and overall readiness to train or compete.[3] Additionally, these tools not only have the advantages of being noninvasive, inexpensive, time-efficient, and relatively simple to administer,[2,3] they are also sensitive to daily, weekly, and seasonal fluctuations in training load.[4,5]

There is a growing body of evidence suggesting that a reduction in perceived wellness may have an effect on the subsequent external load during training sessions in both elite and amateur male soccer players.[6,7] Malone et al[6] observed a relationship between reduction in players' pretraining perceived wellness (1 individualized z score below their normal) and decreased high-speed distance, sprint distance, maximal velocity, and number of maximal velocity efforts during the training session later that day. Clemente[7] showed that pretraining wellness status is moderately to largely correlated to external loads during small-sided games; in particular, greater delayed-onset muscle soreness (DOMS) may be moderately to largely detrimental to total, jogging, and sprinting distances. In contrast, nonsignificant effects were detected in collegiate female soccer players throughout all training sessions of a competitive season.[8] Still, it remains questionable whether soccer players adjust their running and movement intensity during match-play as they do in training in response to changes in matchday (MD) perceived wellness.

A limited number of studies have explored whether changes in MD perceived wellness exert influence on subsequent running performance during team sport matches,[9–11] with minimal focus on soccer.[12] Ihsan et al[9] reported that, when normalized to game-playing time, changes in prematch overall wellness (ie, summatory of the scores assigned to perceived fatigue, DOMS, mood state, and sleep quality) were largely correlated with variations in total distance covered over the course of a field hockey tournament consisting of 6 matches played over 9 days. However, these authors showed nonsignificant correlation magnitudes for low- and high-speed running, and for number of high-intensity accelerations, and decelerations. These findings were supported by Bellinger et al[10] who revealed trivial and nonsignificant effects of prematch individualized z score, as well as all individual wellness items (ie, mood, energy, stress, leg heaviness, DOMS, sleep quality, and hours slept), on subsequent external load metrics during Australian

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football match-play. Results obtained in HSBC World Rugby Women's Seven Series matches confirmed that external loads were not influenced by prematch perceived wellness when considered separately (ie, perceived fatigue, sleep quality, DOMS, stress, and mood) or summed as overall wellness.[11] In contrast, recent findings indicate that prematch stress, fatigue, and DOMS may impact total, high-speed running, and very high-speed running distances during match-play in youth female soccer players.[12] Given these disparate findings encountered in the literature, further research is needed to draw robust conclusions on this topic. Thus, the aim of this study was to determine the influence of prematch perceived wellness on high-intensity locomotor activities of professional soccer players during in-season matches. This exploratory research could provide insights about whether MD perceived wellness may have an effect on the soccer players' high-intensity actions during official competitive situations.

Methods

Participants

Twenty male soccer players (26.74 [3.27] y; 179.77 [6.06] cm; 76.72 [9.33] kg) of a professional soccer team participated in this study. All players met the following inclusion criteria: they trained 5 times a week (~90 min each training session), were involved in an official match every weekend, and did not present any medical conditions, or acute injuries during the data collection days (ie, MD). Goalkeepers were excluded from the study because their locomotor demands during matches were completely different from outfield players.

This study was carried out in accordance with the Declaration of Helsinki (2013) and approved by the ethics committee of Area Salud Valladolid Este (PI 22-2908). All participants volunteered to participate in the study and were informed of the objectives, procedures, benefits, and risks involved with participation in the study before providing written informed consent.

Design

This longitudinal study was conducted in nonexperimental conditions. Data collection was conducted during the competitive period of 1 complete season and involved the 34 league official matches. To provide ecological validity during the data collection period, the team's coaching and performance staff freely decided their starting line-ups and substitutions during matches without any intervention from the research staff. Wellness scores and external load measurements of each participant were retrospectively included in the statistical analysis only if the participant met the following inclusion criteria: The participant was selected for the starting line-up, and the game-playing time was at least 45 minutes ($n = 294$ individual player observations).

Wellness Monitoring

A 5-point Likert questionnaire (scores 1–5) was administered to assess a player's perceived fatigue, DOMS, sleep quality, and stress. Similarly, a 1 to 5 Likert scale has been previously used to examine self-reported wellness with soccer players.[13] In the current study, 1 indicated "very very high" (fatigue, DOMS, and stress) or "very very bad" (sleep quality) and 5 indicated "very very low" (fatigue, DOMS, and stress) or "very very good" (sleep quality). The questionnaire did not incorporate any color, icon, or "emoji," which affects the psychometric properties of self-report measures and may result in differing player responses. The questionnaire was administered individually 3 hours before each match using a cloud-based software (Google Docs). The use of technology has been suggested as beneficial with the implementation of self-reported questionnaires.[3] Thus, this method was proposed to minimize factors that may influence player's wellness rating, such as peer pressure, and replicating other player's scores. In instances where a participant failed to submit their wellness data through this platform, the team's performance staff reminded them of their obligation. Participants were familiarized with the psychometric tool, as it was daily completed as part of their normal team monitoring routine.

