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Prediction of Subjective Fatigue in Professional Soccer Players: A Data-Driven Method to Optimize Training Approach to the Match

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ABSTRACT

In soccer, predicting players' fatigue experienced immediately before a training session or match can help design training programs and optimize performance. This study aimed to identify the most important predictors of daily and match-day fatigue in six Italian professional soccer teams during a competitive season using a framework of big data analytics. Every morning, the players rated fatigue, sleep quality, muscle soreness, stress, and mood. After each training session or match, the session Rating of Perceived Exertion was obtained and multiplied by duration to calculate the training load (TL). A framework of four machine learning models (Decision Tree classifier, XGBoost classifier, Random Forest Classifier, and Logistic regression) was trained and tested on 30.211 examples (one full season of six teams) to assess their ability to predict the players' match-day fatigue. The machine learning models accurately predicted the players' subjective fatigue (models' range accuracy 70–82%). Specifically, in the prediction of match-day fatigue, stress, and mood of the previous day were the most influential factors. Mediation analysis unveils the relationship between TL of the day before the match and the perception of match-day fatigue, also mediated by mood and muscle soreness. Sport scientists and coaches can apply this framework to simulate the effects of different training programs, thus maximizing players' readiness and mitigating potential drops in performance associated with match-day fatigue in a real-world scenario.

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KEYWORDS
Multidimensional approach; rating of perceived exertion; readiness; wellness

Fatigue is a multifactorial and psychophysiologically complex phenomenon typically elicited by sustained physical and/or cognitive exertion. It is characterized by two primary dimensions: 1) subjective fatigue, which encompasses perceived exertion, sensations of tiredness, and lack of energy, and 2) objective fatigue, which manifests as measurable declines in physical and/or cognitive performance (Bartley & Chute, 1945).

In the context of elite soccer, fatigue arises as a consequence of both competitive matches and training regimens. Match-induced fatigue is associated with transient decrements in physical performance metrics, including reductions in leg muscle strength, maximal sprint velocity, and acceleration/deceleration capacity (Krustrup et al., 2006; Mohr et al., 2004; 2005). These performance impairments are observed during specific phases of play, such as following high-intensity periods within each half (Krustrup et al., 2006; Mohr et al., 2005), at the onset of the second half (Mohr et al., 2004; 2005), and during the latter stages of the match (Krustrup et al., 2006; Mohr et al., 2005; Rahnama et al., 2003; Rampinini et al., 2011; Russell et al., 2016). Fatigue has been shown to adversely affect technical execution, such as passing accuracy and shooting precision (Sun et al., 2022), both post-match (Rampinini et al., 2008; Russell et al., 2011) and following intensive training sessions (Impellizzeri et al., 2008; Smith et al., 2015). Tactical decision-making appears to be negatively affected by fatigue, particularly in key cognitive components such as information processing speed, and perceptual and attentional processes (Coutinho et al., 2017; Gantois et al., 2020; Smith et al., 2015). Elevated fatigue perceptions have been documented during periods of intensified training (Buchheit et al., 2013; Fields et al., 2021; Haddad et al., 2013; Selmi et al., 2018, 2020, 2022) or in the aftermath of competitive fixtures (McLean et al., 2010; Thorpe et al., 2016; Winder et al., 2018) from a subjective point of view.

While these findings have provided valuable insights into the quantification of fatigue and its detrimental effects on soccer performance, the existing body of research is limited by small sample sizes and short observation periods, typically spanning single matches or a few weeks of training. Such constraints hinder the development of robust predictive models capable of forecasting fatigue states in soccer players. The ability to predict fatigue has significant practical implications, particularly in optimizing performance on match days by ensuring players are in a non-fatigued state. In contemporary professional soccer, the widespread adoption of daily monitoring practices has enabled the collection of extensive datasets encompassing external load metrics (e.g., distance covered, speed, and acceleration), internal load indicators (e.g., session-rated perceived exertion [sRPE] and heart rate), and subjective measures (e.g., wellness and recovery questionnaires). This daily monitoring practice enables the collection of very large

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datasets through one or more seasons (Simonelli et al., 2025). Those data could provide foundations for machine learning predictive models for match-day fatigue (MDF), and for the development of individualized training modulation strategies, which could enhance performance optimization in elite soccer players. While the use of machine learning for performance optimization is well established, the combination of machine learning and mediation analysis is a novel aspect of this study. By integrating these two approaches, we are able to explore the complex, indirect pathways through which fatigue impacts performance, offering more comprehensive insights than traditional methods. This innovative approach allows for the identification of not only the direct effects of fatigue on match-day performance but also the mediating factors that influence these relationships. In the present study, we applied a machine learning approach and mediational analysis to thousands of data points resulting from the daily monitoring of each player from six professional soccer teams during a full competitive season, from summer camp to the eventual playoffs. The aim of the study was to develop predictive models that can help identify the most important factors that can predict MDF. Fatigue here refers to the fatigue state experienced by the player in the morning before performing any training or match.

