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Subjective recovery in professional soccer players: A machine learning and mediation approach

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ABSTRACT

Coaches often ask players to judge their recovery status (subjective recovery). We aimed to explore potential determinants of subjective recovery in 101 male professional soccer players of 4 Italian Serie C teams and to further investigate whether the relationship between training load and subjective recovery is mediated by fatigue, sleep quality, muscle soreness, stress and mood. A complete season for each of the four teams was recorded for a total of 16,989 training sessions and matches. Every morning, players rated their perceived fatigue, sleep quality, muscle soreness, stress and mood, and judged their recovery using the Total Quality Recovery (TQR) questionnaire. Training load was obtained after each training session or match. A framework of data analytics of time series was employed to detect the factors associated with subjective recovery. Machine learning and mediation analyses suggest that TQR is primarily associated with ratings of fatigue and muscle soreness at the judgements time, and that these factors mediate most of the relationship between training load of the previous day and subjective recovery. These findings suggest that, to maximize subjective recovery, strategies minimizing fatigue and muscle soreness should be implemented. Reducing the training load of the previous day seems the most effective strategy.

KEYWORDS
Fatigue; football; muscle soreness; training load; wellness

Introduction

Recovery has been defined as a multifaceted restorative process relative to time (Kellmann et al., 2018). It is widely known that an optimal balance between training load and recovery is required to adapt to training and perform optimally (Nedelec et al., 2014). Poor recovery between training sessions and matches is also associated with increased incidence of injury, illness, and overtraining (Gabbett et al., 2014; M et al., 2013).

Because of its multifaceted nature, recovery has been quantified in many ways including performance tests such as countermovement jump (CMJ) (Freitas et al., 2014) and biochemical markers like creatine kinase (CK) concentration (Lazarim et al., 2009). A more practical and commonly used way to assess recovery is to ask athletes to judge their recovery status (i.e., subjective recovery), either informally in daily conversations or formally using specific scales or questionnaires like the Total Quality of Recovery (TQR) scale (Kenttä & Hassmén, 1998). The validity of subjective measures of recovery has been supported by their associations with performance decrements, injury rates, and biochemical markers of recovery (Andersson et al., 2008; Bessa et al., 2016; Brink et al., 2010; Kellmann et al., 2018; Nedelec et al., 2014; Nédélec et al., 2012, 2013, 2015; Rampinini et al., 2011).

Because of its relevance to athletes' performance and health, it is important to explore the determinants of subjective recovery. Short-term intensified training studies have provided experimental evidence that training load and time to recover are key determinants of subjective recovery (Selmi et al., 2020). Small correlational studies also suggest that subjective judgments of recovery status may be influenced by feelings of fatigue and delayed onset muscle soreness (DOMS) (Freitas et al., 2014; Howle et al., 2019). Moreover, it is believed that factors such as stress, mood and sleep quality affect the recovery process in athletes (Heidari et al., 2019; Samuels, 2008; Vitale et al., 2019; Wiese-Bjornstal, 2010).

The relationship between recovery and training load is paramount for optimizing performance and minimizing injury risk in sports. Training load encompasses both external metrics (e.g., distance covered, accelerations) and internal responses (e.g., perceived exertion), influencing athletes' readiness and wellness. Recent studies have employed advanced methodologies such as machine learning to deepen our understanding of this complex relationship. For instance, Pillitteri and colleagues (Pillitteri et al., 2023) used a machine learning approach to investigate the link between internal load and recovery in under-19 professional soccer players, revealing the intricacies of subjective readiness and its association with training demands. Specifically, parameters such as heart rate variability, session rating of perceived exertion, post-match fatigue markers, and match exposure were identified as key factors of recovery, emphasizing the need for individualized monitoring and tailored recovery strategies to optimize performance and reduce injury risk in elite youth athletes. Similarly, Rossi et al., (2022) demonstrated that training load data can be used to forecast players' wellness, emphasizing the utility of combining

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internal and external load metrics to capture recovery dynamics. Despite these advances, the literature highlights ongoing challenges, including the need to address the multifactorial nature of training load–recovery interaction (Gabbett, 2016; Windt & Gabbett, 2017). Addressing these complexities is crucial for improving individualized load management strategies and reducing injury risk in high-performance athletes (Impellizzeri et al., 2020; Kalkhoven et al., 2021).