Considering that using a cumulative wellness score might restrict the ability to identify specific influences of individual wellness components on different external load variables,[9] each wellness item (ie, fatigue, DOMS, sleep, and stress) was considered as an individual wellness component. Each one was analyzed as raw scores (arbitrary units; au), team z scores (au), and individualized z scores (au). A z score is the number of SD the response is above or below the mean of the distribution. To calculate the team z score of any wellness item, the team's average score was subtracted from the player's score, then this value was divided by the team's SD, so the equation reads as follows[14]: (player's score − team's mean)/team's SD. Similarly, individualized z scores were calculated using the following formula[6,10]: (player's score − player's mean)/player's SD.

External-Load Monitoring

External load during matches was monitored with electronic performance devices and tracking systems, in this case using global navigation satellite system technology (Yoomedoo Sports Tracker). The sampling frequency for positioning data was 10 Hz. Each player was fitted with a device on the upper back using a purpose-built harness, and the device was turned on 15 minutes before the warm-up prior to matches in accordance with manufacturer's recommendations. Time-motion parameters were analyzed as follows: total distance covered (TD, meters), very high-speed running distance (VHSRD, >21.0 $km \cdot h^{-1}$, meters), sprint running distance (SPD, >24.0 $km \cdot h^{-1}$, meters), very high-speed running efforts (>21.0 $km \cdot h^{-1}$, number), sprints (SP, >24.0 $km \cdot h^{-1}$, number), average speed (V_{mean}, $km \cdot h^{-1}$), maximum speed ($km \cdot h^{-1}$), very high-intensity accelerations (VHIAcc, >4 $m \cdot s^{-2}$, number), high-intensity accelerations (>3 $m \cdot s^{-2}$, number), high-intensity decelerations (<−3 $m \cdot s^{-2}$, number), and very high-intensity decelerations (< −4 $m \cdot s^{-2}$, number). Following each match, data were downloaded using proprietary software (Analyse FieldWiz, Advanced Sport Instruments). Time of standardized warm-up preceding each match and the between-halves rest times were removed prior to analysis. External loads were reported in raw values without accounting for discrepancies in player' game-playing time.

Statistical Analyses

Data analysis was conducted using the JASP 0.16.3.0 software (University of Amsterdam). Descriptive statistics of the wellness scores and external loads are presented as mean (SD). A descriptive analysis of data normality (ie, Shapiro–Wilk test) and homogeneity of variances (ie, Levene test) were completed first.

Because the presence of nonparametric data and given the greater accuracy and reduced propensity for overfitting when compared with the conventional classification and regression tree modeling,[15–17] different random forest regression models were created to quantify the importance of prematch perceived wellness items on external loads variation. One model was created for each outcome of interest (ie, each external load metric), and all models included raw scores, team z scores, and individualized z scores of each wellness item (ie, fatigue, DOMS, sleep, and stress) as predictor variables. Consistent with modeling using machine learning approaches, the data set was split into training and testing sets (80% and 20% of the data, respectively). Each model was optimized with respect the out-of-bag error. Coefficient of determination (R^2), mean squared error (MSE), root MSE (RMSE), and mean absolute error (MAE) were used to evaluate the prediction error rates and model performance in the regression analysis. Final selected models had the highest R^2 (R^2 is upper-bounded by the value 1, attained for perfect fit, while the value 0 corresponds to a trivial fit) and lowest MSE, RMSE, and MAE (a lower limit 0 in MSE, RMSE, and MAE implies a perfect fit, and values progressively and infinitely growing for worse performing models).[18] Considering that MSE, RMSE, and MAE values alone may fail to indicate the quality of the performance of a regression method, both on good and bad cases,[18] the percentage of the variance in the dependent variable (ie, each external load metric) that is determined collectively by the independent variables (ie, raw scores, team z scores, and individualized z scores of each wellness item) was carried out based on R^2. R^2 was interpreted according to the following thresholds[19]: very weak (<.3), weak or low (.3–.5), moderate (.5–.7), and strong (>.7). Finally, the variable importance of the random forest regression models was evaluated using the Mean Decrease in Accuracy (MDA), which quantifies the decrease of accuracy when a given input variable is permuted.[15] A variable is identified as important if it has a positive effect on the prediction performance, estimated by the out-of-bag error.[15] Concretely, the larger the MDA of each wellness item, the more relevant the variable was for the overall prediction accuracy of external loads during matches. The MDA helped to detect which variables are important and ranked them to focus on the most relevant for further exploration.

Afterward, several linear mixed models were created to determine the influence of the most important wellness items on externals loads. This statistical method was selected after checking that residuals of the linear mixed models did not violate the assumption of normality. Linear mixed models incorporated individualized z scores of each wellness item (ie, fatigue, DOMS, sleep, and stress) as fixed factors and player identity as the random factor. The Akaike information criterion was used for evaluating how well the linear mixed models fit the data they were created from. After fitting the linear mixed models, significant main effects were observed at $P < .05$.