Methods

Subjects

Six Italian professional third division (Serie C) soccer teams were recruited for this study for a total of 171 players. Six complete championship seasons were recorded from summer camp on for each team. The data recording was conducted between July 17, 2017, and May 11, 2023. For the timeframe in which the players were part of one of these six teams, data collection was carried out daily and without interruptions. None of the teams have coaches or tactical ideas in common. Descriptive statistics of the players are provided in Table 1. After a detailed description of the procedure and possible risks, players voluntarily decided to participate by signing an informed consent. The project was conducted according to the Declaration of Helsinki and was approved by the Bioethics Committee of the University of Bologna.

Data collection

Every morning, usually in private and at a consistent time, and always before any training session or match, players completed a wellness questionnaire composed of five single-item scales previously used in professional soccer (Perri et al., 2021). Specifically, the five single-item scales measured fatigue, sleep quality, muscle soreness, stress, and mood. The single-item measures were described with the simple statement of "Please describe how you currently feel (according to the following items)." All items were rated on a five-point scale response option, where 1 was the lowest score and 5 was the highest score, and the anchors referred to the content of the item. Specifically, the verbal anchors were 1 = "not at all tired" 5 ="very tired" for fatigue (item 1), 1 = "very good" 5 ="very bad" for sleep quality (item 2), 1 = "none" 5 = "very sore" for muscle soreness (item 3), 1 = "very relaxed" 5 = "very stressed" for stress (item 4), 1 = "very positive" 5 = "very negative" for mood (item 5) (Perri et al., 2021). The questionnaire was based on previous research assessing sleep quality, fatigue, muscle soreness (Gastin et al., 2013; Lathlean et al., 2018; Selmi et al., 2020), stress, and mood (McLean et al., 2010). These have been extensively applied in team-sport settings, showing practical reliability/sensitivity to training load manipulations, recovery status, and psychophysiological dimensions. Approximately 30 minutes after the end of each training session or match, players rated the perceived exertion (sRPE) using the 10-point category ratio scale (CR-10 Borg's scale), where 0 corresponds to rest and 10 to maximal effort (Borg, 1998). The training load (TL) for each session or match was calculated as the product of sRPE and session duration in minutes (time). The convergent validity with heart rate-based measures (Borg, 1998) and standardized 30-minute post-exercise administration support its acceptability for daily monitoring (Impellizzeri et al., 2004). The reliability of this method has been previously reported (Impellizzeri et al., 2004). In the analysis, TL refers to the load from the previous day's session or match, relative to the fatigue, sleep quality, muscle soreness, stress, and mood ratings provided. TL can be considered a higher-order construct encompassing its sub-dimensions, namely sRPE and time (Staunton et al., 2022). Players were familiar with the rating system, having practiced it throughout the preseason under the guidance of the club's head of performance. To account for intra-individual differences in scoring, all single-item values (i.e., fatigue, muscle soreness, sleep quality, mood, and stress) and TL were normalized for each player on a 0–1 scale, with 0 representing the individual minimum and 1 the individual maximum. To generate the multiclass dependent features for the machine learning models, fatigue scores were divided into three categories based on player-specific data distribution: low (< 33rd percentile); moderate (33rd–66th percentile); severe (> 66th percentile), as shown in Table 2. Figure S1 shows the distribution of these fatigue classes across the season for all teams.

Table 1. Players' descriptive statistics (mean ± standard deviation).

Teams	Players (n)	Age (yrs)	Height (cm)	Weight (kg)
Team 1	25	22.78±5.91	181±4	78.94±4.51
Team 2	29	21.14±3.44	182±5	79.12±7.56
Team 3	30	24.87±4.96	181±6	74.25±8.55
Team 4	27	21.91±3.95	180±4	73.17±5.87
Team 5	33	23.68±4.97	182±6	77.72±5.57
Team 6	27	22.97±3.92	179±5	75.37±7.12

Table 2. Fatigue classes' descriptive statistics. Standard deviation (SD), min and max refer to standard deviations, minimum and maximal values, respectively, while 25%, 50%, and 75% refer to the interquartile range values.