The main aim of the present study was to further explore potential determinants of subjective recovery (training load, fatigue, sleep quality, muscle soreness, stress and mood) using machine learning analysis on a large data set collected in the field during an entire professional soccer season. Moreover, we explored whether the hypothesised relationship between training load and subjective recovery is mediated by fatigue, sleep quality, muscle soreness, stress and mood.

Methods

Subjects

One hundred and one male players (23.5 ± 4.0 yrs, 73.8 ± 7.4 kg, 180 ± 5 cm) from four professional Italian soccer clubs competing in the third Italian division (Serie C) were recruited for this study. The data recording was conducted on a complete championship season for each team, from summer camp onwards. A total of 16,989 training or match sessions (113 ± 52 per player) were recorded. The data recording was conducted between 16 July 2020 and 11 May 2023. 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 local University.

Data recording

Every day, usually in private and at a consistent time in the morning, in any case before each training session or match, the players filled six scales using the Google Forms app on their mobile phones. First, the players provided subjective ratings of fatigue, sleep quality, muscle soreness, stress and mood using the Wellness Questionnaire (WQ) (Perri et al., 2021). This questionnaire consists of five single items with a 5-point Likert scale where 1 and 5 indicate the highest and lowest values of wellness for each item, respectively (Gastin et al., 2013; McLean et al., 2010). The sixth scale the players had to fill in was the Total Quality Recovery (TQR) scale. This instrument evaluates the players' recovery status (Senttä & Hassmén, 1998) by a self-reported single-item scale ranging between 6 and 20. Values of about 6 refer to no recovery at all, while 20 means that the athlete fully recovered. The WQ and TQR data were recorded also during recovery days. Finally, about 30 min after the end of each training session or match, the players rated how hard the training session or match was (sRPE) by using the 10-point scale (CR-10 Borg' scale), where 0 refers to resting state and 10 to maximal effort (Borg, 1998). The Training Load (TL) for each training session or match was computed as the product between sRPE and the duration in minutes (time) and, in each analysis, refers to the load of the training session or match performed the day before the subjective ratings of recovery, fatigue, sleep quality, muscle soreness, stress and mood were provided. However, we decided to include sRPE and time separately in the machine learning approach to differentiate between the intensity and duration of the training session/match. Training load can be simply described as a label attributed to a higher-order construct overarching other interrelated sub-dimensions such as sRPE and time specifically (Staunton et al., 2022).

Data preprocessing

Data preprocessing permits to aggregate the data time series to create indexes that provide more details about players' history. In particular, 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): i) exponential weighted moving average of the past 7 days (Acute); ii) exponential weighted moving average of the 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)) (Rossi et al., 2021).

Machine learning approach

Extreme Gradient Boosting Regressor (XGBR) model (multidimensional non-linear supervised regression machine learning model) was fitted on 21 independent features (i.e. fatigue, sleep quality, muscle soreness, stress, mood ratings of the current day, sRPE and time of the previous day, and their acute, and chronic aggregations) with the aim of predicting the players' recovery status (TQR score, i.e., recovery perception). The XGBR model was trained on 70% of the total observations (train set) where the best subset of features was obtained by a Recursive Feature Elimination with 10 Cross-Validation (RFECV) based on the XGBR model. We ensured that any player was not inserted in both training and testing, as well as in RFECV, in order to avoid possible overfitting problems. In the train set, the best hyperparameters of XGBR were also fitted by a grid search approach. The grid search parameters tested are: learning rate = 0.01, 0.03, 0.05, 0.07, 0.09; max depth = 5, 10, 15, 20, None; colsample by tree = 0.1, 0.3, 0.5, 0.7, 0.9; number of estimators = 100, 500, 1000. The best XGBR hyperparameters selected with the grid search approach were: learning rate = 0.03; max_depth = 10; callsample by tree = 0.7; number of estimators: 1000. Moreover, a multiple linear model (LM) was used as the 'baseline' model. Actually, we assessed the performance accuracy of this simple model in order to understand if the XGBR model was able to more accurately predict the next day's recovery.

The predictive performance on both XGBR and LM models was assessed on the test set (30% of observations not included in the train set) in order to avoid any overfitting problem. Mean Squared Error (MSE), Root Mean Squared Error (RMSE) and

Pearson's correlation coefficient (r) were used to evaluate the predicting performance of the models.