Results

Table 1 shows the descriptive results (M [SD]) of prematch perceived fatigue, DOMS, sleep quality, and stress, which are reported as raw scores, team z scores, and individualized z scores. Participants' game-playing time was 86.109 (14.967) minutes. External loads encountered by the players during match play are also described in Table 1.

The evaluation metrics of the random forest regression models are presented in Table 2. Models' accuracy depended on the outcome of interest (ie, each external load metric). The highest percentage of variation explained by prematch perceived wellness was attained in SP ($R^2 = 54.2\%$; moderate). The percentage of the variance in V_{mean},

Table 1 Descriptive Statistics of the Wellness Scores and External-Load Measurements

Variable	Mean (SD)
Fatigue, au	3.820 (0.402)
Fatigue team z score, au	–0.025 (0.974)
Fatigue individualized z score, au	–0.010 (0.980)
DOMS, au	4.218 (0.656)
DOMS team z score, au	–0.001 (0.990)
DOMS individualized z score, au	–0.026 (0.987)
Sleep, au	4.054 (0.315)
Sleep team z score, au	0.003 (1.026)
Sleep individualized z score, au	0.004 (0.992)
Stress, au	3.857 (0.379)
Stress team z score, au	–0.012 (0.966)
Stress individualized z score, au	–0.024 (0.943)
Total distance covered, m	9022.857 (1570.414)
VHSRD (>21.0 km·h^{-1}), m	331.803 (148.670)
Sprint running distance (>24.0 km·h^{-1}), m	130.034 (81.958)
VHSRE (>21.0 km·h^{-1}), n	26.276 (10.060)
Sprints (>24.0 km·h^{-1}), n	10.133 (5.589)
Mean speed, km·h^{-1}	6.146 (0.745)
Maximum speed, km·h^{-1}	29.184 (2.036)
VHIAcc, >4 m·s^{-2}), n	5.813 (3.965)
HIAcc (>3 m·s^{-2}), n	36.653 (11.782)
HIDec (<–3 m·s^{-2}), n	36.633 (10.052)
VHIDec (<–4 m·s^{-2}), n	12.850 (5.714)

Abbreviations: au, arbitrary units; DOMS, delayed-onset muscle soreness; HIAcc, high-intensity accelerations; HIDec, high-intensity decelerations; VHIAcc, very high-intensity accelerations; VHIDec, very high-intensity decelerations; VHSRD, very high-speed running distance; VHSRE, very high-speed running efforts.

Table 2 Evaluation Metrics of the Random Forest Regression Models

Variable	OOB	MSE	RMSE	MAE	R^2
Total distance covered, m	1.146	0.780	0.883	0.695	.113
VHSRD (>21.0 km·h^{-1}), m	0.739	0.582	0.763	0.601	.467
SPD (>24.0 km·h^{-1}), m	0.748	0.714	0.845	0.713	.374
VHSRE (>21.0 km·h^{-1}), n	0.628	0.723	0.850	0.654	.276
Sprints (>24.0 km·h^{-1}), n	0.843	0.636	0.797	0.605	.542
Mean speed, km·h^{-1}	0.619	0.564	0.751	0.590	.491
Maximum speed, km·h^{-1}	0.901	0.978	0.989	0.825	.132
VHIAcc, >4 m·s^{-2}), n	0.620	0.552	0.743	0.601	.316
HIAcc (>3 m·s^{-2}), n	0.806	0.716	0.846	0.640	.181
HIDec (<–3 m·s^{-2}), n	0.727	1.046	1.023	0.849	.293
VHIDec (<–4 m·s^{-2}), n	0.919	0.527	0.726	0.587	.182

Abbreviations: HIAcc, high-intensity accelerations; HIDec, high-intensity decelerations; MAE, mean absolute error; MSE, mean squared error; OOB, out-of-bag error; RMSE, root-mean-squared error; R^2, coefficient of determination; SPD, sprint running distance; VHIAcc, very high-intensity accelerations; VHIDec, very high-intensity decelerations; VHSRD, very high-speed running distance; VHSRE, very high-speed running efforts.

VHSRD, SPD, and VHIAcc attributable to the wellness items were low ($R^2 = 49.1\%$, $R^2 = 46.7\%$, $R^2 = 37.4\%$, and $R^2 = 31.6\%$, respectively). The percentage of variation of the rest external loads showed that prematch perceived wellness had a very weak effect, being the total distance covered of the external load metric with the lowest variance explained among those calculated ($R^2 = 11.3\%$).

Figure 1 shows MDA plots of the random forest regression models, and each MDA plot expresses how much accuracy the model losses by excluding each input variable. Overall, individualized *z* scores of each wellness item were found to have higher MDA scores than raw scores and team *z* scores. As variables with highest MDA scores were the most important variables and the other variables follow in order of importance, individualized *z* scores should be considered the most important variables to estimate the proportion of external loads variance.

Table 3 displays the linear mixed models results for the effect of the individualized *z* scores of each wellness item (ie, fatigue, DOMS, sleep, and stress) on external loads. Only individualized *z* scores of DOMS showed significant effects on SPD and SP during matches ($P < .05$).