Team	Class	Count	Mean	SD	min	25%	50%	75%	max
Team 1	*Low*	3619	1.76	0.43	1	2	2	2	2
	Moderate	1098	2.44	0.50	2	2	2	3	3
	Severe	1006	3.24	0.52	2	3	3	3	5
Team 2	*Low*	3777	1.61	0.49	1	1	2	2	2
	Moderate	882	2.56	0.50	2	2	3	3	3
	Severe	1441	3.23	0.45	3	3	3	3	5
Team 3	*Low*	3966	1.59	0.49	1	1	2	2	2
	Moderate	539	2.62	0.51	2	2	3	3	4
	Severe	724	3.23	0.45	3	3	3	3	5
Team 4	*Low*	2589	1.71	0.45	1	1	2	2	2
	Moderate	604	2.61	0.51	2	2	3	3	4
	Severe	433	3.33	0.63	2	3	3	4	5
Team 5	*Low*	2500	1.46	0.74	1	1	2	3	3
	Moderate	994	2.43	0.84	2	2	3	3	4
	Severe	1105	2.73	0.75	2	3	3	4	5
Team 6	*Low*	3276	1.63	0.48	1	1	2	2	2
	Moderate	797	2.28	0.45	2	2	3	3	3
	Severe	861	3.17	0.43	2	3	3	3	5

Data analysis

In this section, we describe all the analyses conducted in this study. First, a machine learning analysis was conducted to predict MDF by previous week daily perceived variables (i.e., sleep, muscle soreness, fatigue, stress, mood, sRpe, and time), from day −6 to day −1. Informed by the outcomes of the prediction analyses, a mediation analysis was conducted to assess whether MDF is directly affected by TL or if this relationship is mediated by other perceived daily variables (i.e., fatigue, muscle soreness, sleep quality, mood, and stress). All the analyses were performed using Python 3.8 programming language.

Machine learning approach

The analysis of MDF was structured to predict subjective fatigue status on match day. Predictive variables included daily measures collected across the weekly schedule (from day −6 to day −1), encompassing perceived variables (i.e., sleep, muscle soreness, fatigue, stress, mood, sRpe, and time). Furthermore, all variables from the weekly microcycle were integrated to predict MDF. Only weeks with one match per week were used for the analysis.

A framework of big data analytics was developed to predict players' MDF. Four machine learning models were trained and tested: 1) Decision Tree classifier (DTC); 2) XGBoost classifier (XGB); 3) Random Forest Classifier (RFC); 4) Logistic regression (LR). All models were trained using default hyperparameters, as preliminary tests indicated that hyperparameter tuning provided only marginal performance improvements while increasing the risk of overfitting and computational cost. Therefore, default settings were preferred to maintain model simplicity, reproducibility, and robustness. Additionally, to assess the validity of the models trained, their predictive performance was compared to that of a stratified dummy classifier model (Bs). The Bs model predicts classes based solely on their distribution in the training set, providing a simple baseline for comparison. If the machine learning models achieve high predictive accuracy but perform similarly to or worse than the Bs model, it would indicate limited predictive capability.

Model validation was performed using a train-test split approach. The dataset was randomly divided into a training set (70% of the total dataset) and a test set (30% of the entire dataset). The training set was used to train the machine learning models, while the test set was used to evaluate their predictive performance. A stratified split was applied to ensure that the distribution of the target classes was preserved in both the training and test sets.

In the training set of both validation approaches, a Recursive Feature Elimination with 3-folds Cross-Validation (RFECV) was performed to select the most important features for fatigue prediction. This approach reduces the feature space dimensionality, improving both model interpretability and predictive accuracy.

Model performance was evaluated by computing precision, recall, and F1-score for each class and overall accuracy, defined as the proportion of correctly classified instances over the total number of instances. Precision (specificity) is the ratio of correctly predicted positive observations to the total predicted positive observations, while recall (sensitivity) is the ratio of correctly predicted positive observations to all observations in the actual class. The F1-score is the weighted mean of precision and recall. Finally, accuracy is calculated as the ratio of correctly predicted observations to the total number of observations.

To explain the model's decision-making processes at both global and local levels, SHapley Additive exPlanations (SHAP) values were computed. SHAP enables the exploration of variable relationships within each prediction by assigning an importance value to every feature based on a linear contribution model. This approach allows for the evaluation of each feature's influence on the final prediction. Moreover, aggregated SHAP values illustrate how each predictor contributes, either positively or negatively, to the target variable. Understanding the rationale behind a model's prediction is often as crucial as the prediction's accuracy itself. Indeed, it provides deeper insights into the underlying differences between fatigue classes.