Shapley Additive exPlanations (SHAP) method was used to explain the decision-making process created by XGBR to predict TQR. To explain the output of the machine learning models, SHAP uses a game theory approach. By giving a pre-trained regressor, SHAP explainer creates a value for each independent feature that represents how much they influenced the regressor's decision-making process by providing a global and a local explanation of the machine learning model.

Mediation analysis

A correlation analysis for repeated measures based on an auto-regressive model was conducted on the entire dataset between the TQR ratings and the following variables:

(1) TL, TL_{acute} and $TL_{chronic}$;
(2) Fatigue, sleep quality, muscle soreness, stress and mood rated at the same time as the TQR ratings.

Second, where the assumption of statistically significant correlation were met, a mediation analysis was conducted with the aim of detecting if the hypothesised relationship between training load variables and TQR was mediated by one or more of the five WQ variables listed above. In order to take in consideration the assumption of related pairs, a repeated measures mediation analysis was performed. In particular, Marginal Regression Model using Generalised Estimating Equations based on Autoregressive covariance structure was used to meet both time series and repeated measures assumptions. Specifically, mediation analysis was conducted for TL and its acute and chronic aggregations if the assumption of statistically significant correlations were met (i.e., the mediation model was built on variables that are both correlated with dependent and independent features). The RMSE was used as indicators of model goodness. Moreover, in the context of GEE, where observations may be correlated within clusters or subjects, in order to evaluate the strength of the relationship it is more appropriate to use a correlation-like measure that accounts for the correlation structure. One such measure is the Intraclass Correlation Coefficient (ICC), which quantifies the proportion of total variance that is due to between-cluster (or between-subject) variability. The ICC ranges between 0 and 1. Higher values of ICC indicate a stronger correlation within clusters (higher inter-cluster variability) relative to the total variability, while lower values indicate a weaker correlation within clusters (lower inter-cluster variability) relative to the total variability. An ICC close to 0 suggests that observations within clusters are almost independent, while an ICC close to 1 suggests high correlation between observations within clusters.

The data preprocessing, machine learning and mediation analysis was conducted by using Python 3.9 language programming.

Results

Machine learning approach

Thirteen out of 21 independent features were selected by the RFECV approach. Figure 1 shows a strong correlation and a small error between TQR observed and predicted ($r = 0.81$, MSE = 1.27, RMSE = 1.13). LM showed a lower prediction accuracy ($r = 0.57$, MSE = 2.46, RMSE = 1.57) ensuring that the XGBR model is sensible to TQR prediction.

Table 2 shows the features selected and their importance to predict TQR by XGBR. Fatigue is the most important feature (importance = 37.2%) followed by muscle soreness (importance = 12.0%), $mood_{chronic}$ (importance = 7.9%) and $fatigue_{chronic}$ (importance = 7.4%). The other daily features (i.e., sRPE and sleep) show a cumulative importance of

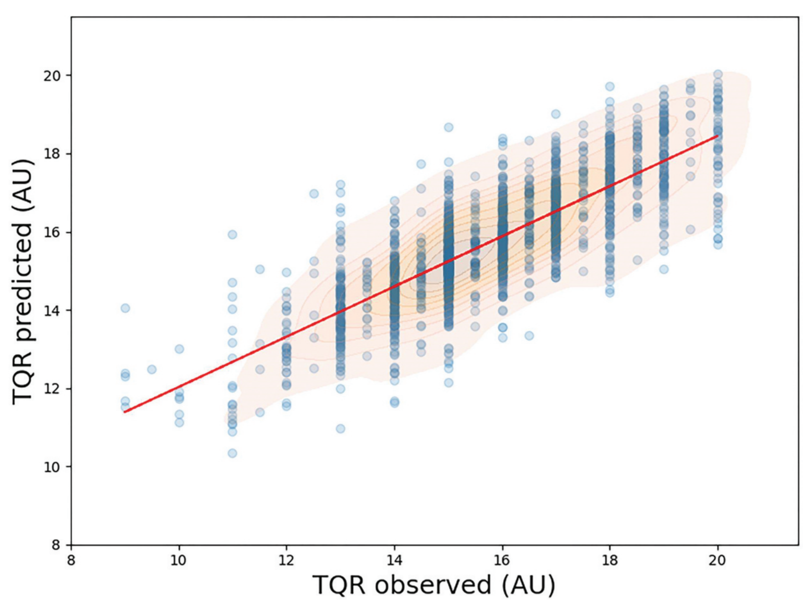

Figure 1. Scatter density plot of the TQR observed and predicted.