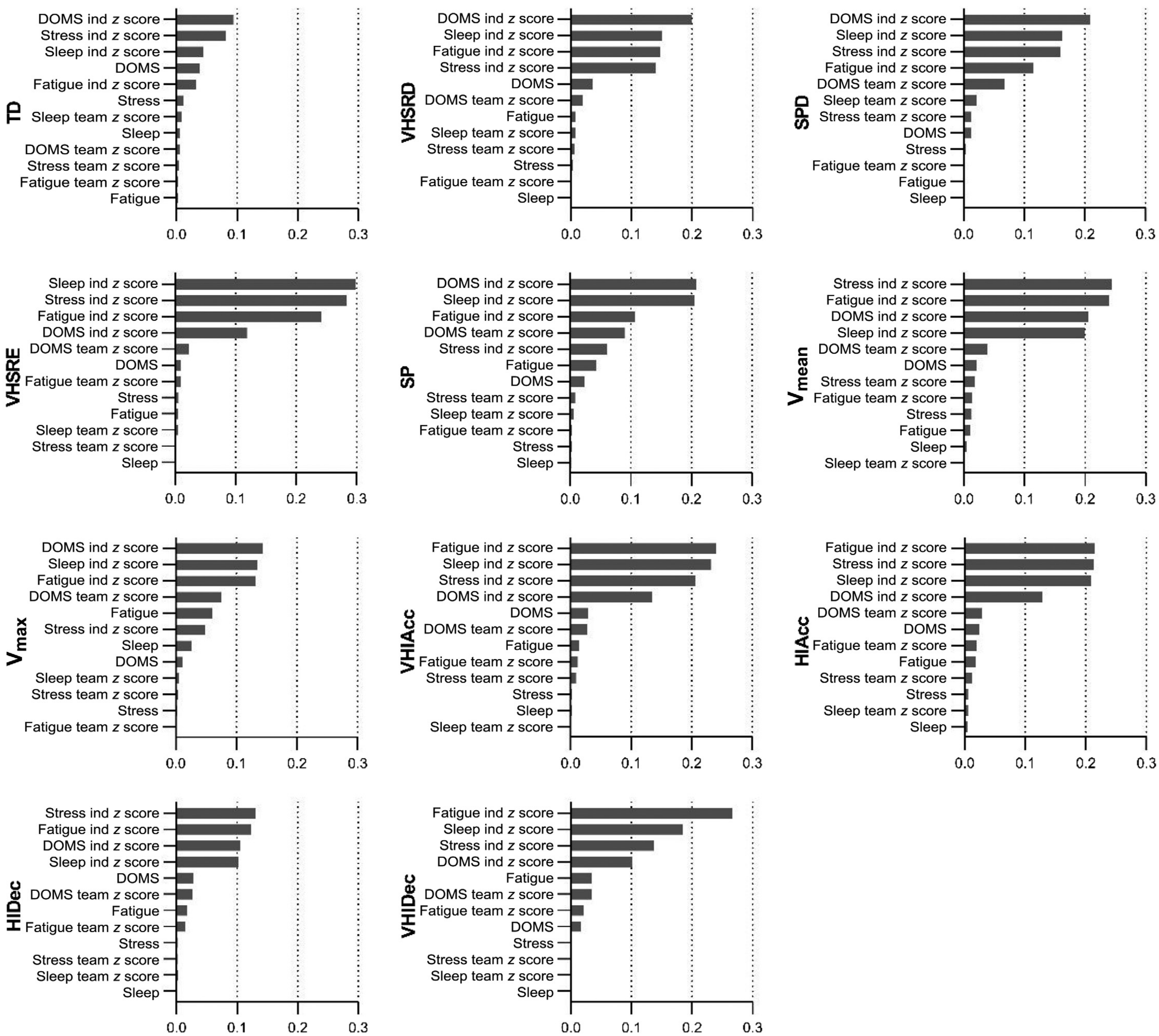

Figure 1 — MDA plots of the random forest regression models showing, in ascending order of importance, the variables with importance to influence each external-load metric. The *x*-axis represents the MDA scores. DOMS indicates delayed-onset muscle soreness; HIAcc, high-intensity accelerations; HIDec, high-intensity decelerations; MDA, mean decrease in accuracy; SP, sprints; SPD, sprint running distance; TD, total distance covered; VHIAcc, very high-intensity accelerations; VHIDec, very high-intensity decelerations; VHSRD, very high-speed running distance; VHSRE, very high-speed running efforts; V_{max}, maximum speed; V_{mean}, average speed.