Mediation analysis

TL is, by definition, the only logical key available to practitioners to affect and modulate fatigue for each player. To detect whether and how the relationship between TL and MDF is direct or mediated by other perceived daily variables (i.e., mood, sleep quality, muscle soreness, and stress), a mediation analysis was conducted. To assess the influence of TL on MDF, data preprocessing is mandatory to evaluate daily and historical influence. Data preprocessing aggregates the data time series to create indexes that provide additional details about players' history. In addition to day-1 data, two types of aggregations were computed for each independent feature (i.e., fatigue, sleep quality, muscle soreness, stress, mood ratings of the current day, sRPE, and time of the previous day): 1) exponential weighted moving average of past seven days (acute); 2) exponential weighted moving average of past 28 days (chronic). The weight of both acute and chronic aggregation methods was computed with a specified decay in terms of span (2/(SPAN +2)).

Considering the assumption of related pairs, a repeated measures mediation analysis was performed. Specifically, marginal regression model using generalized estimating equations based on autoregressive covariance structure was employed to account for time series nature of the data and the repeated measures design.

Results

Machine learning approach

Table S1 in the supplementary material provides the prediction goodness of the machine learning models. In particular, XGB shows the highest predictive goodness for fatigue in all the teams (Team 1: accuracy = 0.71; Team 2: accuracy = 0.70; Team 3: accuracy = 0.80; Team 4: accuracy = 0.76; Team 5: accuracy = 0.80; Team 6: accuracy = 0.66) in predicting MDF. Supplementary material Table S1 shows that all the machine learning models are valid to estimate MDF because the XGB model shows higher predictive performance (accuracy around + 0.25) compared to the baseline one (B_s).

Figure 1 and Table 3 show the importance of each feature on the decision-making process for MDF in all six soccer teams. All the variables of the day before the match are in the decision-making to predict MDF together with mood d-2. Specifically, stress d-1, mood d-1, mood d-2, and sleep d-1 (9.30%, 9.40%, 7.61%, and 8.53%, respectively) are the most relevant variables in the prediction. Muscle soreness d-1, fatigue d-1, sRPE d-1, and time d-1 also have relevance in the prediction model even if lower than the previous ones. All the other physical, psychological, or environmental variables describe a *mare magnum* with little importance in the decision-making of the process.

The general feature influence of every feature for all the teams is reported in Figure 2. The influence of each feature on MDF prediction slightly changes among soccer teams, indicating that the fatigue status is affected differently in accordance with player, team, and training schedule characteristics. Even with this small difference between teams, the models could be considered generalizable due to the fact that the best model trained on each team is accurate in predicting fatigue classes in the others. As a matter of fact, the accuracy of the best model trained on one team and tested on the other teams is strong (Table 4). Not surprisingly, Figure 2 highlights how every fatigue-1, sleep-1, stress-1, and mood-1 appears to have a strong negative correlation with low fatigue class, while muscle soreness-1 has a moderate negative correlation with low fatigue class. Contrariwise, sRpe-1, sleep −1, mood-1, and mood-2 appear to have a positive correlation with severe fatigue class.

Mediation analysis

Since TL is the only key that practitioners can control to modulate individual fatigue, it is logical to explore its relationship with MDF. The machine learning analysis indicates that perceived variables from the previous day (i.e., mood, sleep quality, muscle soreness, and stress) had greater importance than TL, prompting a mediation analysis. This analysis aims to determine whether the relationship between TL and MDF is mediated or moderated by the previous day's perceived variables.

Significant relationships with MDF were detected for both TL of the previous day (TL d-1) and perceived daily variables' scores. The analysis was performed for TL d-1, $TL_{acute,}$ $TL_{chronic}$.

Figure S2 represents the mediation analysis of TL d-1 on MDF. A statistically significant total influence of TL d-1 on MDF was detected (coefficient = 0.0088 [0.006, 0.010]; p-value < .001; RMSE = 0.78; ICC = 0.62). The mediation analysis (Figure S2) shows a statistically significant direct influence (coefficient = 0.006 [0.004, 0.007]; p-value < .001; RMSE = 0.62; ICC = 0.72) of TL d-1 on MDF. This relation is mediated by muscle soreness (coefficient = 0.002 [0.001, 0.003]; p-value < .001; RMSE = 0.65; ICC = 0.70), mood (coefficient = 0.001 [0.001, 0.002]; p-value < .001; RMSE = 0.77; ICC = 0.63). The other items do not mediate this relationship.