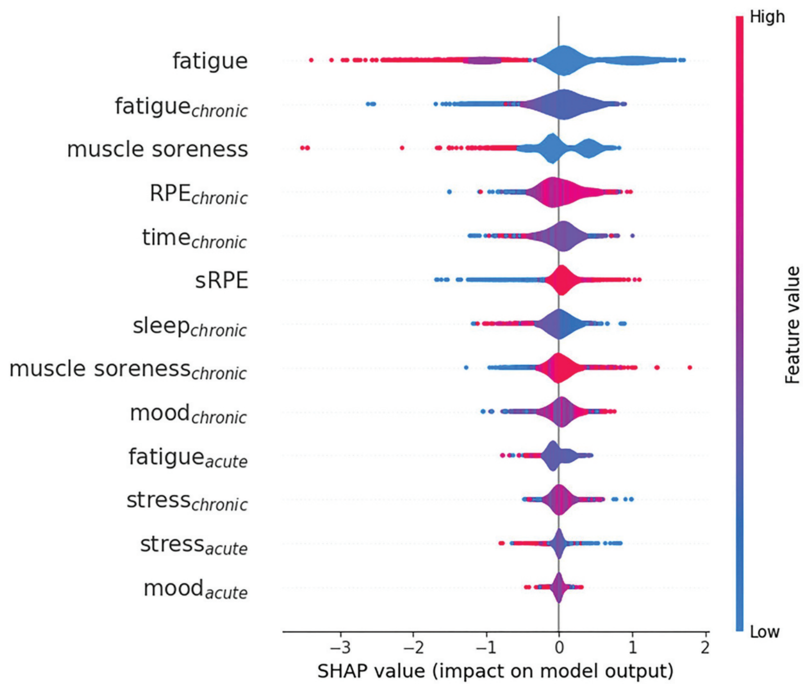

Figure 2. Global explanation of the fitted XGBR model based on SHAP analysis. Influence of independent features on subjective recovery (TQR). The predictors are ranked in descending order in accordance with the features importance. Each point on this plot is a Shapley value for a feature and an instance. The position on the y-axis is determined by the feature and on the x-axis by the Shapley value. The colour represents the value of the feature from low (blue) to high (red), progressively.

about 5.6% resulting in a total importance of about 54.8%. Otherwise, the weekly aggregations (i.e., $fatigue_{acute}$ and $sleep_{acute}$) show a cumulative importance of 6.3%, while the chronic aggregations (i.e., $mood_{chronic}$, $fatigue_{chronic}$, $stress_{chronic}$, muscle $soreness_{chronic}$, $sleep_{chronic}$, $sRPE_{chronic}$ and $time_{chronic}$) describe an overall importance of 38.9%. Figure 2 shows the global explanation (indications of the relationship between the value of a feature and the impact on the prediction) of the XGBR decision-making process.

Mediation analysis

Descriptive statistics of all the features included in this study is provided in Table 1. Significant relationships with TQR were

Table 1. Descriptive statistics.

Features	mean	SD	min	25%	50%	75%	max
sRPE	4.14	1.91	0.5	3	4	5	10
time	73.5	23.3	31	60	73	87	170
TL	320	208	18	180	280	413	1360
fatigue	2	0.75	1	2	2	2	5
sleep	1.91	0.78	1	1	2	2	5
muscle soreness	1.82	0.75	1	1	2	2	5
stress	2.17	0.77	1	2	2	3	5
mood	2.05	0.81	1	1	2	3	5
TQR	15.81	1.93	6	15	16	17	20

sRPE: session rating of perceived exertion. TL: training load; TQR: total quality recovery.