Table 3 Results of the Linear Mixed Models, Including the Main Effects of the Individualized *z* Scores on External Loads

Variable	F	Estimate	SE	P	AIC
TD, m					5127.927
Fatigue	0.111	44.419	133.554	.744	
DOMS	0.003	−6.320	112.751	.956	
Sleep	0.286	−56.834	106.326	.600	
Stress	0.593	90.954	118.096	.459	
VHSRD (>21.0 km·h^{-1}), m					3643.405
Fatigue	0.354	−5.131	8.623	.562	
DOMS	3.327	14.037	7.696	.077	
Sleep	0.028	−1.119	6.632	.868	
Stress	0.024	−1.237	8.012	.881	
SPD (>24.0 km·h^{-1}), m					336.828
Fatigue	0.139	−1.839	4.925	.711	
DOMS	5.342	10.169	4.400	.024*	
Sleep	0.304	−2.169	3.829	.584	
Stress	0.018	−0.593	4.479	.896	
VHSRE (>21.0 km·h^{-1}), n					2079.943
Fatigue	0.547	−0.492	0.665	.470	
DOMS	2.278	0.827	0.548	.601	
Sleep	0.291	0.307	0.569	.142	
Stress	0.203	−0.224	0.497	.656	
SP (>24.0 km·h^{-1}), n					527.638
Fatigue	0.108	−0.130	0.395	.746	
DOMS	4.886	0.624	0.282	.029*	
Sleep	0.307	−0.167	0.301	.587	
Stress	0.048	−0.074	0.338	.831	
V_{mean}, km·h^{-1}					751.548
Fatigue	0.008	−0.004	0.038	.928	
DOMS	0.184	0.020	0.047	.672	
Sleep	1.581	0.054	0.043	.233	
Stress	0.803	−0.038	0.042	.392	
V_{max}, km·h^{-1}					1265.404
Fatigue	0.112	−0.042	0.126	.739	
DOMS	3.239	0.222	0.123	.073	
Sleep	0.323	0.060	0.106	.571	
Stress	0.364	−0.081	0.135	.557	
VHIAcc (>4 m·s^{-2}), n					1509.827
Fatigue	0.543	0.203	0.276	.469	
DOMS	0.432	0.179	0.272	.517	
Sleep	0.075	−0.051	0.187	.787	
Stress	1.108	−0.200	0.198	.319	
HIAcc (>3 m·s^{-2}), n					2214.164
Fatigue	0.055	−0.165	0.708	.817	
DOMS	0.526	0.529	0.730	.482	
Sleep	0.088	−0.164	0.552	.770	
Stress	0.451	0.411	0.612	.509	
HIDe (<−3 m·s^{-2}), n					2146.887
Fatigue	0.026	−0.127	0.791	.875	
DOMS	0.094	0.219	0.713	.763	
Sleep	0.002	−0.042	0.867	.963	
Stress	1.969	0.920	0.655	.178	
VHIDec (<−4 m·s^{-2}), n					1814.279
Fatigue	2.932	−0.625	0.365	.103	
DOMS	0.177	−0.141	0.334	.676	
Sleep	0.525	0.213	0.294	.479	
Stress	0.099	−0.100	0.319	.757	

(continued)

Abbreviations: AIC, Akaike information criterion; DOMS, delayed-onset muscle soreness; HIAcc, high-intensity accelerations; HIDec, high-intensity decelerations; Ind *z*, individualized *z* score; SE, standard error; SP, sprints; SPD, sprint running distance; TD, total distance covered; VHIAcc, very high-intensity accelerations; VHIDec, very high-intensity decelerations; VHSRD, very high-speed running distance; VHSRE, very high-speed running efforts; V_{max}, maximum speed; V_{mean}, average speed.
*Statistically significant ($P < .05$).

Discussion

The aim of this study was to determine the influence of prematch perceived wellness on high-intensity locomotor activities of professional soccer players during in-season matches. The main finding shows that sprint performance of professional soccer players during in-season matches may be slightly influenced by the players' day-to-day variation of prematch perceived DOMS. However, the practical significance of this finding should be interpreted with caution given the amount of variance in high-intensity locomotor activities accounted by the models.

The use of machine learning techniques, such as random forest regression, could be especially interesting to help understand why soccer players vary their running performance between matches. Random forests were formally developed by Breiman,[15] as a classification and regression ensemble learning method and emerged as an efficient algorithm capable of handling high-dimensional data. They can incorporate nonlinear effects and are superior to alternate methods at modeling complex interactions when the interactions are not, or cannot be, prespecified.[16] Despite the fact that MSE, RMSE, and MAE are commonly used in machine learning studies, it has been argued that it is impossible to detect the quality of the performance of a regression method by just looking at their singular values.[18] In this regard, the highest percentage of variation explained by prematch perceived wellness was attained in SP ($R^2 = 54.2\%$), followed by V_{mean}, VHSRD, SPD, and VHIAcc ($R^2 = 49.1\%$, $R^2 = 46.7\%$, $R^2 = 37.4\%$, and $R^2 = 31.6\%$, respectively). This indicates that variations in SP, V_{mean}, VHSRD, SPD, and VHIAcc during official matches seem to be weakly-to-moderately influenced by changes in MD perceived wellness. Previous reviews with a large number of observations also showed predominantly trivial to moderate relationships between MD perceived wellness and running performance during team sport matches.[20,21]