Figure S3 represents the mediation analysis of TL $d\text{-}1_{acute}$ on MDF. A statistically significant relationship of TL $d\text{-}1_{acute}$ on MDF was detected (beta coefficient = 0.218 [0.138, 0.298]; p-value < .001; RMSE = 0.27; ICC = 0.94). The mediation analysis (Figure S3) shows a statistically significant direct influence (coefficient = 0.154 [0.087, 0.220]; p-value < .001, RMSE = 0.25; ICC = 0.95) of TL_{acute} on MDF. This relation is mediated by muscle soreness (coefficient = 0.067 [0.032, 0.102]; p-value < .001, RMSE = 0.25; ICC = 0.95). The other perceived variables do not mediate this relationship.

Figure S4 represents the mediation analysis of TL $d\text{-}1_{chronic}$ on MDF. A statistically significant relationship of TL $d\text{-}1_{chronic}$ on MDF was detected (beta coefficient = 0.117 [0.028, 0.207]; p-value = .01; RMSE = 0.27; ICC = 0.94). The mediation analysis (Figure S4) shows a statistically significant direct influence (coefficient = 0.073 [0.002, 0.148]; p-value = .05, RMSE = 0.25; ICC = 0.95) of $TL_{chronic}$ on MDF. This relation is mediated by muscle soreness (coefficient = 0.045 [0.001, 0.063]; p-value < .001, RMSE = 0.25; ICC = 0.95). The other perceived variables do not mediate this relationship.