Table 2. Autoregressive model for repeated measures correlation analysis.

model parameters	coefficient	SD	z-score	p-value
Intercept (AU)	18.51	0.41	45.35	<0.001
Fatigue (AU)	−1.35	0.15	−9.11	<0.001
Intercept (AU)	16.97	0.33	50.86	<0.001
Sleep (AU)	−0.61	0.12	−5.14	<0.001
Intercept (AU)	17.81	0.35	50.30	<0.001
Muscle soreness (AU)	−1.10	0.14	−7.77	<0.001
Intercept (AU)	16.66	0.39	43.19	<0.001
Stress (AU)	−0.39	0.14	−2.72	<0.01
Intercept (AU)	16.49	0.41	40.75	<0.001
Mood (AU)	−0.33	0.16	−2.05	<0.05
Intercept (AU)	15.27	0.21	73.90	<0.001
TL (sRPE*time)	2.3e-3	1.1e-3	6.13	<0.001

TL: training load; sRPE: session rating of perceived exertion; AU: arbitrary units.

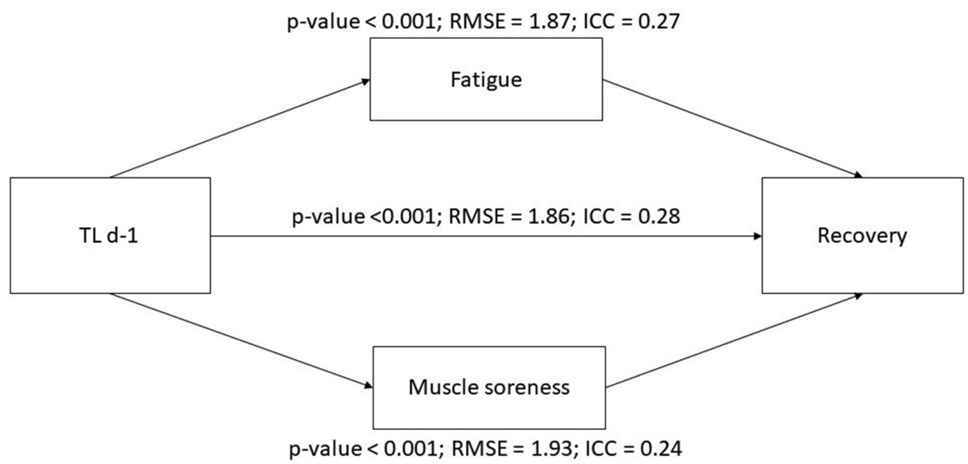

Figure 3. Directed acyclic graph showing the outcomes of the mediation analysis. RMSE: Root Mean Square Error; ICC: Intraclass Correlation Coefficient; TL d-1: Training Load of the previous day.

detected for both TL and WQ variables (Table 2). In order to detect if the relationship between TL and TQR is mediated by the WQ variables, a mediation analysis was conducted. The analysis was performed for TL, TL_{acute}, $TL_{chronic}$. A statistically significant relationship of TL on TQR was detected (beta coefficient = 0.002 [0.001, 0.002]; p-value <0.001; RMSE = 1.96; ICC = 0.22). The mediation analysis (Figure 3) shows a statistically significant direct effect (beta coefficient = 0.001 [0.001, –0.002]; p-value <0.001; RMSE = 1.86; ICC = 0.28) of TL on TQR. This relation is mediated by muscle soreness (beta coefficient = 0.0006 [0.0003, 0.0008]; p-value <0.001; RMSE = 1.93; ICC = 0.24) and fatigue (beta coefficient = 0.0005 [0.0002, 0.0007]; p-value <0.001; RMSE = 1.87; ICC = 0.27). The other WQ variables (sleep quality, stress, mood) did not qualify as mediators of the relationship between TL and TQR.

The relationships between TL_{acute} (beta coefficient = 0.0003 [–0.001, 0.002]; p-value = 0.70; RMSE = 1.94; ICC = 0.21) and $TL_{chronic}$ (beta coefficient = 0.0007 [–0.003, 0.004]; p-value = 0.69; RMSE = 1.94; ICC = 0.21) with TQR are not statistically significant and, therefore, no further mediation analysis was required because the assumption for conducting the mediation analysis was not met.

Discussion

The aim of this study was to explore potential determinants of subjective recovery in professional soccer players using machine learning analysis and to further investigate whether the relationship between training load and subjective recovery is mediated by fatigue, sleep quality, muscle soreness, stress and mood.