Besides improved accuracy, a key advantage of random forests over alternative machine learning algorithms are variable importance measures.[15,22] In this regard, the current results indicate that individualized *z* scores should be considered the most important variables to estimate the proportion of external loads variance during matches. This interesting finding reinforce the importance of consider wellness responses in the context of the typical day-to-day variation for each player. It should be understood that wellness data is not standardized between individuals.[3] Some players may regularly report within a very narrow range of scores, while others may vary substantially. Furthermore, the value a player considers as their normal may be the midpoint on the scale or at the lower, or, upper end of the scale, so equivalent scores may not indicate equivalent levels of fatigue, DOMS, sleep quality, or stress. This explain why the interpretation of wellness scores needs to take into account the individual's reporting habits.[23] Therefore and according to previous suggestions,[10,23] the use of individualized *z* scores is strongly recommended to analyze the possible impact of prematch perceived wellness on high-intensity locomotor activities during subsequent soccer matches. It is important to consider this finding in relation to the practicality of utilizing the self-report wellness measures throughout an entire training microcycle, as individualized *z* scores may account for individual variations in perceived wellness during a typical training microcycle, which appear to have an influence on subsequent competition running performance of players.[24]

The current results indicate that only individualized *z* scores of DOMS showed significant effects on SPD and SP during matches. Although the exacty underlying mechanisms needs to be elucidated, this finding could be, cautiously, justified by the metabolic stress and mechanical and neural alterations related to exercise-induced muscle damage experienced by players in the previous training days. Exercise-induced muscle damage is a condition characterized by transient ultrastructural myofibrillar disruption, loss of muscle strength and power, DOMS, swelling, reduced range of motion, and systemic efflux of myocellular enzymes and proteins.[25,26] Concretely, DOMS becomes manifest when the injured non-nociceptive sensory fibers of the muscle spindle stop inhibiting the effects of the injured, hyperexcited nociceptive sensory fibers.[27] This neural microdamage is particularly related to sprinting performance, as maximal intensity sprint exercise necessitates extremely high levels of neural activation,[28] and DOMS may explain reductions in voluntary activation.[29] However, recovery time courses of DOMS and other physiological load-adaptation pathways (ie, cardiocirculatory, metabolic, neuromuscular, and central) most likely differ,[30] so other mechanisms may also explain the current finding. In this regard, soccer match-related variations in high-intensity locomotor activities could be attributed to changes in physiological milieu but also to psychological factors, pacing strategies, contextual factors, or a combination of mutually inclusive factors.[31,32] While the match location, result of the previous match, and the quality of the upcoming opposition do not influence perceived wellness on the morning before a soccer match,[13] it is widely demonstrated that contextual factors are associated with match-related external loads variation.[31] Indeed, it has been suggested that highly trained players may adopt a pacing strategy using only a proportion of their physical potential due to contextual factors (eg, tactics, opponents, weather, and players' expectations).[32] Thus, a plausible influence of contextual factors and players' pacing strategies in the current results should not be discarded.

One study conducted with youth female soccer players obtained a similar finding to the above-mentioned, as prematch-increased DOMS was associated with decreased VHSRD (>19.0 km·h^{-1}) during match-play.[12] In fact, some studies conducted in team sports also reported analogue findings to the current ones, suggesting no influence of prematch perceived wellness on other metrics (ie, total distance covered, distance covered at low- or medium-speed thresholds, and number of accelerations and decelerations at low- or medium-intensity thresholds).[9,11] However, opposed results to the current ones have also been shown, as the effects of prematch perceived wellness items on external loads were not consistent.[10–12] These discrepancies may be explained by the individual interpretation of the scale and scoring,[3] the current lack of a comprehensive theoretical framework underpinning wellness as a construct,[33] and the lack of validation of each wellness item using established methods, such as clinimetrics.[21,23,33] These factors need to be acknowledged, as each player may interpret and assign wellness scores differently, but this greater interpretability is also related to the issues with the scales themselves as it is yet to be precisely determined whether the single items can reflect complex and multifactorial constructs accurately. Other factors behind such disparate findings may be the different statistical analyses (eg, correlation measures or linear mixed models) and approaches (eg, raw scores or *z* scores, normalized or nonnormalized data), the data collection period (eg, in-season competitive period or tournaments with congested schedules) and the sport-specific locomotor demands and rules (eg, limited or unlimited substitutions).

This manuscript has several limitations. First, the 5-point Likert questionnaire used in this study reflects custom measures widely used in studies and practice,[20,21] but it was not evaluated with a rigorous process of validity as recommended.[21,23,33] Thus, futures studies should consider the psychometric properties of the self-report wellness questionnaires, as the findings related to these scales may not be interpretable without a framework to understanding what the scales really refer to. Second, the use of technology-based solutions was proposed to overcome the influence of peer pressure on player responses, but it was not possible to confirm whether the participants completed the questionnaire prior to joining their teammates (ie, in their own time) or once all participants had arrived at the venue and were in each other's presence. Third, time-motion parameters were analyzed using arbitrary (ie, absolute) thresholds, so the variability between players' speeds at which they begin to run at very high speed is another limitation of the current study. With the aim to mitigate between-player variability through the identification of a unique running speed threshold, it should be advisable to replicate this study using individualized running speed thresholds. Furthermore, while the recently released Global Navigation Satellite System technology utilized in this study has not been validated, it was chosen due to its adoption by the team involved in this research, and because it may serve as a representative 10-Hz Global Navigation Satellite System, similar to others with widespread application in team sports training and research. Last, only including starters may artificially exclude players who may have scored low on their wellness questionnaire, which would have had an impact on the current findings, so future studies should also include substitutes. In this regard, other contextual factors were not considered in this manuscript, so further research with multivariate approaches should include data from different seasons, playing levels, and teams to obtain robust conclusions on this topic.