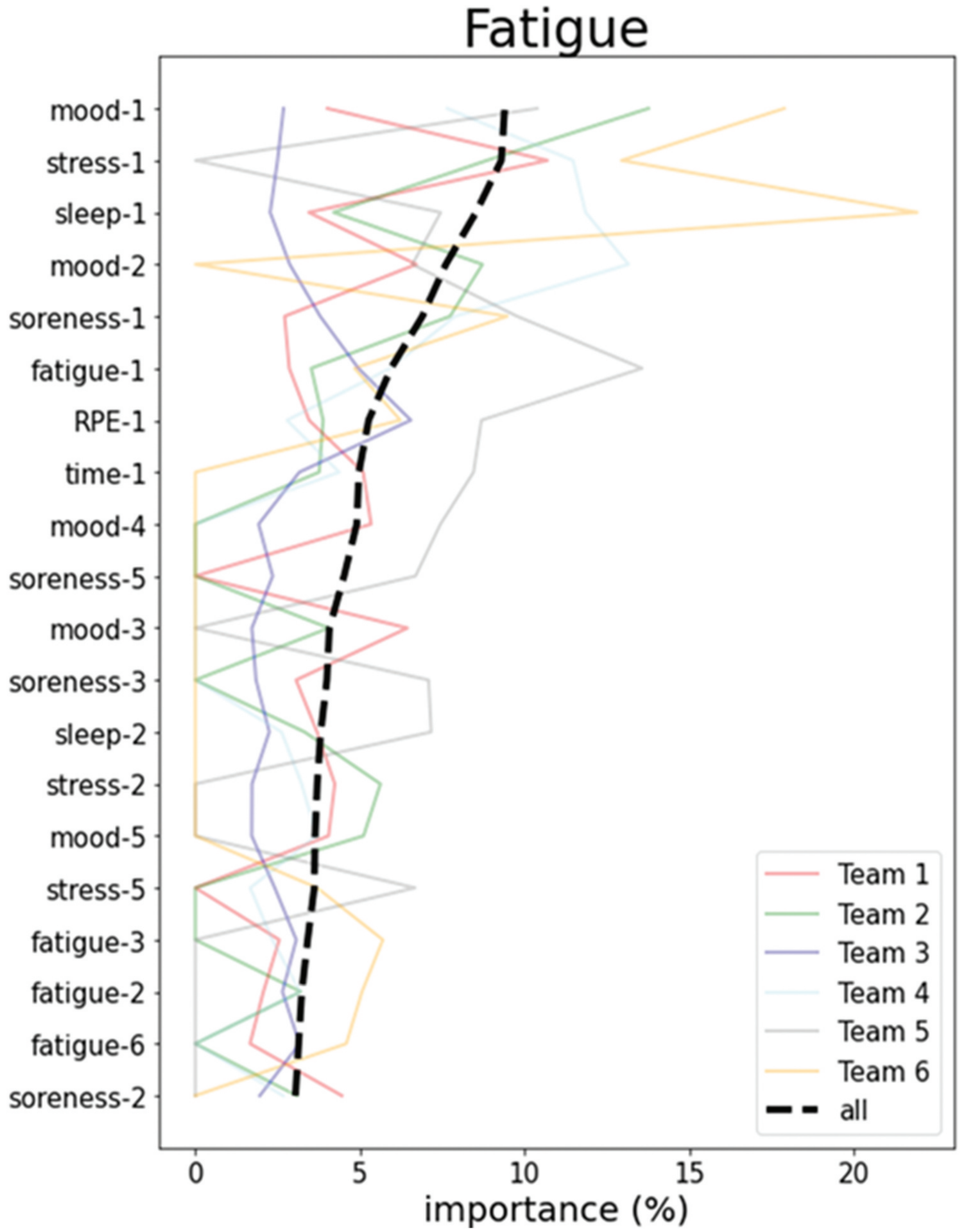

Figure 1. Feature importance for the best machine learning models for the perceptual variables in all the teams in predicting fatigue. sRPE = session rating of perceived exertion.

Discussion

In real-world scenarios, accurately predicting the fatigue status of individual players is paramount for informed training prescription and periodization throughout the season. The aim of the present study was to investigate the influence of sRPE, session duration, and self-reported perceived variables (i.e., fatigue, muscle soreness, stress, mood, and sleep quality) on MDF in professional soccer players. The goal was to provide coaches with a practical tool to monitor training stimuli and prevent states of overreaching and/or overtraining.

In a match-day context, the relatively low importance of fatigue, muscle soreness, and training duration/intensity in predicting MDF is not surprising. This can be attributed to the common practice of prescribing moderate-to-low training loads in the days leading up to the match, aiming to minimize players' fatigue by match day. In our study, the most important factors predicting MDF were stress, mood, and sleep quality in the day(s) preceding the match. We tentatively interpret these findings as indicative of a residual fatigue component that is predominantly mental rather than physical. This interpretation aligns with existing evidence suggesting that mental fatigue impairs soccer performance (Smith et al., 2015; Van Cutsem et al., 2017). These findings have two practical implications. First, beyond the physical tapering typically implemented before a match, coaches and support staff (e.g., the team psychologist) should manage players' psychological load in the final day(s) before competition. Practical interventions may include relaxation techniques and promoting good sleep hygiene (Proost et al., 2022). Given that psychological load is not always easy to manage, coaches and other staff should also employ other strategies to reduce mental fatigue on the day of the match, such as alimentary (e.g., caffeine), behavioral (e.g.,

Table 3. Feature importance in each team.