The evidence provided by the present study suggests that the subjective judgements of recovery status by soccer players are primarily influenced by the feelings of fatigue and muscle soreness at the time such judgements are made. These feelings also seem to mediate most of the relationship between training load of the previous day and subjective recovery. Interestingly and confirmed by mediation analysis, both training load of the previous week and training load of the previous 4 weeks were not associated with subjective recovery. In fact, rather than being direct, the relationship between training load and subjective recovery seems to be strongly mediated by the perception of fatigue. A similar approach was adopted by a recent study on endurance training, which investigated the complex relationships between internal load and subjective recovery status in elite athletes using machine learning techniques (Rothschild et al., 2024). The study identified training load, sleep quality, and heart rate variability as key predictors of daily recovery during long-term endurance training. This study contributed to highlight how advanced data-driven approaches can be employed to better understand the multifactorial dynamics of training demands and subjective recovery metrics, providing relevant insights for improving load management strategies in endurance athletes (Rothschild et al., 2024).

An important result of this study is that it is possible to predict the soccer players' subjective recovery based on TL components (sRPE and time) and ratings of fatigue, sleep quality, muscle soreness, stress and mood. As a matter of fact the machine learning approach shows a very low error (MSE = 1.27 and RMSE = 1.13) suggesting that the model is very accurate in estimating the TQR scores (Figure 1). Although other factors may also play a role, the high accuracy of our model suggests that the combination of training load, fatigue, sleep quality, muscle soreness, stress and mood can explain a lot about the subjective recovery of professional soccer players.

In this study, a machine learning model was employed to gain insights into the impact of subjective ratings (i.e., fatigue, sleep quality, muscle soreness, stress and mood) on the recovery construct, rather than the development of a predictive model. The evaluation of the model's quality was essential to confirm the presence of a cause–effect relationship in the underlying dynamics. The machine learning approach (Table 3) suggests that players' judgement of their recovery is mainly affected by the fatigue and muscle soreness experienced when providing the TQR rating (49.2%). Moreover, except for sleep that shows a minimal importance (1.8%), the other WQ variables (mood and stress) do not significantly contribute to the prediction of subjective recovery. Additionally,

Table 3. Feature importance (SHAP mean) of the best subset of the features selected by RFECV for XGBR.

Feature	Importance (%)
fatigue	37.20
muscle soreness	12.00
$mood_{chronic}$	7.93
$fatigue_{chronic}$	7.42
$stress_{chronic}$	5.37
muscle $soreness_{chronic}$	5.25
$sleep_{chronic}$	4.47
$sRPE_{chronic}$	4.43
$time_{chronic}$	4.04
sRPE	3.79
$fatigue_{acute}$	3.14
$sleep_{acute}$	3.12
sleep	1.85

RFECV: Recursive Feature Elimination with 10 Cross-Validation; XGBR: Extreme Gradient Boosting Regressor; sRPE: session rating of perceived exertion.

even if the chronic aggregation (previous 4 weeks) of each WQ variable and TL components shows a low importance to predict subjective recovery, the sum of these chronic parameters reaches an overall importance of 38.9%. This finding suggests that chronic stress, mood and sleep quality, together with the training history of the players, affect their subjective recovery. In fact, chronic stress elevates cortisol levels, impairing muscle repair and adaptation, while mood and sleep quality influence fatigue perception and recovery processes like hormone regulation and cognitive restoration. Training history shapes physical conditions and recovery capacity, making these factors critical in assessing and managing athletes' recovery. Conversely, the acute aggregations (previous week) of fatigue and sleep contribute only marginally to the prediction of subjective recovery, and the other acute aggregations (muscle soreness, stress, mood and TL components) do not contribute at all.

Interestingly, the machine learning approach shows only a marginal importance for sRPE (3.8%) and time of the previous day did not directly contribute significantly to the prediction of subjective recovery. There are two possible explanations for such findings. The first is that the training load of the previous day has only a small effect on subjective recovery. The second, and more likely explanation, is that the effect of training load of the previous day is mediated to a large extent by its effects on fatigue and muscle soreness. To test this hypothesis and further explore the relationships between training load of the previous week and previous 4 weeks, a mediation analysis approach was employed. This finding aligns with existing literature. Studies have reported that acute training load often has a limited direct impact on subjective recovery, with its effects being largely mediated by factors like fatigue and muscle soreness (Kellmann et al., 2018; Nedelec et al., 2014). The mediation analysis approach used here is consistent with research emphasizing the indirect pathways through which training load influences recovery, particularly when considering cumulative load over multiple weeks.