Practical Applications

The current results support the inclusion of a perceived wellness questionnaire into monitoring practices by professional soccer teams. Analyzing individual changes in MD perceived wellness data may assist practitioners in understanding how prepared players are and how they are going to cope with match-related demands. As previously exposed, it is feasible that players with greater day-to-day variation of DOMS may incorporate an altered movement strategy within matches with an element of self-pacing that result in reduced sprint performance. Thus, coaches and performance staff may consider this information when adjusting player rotations, substitutions, and match loads. This could help to balance training and match loads and recovery over extended periods of time. Additionally, the current results highlight the importance of strategic tapering (ie, balance between moderate and light loads prematch) and physiological and psychological recovery strategies for optimal physical output during subsequent matches. Finally, monitoring self-report wellness could provide important information needed to explain intraindividual variations in high-intensity locomotor activities, but this information should be analyzed in conjunction with other factors that influence match-running performance.

Conclusions

This exploratory research provides new information on the potential effect that match-day perceived wellness has on subsequent running performance of professional soccer players during in-season matches. Individualized z scores should be considered the most important variables to estimate the proportion of external-load variation during match play, but the proportion of the variance that may be explained from the prematch perceived wellness suggests a limited capacity in relation to external-load measures. In this regard, only individualized z scores of DOMS showed significant effects on sprint running distance and number of sprints during matches. Thus, sprint performance of professional soccer players during in-season matches may be slightly influenced by the players' day-to-day variation of prematch perceived DOMS.

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References

1. Impellizzeri FM, Marcora SM, Coutts AJ. Internal and external training load: 15 years on. *Int J Sports Physiol Perform*. 2019; 14(2):270–273. doi:10.1123/ijspp.2018-0935
2. Halson SL. Monitoring training load to understand fatigue in athletes. *Sports Med*. 2014;44(suppl 2):S139–S147. doi:10.1007/s40279-014-0253-z
3. Saw AE, Main LC, Gastin PB. Monitoring athletes through self-report: factors influencing implementation. *J Sports Sci Med*. 2015; 14(1):137–146. PubMed ID: 25729301
4. Fessi MS, Nouira S, Dellal A, Owen A, Elloumi M, Moalla W. Changes of the psychophysical state and feeling of wellness of professional soccer players during pre-season and in-season periods. *Res Sports Med*. 2016;24(4):375–386. doi:10.1080/15438627.2016.1222278
5. Saw AE, Main LC, Gastin PB. Monitoring the athlete training response: subjective self-reported measures trump commonly used objective measures: a systematic review. *Br J Sports Med*. 2016; 50(5):281–291. doi:10.1136/bjsports-2015-094758
6. Malone S, Owen A, Newton M, et al. Wellbeing perception and the impact on external training output among elite soccer players. *J Sci Med Sport*. 2018;21(1):29–34. doi:10.1016/j.jsams.2017.03.019
7. Clemente FM. Associations between wellness and internal and external load variables in two intermittent small-sided soccer games. *Physiol Behav*. 2018;197:9–14. doi:10.1016/j.physbeh.2018.09.008
8. Bertschy M, Howard JT, Oyama S, Zhang T, Cheever K. Effectiveness of daily subjective wellness measurements via mobile applications in predicting perceived exertion and training load. *Proc Inst Mech Eng Part P J Sport Eng Technol*. 2023;237(4):283–290. doi:10.1177/17543371211049066
9. Ihsan M, Tan F, Sahrom S, Choo HC, Chia M, Aziz AR. Pre-game perceived wellness highly associates with match running performances during an international field hockey tournament. *Eur J Sport Sci*. 2017;17(5):593–602. doi:10.1080/17461391.2017.1301559
10. Bellinger PM, Ferguson C, Newans T, Minahan CL. No influence of prematch subjective wellness ratings on external load during elite Australian football match play. *Int J Sports Physiol Perform*. 2020; 15(6):801–807. doi:10.1123/ijspp.2019-0395
11. Conte D, Guerriero A, Lupo C, Schultz Arruda AF, Kamarauskas P. Influence of congested match schedules, pre-match well-being and level of opponents on match loads during world rugby women's sevens series. *Int J Environ Res Public Health*. 2021;18(22):12132. doi:10.3390/ijerph182212132
12. Sydney MG, Wollin M, Chapman DW, Ball N, Mara JK. Impaired pre-competition wellbeing measures can negatively impact running performance in developmental youth female soccer players. *Biol Sport*. 2024;41(1):145–152. doi:10.5114/biolsport.2024.129480
13. Abbott W, Brownlee TE, Harper LD, Naughton RJ, Clifford T. The independent effects of match location, match result and the quality of opposition on subjective wellbeing in under 23 soccer players: a case study. *Res Sports Med*. 2018;26(3):262–275. doi:10.1080/15438627.2018.1447476
14. Turner AN, Jones B, Stewart P, et al. Total score of athleticism: holistic athlete profiling to enhance decision-making. *Strength Cond J*. 2019;41(6):91–101.
15. Breiman, L. Random forests. *Mach Learn*. 2001;45:5–32. doi:10.1023/A:1010933404324
16. Cutler DR, Edwards TC Jr, Beard KH, et al. Random forests for classification in ecology. *Ecology*. 2007;88(11):2783–2792. doi:10.1890/07-0539.1
17. Siroky, D. S. Navigating random forests and related advances in algorithmic modeling. *Stat Surv*. 2009;3:147–163. doi:10.1214/07-SS033
18. Chicco D, Warrens MJ, Jurman G. The coefficient of determination R-squared is more informative than SMAPE, MAE, MAPE, MSE and RMSE in regression analysis evaluation. *PeerJ Comput Sci*. 2021;7:e623. doi:10.7717/peerj-cs.623
19. Moore DS, Notz W, Fligner MA. *The basic practice of statistics*. W.H. Freeman and Co; 2013.

