



Research article

Association between internal load responses and recovery ability in U19 professional soccer players: A machine learning approach

Guglielmo Pillitteri^a, Alessio Rossi^{b,c}, Carlo Simonelli^d, Ignazio Leale^a, Valerio Giustino^a, Giuseppe Battaglia^{a,*}^a Sport and Exercise Sciences Research Unit, Department of Psychology, Educational Science and Human Movement, University of Palermo, Palermo, Italy^b Department of Computer Science, University of Pisa, Pisa, Italy^c National Research Council (CNR), Institute of Information Science and Technologies (ISTI), Pisa, Italy^d Department of Biomedical and Neuromotor Sciences, University of Bologna, Bologna, Italy

ARTICLE INFO

Keywords:

Soccer
Sport performance
Training load
Recovery
Injury prevention
Machine learning

ABSTRACT

Background: The objective of soccer training load (TL) is enhancing players' performance while minimizing the possible negative effects induced by fatigue. In this regard, monitoring workloads and recovery is necessary to avoid overload and injuries. Given the controversial results found in literature, this study aims to better understand the complex relationship between internal training load (IL) by using rating of perceived exertion (RPE), recovery, and availability (i.e., subjective players' readiness status).

Methods: In this cross-sectional study, twenty-two-professional soccer players (age: 18.5 ± 0.4 years, height: 177 ± 6 cm, weight: 67 ± 6.7 kg) competing in the U19 Italian Championship were monitored using RPE scale to assess IL, and TreS scale to detect information about recovery and training/match availability during an entire season (2021–2022).

Results: Autocorrelation analysis showed a repeated pattern with 7 days lag (weekly microcycle pattern) for all the variables considered (i.e., TL, recovery, and availability). For recovery ($r = 0.64$, $p < 0.001$) and availability ($r = 0.63$, $p < 0.001$) the best lag for both of them is 1 day. It indicates that recovery and availability are related to the past day value. Moreover, TL was found to be negatively affected by recovery and availability of the current day (lag = 0 day). Cross-correlation analysis indicates that TL is negatively affected by recovery ($r = 0.46$, $p < 0.001$) and availability ($r = 0.42$, $p < 0.001$) of the current day (lag = 0 day). In particular, lower recovery and availability will result in following lower TL. Furthermore, we found that TL negatively affects recovery ($r = 0.52$, $p < 0.001$) and availability ($r = 0.39$, $p < 0.01$) of the next day (lag = 1 day). In fact, the higher the TL in a current day is, the lower the recovery and availability in the next day will be.

Conclusion: In conclusion, this study highlights that there is a relationship between TL and recovery and that these components influence each other both on the same day and on the next one. The use of RPE and TreS scale to evaluate TL and recovery/availability of players allows practitioners to better adjust and schedule training within the microcycle to enhance performance while reducing injury risk.

* Corresponding author.

E-mail address: giuseppe.battaglia@unipa.it (G. Battaglia).

1. Introduction

The objective of soccer training is enhancing players' performance while minimizing the possible negative effects induced by fatigue such as injuries [1–6]. It is well known that soccer players are subjected to a given load during both training and competitions that induces a certain degree of neuromuscular, metabolic, and mental fatigue. Indeed, the improper management of training load (TL) could be considered as one of the main risk factors in non-contact injuries [7–9]. TL has been defined as “a higher-order construct reflecting the amount of physical training that is actually done and experienced by the athletes” [7,10–12]. TL is described by its two components known as internal load (IL) and external load (EL) [13–15]. The EL (i.e., physical work prescribed in the training plan) induces internal responses related to psychological, physiological, biochemical, metabolic, and biomechanical stress stimuli [15–18]. Meanwhile, the acute dose–response paradigm indicates that specific internal responses such as heart rate (HR) or rating of perceived exertion (RPE), are induced by external training factors (e.g., high speed distance, sprinting distance, metabolic power, and accelerations/decelerations) [17,19,20]. Hence, monitoring EL and IL is essential for the management of soccer players during both training and competition to maximize athletic performance and potentially minimize injury risk [20–22]. Indeed, a training characterized by prolonged and high-load, with an inadequate balance between training volume, intensity, and recovery, can lead to poor adaptation [23–25] inducing to a condition of overreaching [23,26]. Kenttä and Hassmén (1998) indicated that training recovery is a critical component for adaptation and performance, and it permits to avoid the potential maladaptive physical and psychological effects of fatigue [12,24]. Indeed, Nédélec et al. (2015) reported that high TL reduces wellness and is related to the perceived sleep, stress, fatigue, and muscle soreness in professional soccer players [23,27,28]. In this way, the literature suggests to evaluate muscle soreness