The first step of this mediation approach showed that neither TL_{acute} nor $TL_{chronic}$ is associated with subjective recovery. Only the training load of the previous day is significantly correlated with subjective recovery. Further analysis of the factors mediating such correlation revealed that fatigue (25%) and muscle soreness (30%) experienced, when providing the TQR scores, mediated most of the relationship between training load of the previous day and subjective recovery. The present findings based on mediation analysis of a large set of ecological data are corroborated by smaller intervention studies. For example, Selmi et al (Howle et al., 2019) found that intensified training in a group of 15 professional soccer players increased subjective feelings of fatigue and muscle soreness and reduced TQR scores. Furthermore, these authors found that TL was positively associated with subjective feelings of fatigue and muscle soreness, and negatively with TQR scores. Interestingly, as in our study, Selmi et al (Selmi et al., 2020). found no correlations of TL with subjective ratings of sleep and stress.

Although fatigue and muscle soreness experienced when providing the TQR scores mediated most of the relationship between the training load of the previous day and subjective recovery (indirect effect), there was also an important direct effect of TL. One possible explanation for this finding is that there are other important mediators that were not measured in the present study. However, a true direct effect of the training load of the previous day on the players' judgement of their recovery status is also plausible. For example, strong feelings of fatigue and muscle soreness after a day of rest may be interpreted more negatively in terms of recovery (i.e., poor recovery) compared to the same feelings experienced the day after an intense training session (i.e., expected recovery). Overall, while some effects of training load may appear direct, they are likely influenced by unmeasured or latent mediators not considered in our model. Philosophically speaking, this reflects the complexity of psychophysiological processes and the difficulties in isolating independent effects.

Although a very large set of ecological data from professional soccer players was collected and a complex statistical analysis was performed, the main limitation of this study is its correlative nature, as causality can only be determined through experimental designs like randomized controlled trials. Another important limitation is the use of the WQ to measure fatigue, sleep quality, muscle soreness, stress and mood. Although widely used in both research and practice, the five single-item scales of the WQ have not been validated against criterion measures of the same constructs. Its ordinal nature can limit analytical depth compared to continuous scales, reducing sensitivity to subtle response variations and hindering precise representation of complexity. Furthermore, our measures of TL refer only to training duration and sRPE, which is a subjective measure of exertion. Other training characteristics that we did not measure may affect muscle soreness and, thus, subjective recovery. These include, the prevalence of eccentric over concentric muscle contractions or the accustomization of the player to a specific training modality.

Finally, despite our findings may be applicable also to other teams, particularly at the same competitive level, caution is warranted when generalizing the use of current algorithms. In fact, the model provided should be 'trained' specifically for each team, due to the fact that every team has its own characteristics such as, for example, different players' physical fitness and training scheduled programmes.

Practical applications

The findings of this study have several practical applications. From a programming perspective, our study suggests that reducing the internal load of the training session performed the previous day is the most effective strategy if the goal is to maximise subjective recovery. Indeed, this practice is already commonly used by coaches before an important match (Impellizzeri et al., 2004). Reducing the internal training load of the whole week before a match does not seem so important in terms of subjective recovery.

Therefore, interventions specifically targeting mental fatigue (e.g., psychological load management) (M. Smith et al., 2015; M. R. Smith et al., 2016) and muscle soreness (e.g., active recovery) (Heiss et al., 2019) may improve subjective recovery of soccer players, and should be considered by coaches and practitioners throughout the weekly training routine. Further experimental studies should be employed to verify these hypotheses.

Conclusions

The big data analytics employed in this study, through machine learning and mediation analyses, suggest that subjective recovery is primarily associated with ratings of fatigue and muscle soreness at the time of such judgments, and that these factors are the most important mediators of the relationship between training load of the previous day and subjective recovery. Overall, these findings suggest that, to maximize subjective recovery of professional soccer players, coaches and staff should implement strategies to minimize fatigue and muscle soreness. From a programming perspective, reducing the training load of the previous day seems the most effective strategy. Experimental studies are needed to confirm these correlative findings and establish a stronger link between fatigue, muscle soreness, subjective recovery and, ultimately, soccer performance.

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