20. Duignan C, Doherty C, Caulfield B, Blake C. Single-item self-report measures of team-sport athlete wellbeing and their relationship with training load: a systematic review. *J Athl Train*. 2020;55(9):944–953. doi:10.4085/1062-6050-0528.19
21. Sansone P, Rago V, Kellmann M, Alcaraz PE. Relationship between athlete-reported outcome measures and subsequent match performance in team sports: a systematic review. *J Strength Cond Res*. 2023;37(11):2302–2313. doi:10.1519/JSC.0000000000004605
22. Liaw, A. & Wiener, M. Classification and regression by random forest. *R News*. 2002;2:18–22.
23. Saw AE, Kellmann M, Main LC, Gastin PB. Athlete self-report measures in research and practice: considerations for the discerning reader and fastidious practitioner. *Int J Sports Physiol Perform*. 2017; 12(suppl 2):S2127–S2135. doi:10.1123/ijspp.2016-0395
24. Evans DA, Jackson DT, Kelly AL, et al. Monitoring postmatch fatigue during a competitive season in elite youth soccer players. *J Athl Train*. 2022;57(2):184–190. doi:10.4085/1062-6050-0245.21
25. Cheung K, Hume P, Maxwell L. Delayed onset muscle soreness: treatment strategies and performance factors. *Sports Med*. 2003; 33(2):145–164. doi:10.2165/00007256-200333020-00005
26. Peake JM, Neubauer O, Della Gatta PA, Nosaka K. Muscle damage and inflammation during recovery from exercise. *J Appl Physiol*. 2017;122(3):559–570. doi:10.1152/japplphysiol.00971.2016
27. Sonkodi B, Berkes I, Koltai E. Have we looked in the wrong direction for more than 100 years? Delayed onset muscle soreness is, in fact, neural microdamage rather than muscle damage. *Antioxidants*. 2020; 9(3):212. doi:10.3390/antiox9030212
28. Ross A, Leveritt M, Riek S. Neural influences on sprint running: training adaptations and acute responses. *Sports Med*. 2001;31(6): 409–425. doi:10.2165/00007256-200131060-00002
29. Byrne C, Twist C, Eston R. Neuromuscular function after exercise-induced muscle damage: theoretical and applied implications. *Sports Med*. 2004;34(1):49–69. doi:10.2165/00007256-200434010-00005
30. Skorski S, Mujika I, Bosquet L, Meeusen R, Coutts AJ, Meyer T. The temporal relationship between exercise, recovery processes, and changes in performance. *Int J Sports Physiol Perform*. 2019;14(8): 1015–1021. doi:10.1123/ijspp.2018-0668
31. Paul DJ, Bradley PS, Nassis GP. Factors affecting match running performance of elite soccer players: shedding some light on the complexity. *Int J Sports Physiol Perform*. 2015;10(4):516–519. doi:10.1123/IJSPP.2015-0029
32. Waldron M, Highton J. Fatigue and pacing in high-intensity intermittent team sport: an update. *Sports Med*. 2014;44(12):1645–1658. doi:10.1007/s40279-014-0230-6
33. Jeffries AC, Wallace L, Coutts AJ, McLaren SJ, McCall A, Impellizzeri FM. Athlete-reported outcome measures for monitoring training responses: a systematic review of risk of bias and measurement property quality according to the COSMIN guidelines. *Int J Sports Physiol Perform*. 2020;15(9):1203–1215. doi:10.1123/ijspp.2020-0386