	Team 1	Team 2	Team 3	Team 4	Team 5	Team 6	all	SD
mood_1	4.01	13.77	2.68	7.66	10.38	17.90	9.40	5.31
stress_1	10.70	8.86	2.50	11.48	0.00	12.95	9.30	3.65
sleep_1	3.45	4.20	2.27	11.86	7.45	21.94	8.53	6.78
mood_2	6.71	8.72	2.87	13.16	6.59	0.00	7.61	3.36
soreness_1	2.71	7.74	3.79	7.89	9.78	9.48	6.90	2.70
fatigue_1	2.85	3.52	4.95	5.93	13.58	4.84	5.95	3.56
sRPE_1	3.45	3.88	6.55	2.78	8.69	6.23	5.27	2.07
time_1	5.10	3.76	3.16	4.37	8.45	0.00	4.97	1.86
mood_4	5.34	0.00	1.92	0.00	7.45	0.00	4.90	2.28
soreness_5	0.00	0.00	2.35	0.00	6.69	0.00	4.52	2.17
mood_3	6.44	4.06	1.72	0.00	0.00	0.00	4.07	1.93
soreness_3	3.06	0.00	1.84	0.00	7.09	0.00	4.00	2.24
sleep_2	3.70	3.32	2.24	2.62	7.17	0.00	3.81	1.75
stress_2	4.24	5.62	1.72	3.23	0.00	0.00	3.70	1.43
mood_5	4.05	5.11	1.71	3.68	0.00	0.00	3.64	1.23
stress_5	0.00	0.00	2.41	1.67	6.67	3.70	3.61	1.91
fatigue_3	2.55	0.00	3.07	2.34	0.00	5.70	3.41	1.35
fatigue_2	2.07	3.20	2.65	3.18	0.00	5.07	3.23	1.01
fatigue_6	1.66	0.00	3.17	0.00	0.00	4.59	3.14	1.19
soreness_2	4.45	3.08	1.96	2.67	0.00	0.00	3.04	0.91
stress_6	0.00	2.55	2.14	0.00	0.00	4.26	2.98	0.92
time_4	0.00	0.00	1.99	3.39	0.00	0.00	2.69	0.70
stress_3	2.19	3.74	1.73	0.00	0.00	0.00	2.56	0.86
stress_4	1.41	3.65	2.11	0.00	0.00	0.00	2.39	0.93
mood_6	2.29	2.94	1.48	2.63	0.00	0.00	2.33	0.54
sleep_3	1.55	2.66	2.64	0.00	0.00	0.00	2.29	0.52
soreness_6	2.16	2.69	1.82	0.00	0.00	0.00	2.22	0.36
sRPE_2	0.00	0.00	2.21	0.00	0.00	0.00	2.21	0.00
time_3	0.97	0.00	2.33	2.02	0.00	3.36	2.17	0.85
sleep_4	1.69	2.92	1.84	0.00	0.00	0.00	2.15	0.55
soreness_4	1.75	0.00	2.40	0.00	0.00	0.00	2.08	0.32
fatigue_4	1.59	0.00	2.56	0.00	0.00	0.00	2.07	0.48
time_5	1.14	0.00	1.71	3.13	0.00	0.00	2.00	0.84
sRPE_3	0.00	0.00	1.99	0.00	0.00	0.00	1.99	0.00
sleep_5	1.91	0.00	1.92	0.00	0.00	0.00	1.91	0.00
sRPE_5	0.00	0.00	1.87	0.00	0.00	0.00	1.87	0.00
sRPE_4	0.00	0.00	1.84	0.00	0.00	0.00	1.84	0.00
sRPE_6	0.00	0.00	1.80	0.00	0.00	0.00	1.80	0.00
fatigue_5	1.30	0.00	2.28	0.00	0.00	0.00	1.79	0.49
time_2	0.95	0.00	2.06	2.36	0.00	0.00	1.79	0.61
time_6	1.18	0.00	2.18	1.95	0.00	0.00	1.77	0.43
sleep_6	1.36	0.00	1.54	0.00	0.00	0.00	1.45	0.09

Note: SD = standard deviation, sRPE = session rating of perceived exertion.

listening to music), and psychological (e.g., extrinsic motivation) countermeasures (Proost et al., 2022). The time and number of tactical/cognitive sessions could be managed as well to avoid a rise in mental fatigue (Proost et al., 2022). Emotional self-regulation could be helpful right before or during the match (i.e., halftime) to avoid the inability to manage aggression (DeWall et al., 2007). Training in how to cope with mental fatigue before matches can be very helpful in a professional soccer context to avoid a detriment in technical skills and cognitive performance (Staiano et al., 2025).

The XGB model trained on a single team demonstrated an accurate performance in predicting fatigue classes in players from other teams, suggesting a certain degree of generalizability across teams (Table 4). However, as expected, a reduction in classification accuracy was observed during external validation (when models were tested on teams different from those used for training) due to the reduced level of personalization. Importantly, the differences observed in feature importance across the six teams suggest that while the underlying physiological and psychological responses to training are partially shared, team-specific contexts modulate the relative weight of each predictor. Nevertheless, the fact that performance remained above baseline even in cross-team settings supports the presence of generalizable patterns in players' responses to load and wellness indicators. Hence, training machine learning algorithms on big datasets that include multiple teams and/or multiple seasons could further enhance the generalizability and robustness of these predictive models.

Limitations

The current research presents some weaknesses. First, as already repeatedly discussed, these data are correlative and, therefore, do not prove a cause-and-effect relationship between fatigue and its predictors. Second, the models discussed here are specific to the teams that were monitored. Although the items of the wellness questionnaire adopted in the present study consist of custom measures widely used in practice (Perri et al., 2021; Selmi et al., 2018, 2020, 2022; Simonelli et al., 2025), their subjective nature represents a limitation, as they haven't been rigorously evaluated for their validity and reliability. In this sense, integrating objective

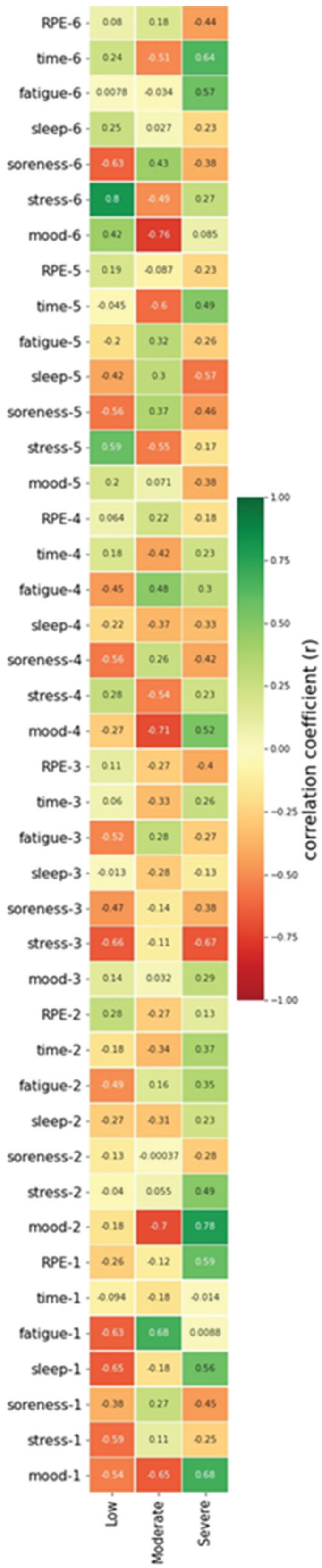

Figure 2. General influence of individuals' features on all the variables and MDF predictions. This plot shows the correlation coefficient between SHAP values (probability to be part of a fatigue class) and features' values. Green bars refer to a positive correlation, while the red ones show a negative relationship. sRPE = session rating of perceived exertion.

Table 4. Accuracy of the XGB model trained on one team and tested on the other teams.

		Training					
		Team 1	Team 2	Team 3	Team 4	Team 6	Team 5
Test	Team 1	—	0.58	0.56	0.54	0.53	0.52
	Team 2	0.51	—	0.53	0.56	0.59	0.57
	Team 3	0.58	0.57	—	0.51	0.51	0.53
	Team 4	0.52	0.55	0.59	—	0.59	0.56
	Team 5	0.54	0.53	0.53	0.57	0.52	—
	Team 6	0.57	0.56	0.60	0.53	—	0.55

metrics, such as GPS-derived external load or heart rate variability, may provide a more comprehensive and robust assessment of players' psychophysiological status.

Furthermore, the predictive models presented in this study are based on the assumption that the patterns observed in the training data will remain consistent over time. However, player condition and team strategies can change throughout a season, which may limit the generalizability of the predictions to other teams or seasons. For a more robust prediction, each team would need to "train" the model with their own data, ideally for a period of at least 10 weeks. This adaptation process would ensure the model is accurately fitted to the specific characteristics of the team, including its playing style and training load.

Finally, while the algorithm offers valuable insights into predicting fatigue, it is important to recognize that it currently cannot be universally applied to all soccer teams. Each team's data would need to be tailored to the model to achieve a reliable and accurate assessment of fatigue prediction. These limitations highlight the necessity for further research to enhance the generalizability and reliability of fatigue prediction models across different contexts in soccer.

Conclusion

In the context of the current training and match scheduling practices of Italian professional soccer, our findings suggest that MDF can be predicted with reasonable accuracy using big data analytics of practical measures of training load and players' subjective status. An accuracy of approximately 73%, about 25% higher than baseline for MDF predictors, was revealed. The prediction of MDF can help in the preparation leading up to the match in understanding, for example, which player can be more suitable for the subsequent match.

Interestingly, psychological variables like stress, mood, and sleep quality experienced by the athlete the day before the match are the most important predictors of MDF. Together with the results of experimental studies showing a negative impact of mental fatigue on soccer performance (Smith et al., 2015; Van Cutsem et al., 2017), our correlative findings suggest that interventions to reduce stress/negative mood and improve sleep quality may improve the match performance of soccer players. Our correlative findings also suggest that the stress perceived by soccer players needs to be considered in the day-to-day modulation of training load based on the current fatigue state.

In conclusion, fitness trainers and coaches can use the framework of big data analytics proposed in this article to predict their players' fatigue status, understanding the influence of other perceptions, judgments, and training load characteristics to improve the decision-making process when designing a training plan. In particular, field experts could maximize the training effect by controlling the fatigue status of the soccer players simulating the scheduled training program. Finally, this approach can be very useful for practitioners of amateur and grassroots with a limited budget. Both status and internal load measures' data collection, as shown above, is virtually free, and it can be taken into account in assessing fatigue using our model.

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