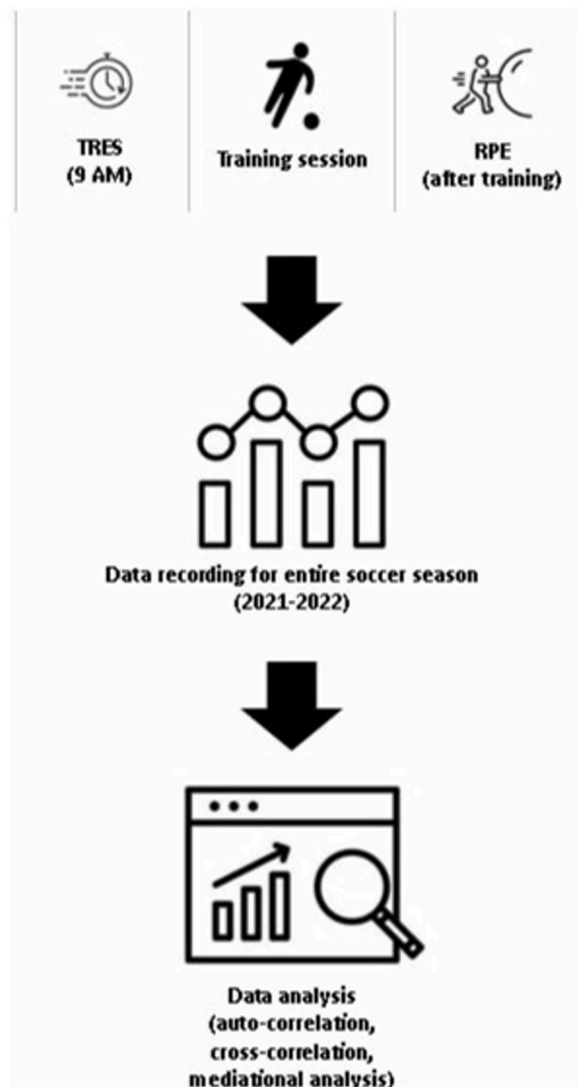


Fig. 1. Research structure diagram.

and fatigue before, during, and after each training session to understand the recovery state from workload [4,5,29–32]. In this way, several research related to markers of fatigue and recovery have been conducted in sports science and exercise physiology area [33–37]. Those included biochemical [4,38], hormonal [4,38], immunological [33,39,40], psychological questionnaires [25,34,41,42], and the assessment of neurological status, such as autonomic nervous system balance [1,43]. However, although a number of scientifically reliable indicators exist, there is currently no single conclusive marker of fatigue [4,30,44]. Therefore, the use of psychological questionnaires to monitor fatigue and recovery status could also be useful as they are inexpensive and easy to apply compared to more complex laboratory assessments [30,45]. Validated self-report questionnaires that are frequently used include the Profile of Mood States (POMS) [46], the Total Quality Recovery (TQR) [7], the Daily Analysis of Life Demands for Athletes (DALDA) [47], the Recovery Stress Questionnaire for Athletes (REST-Q) [48], the Acute Recovery and Stress Scale (ARSS) [49], and the Rating of Fatigue Scale (ROF) [50]. Interestingly, the use of personalized self-assessment questionnaires has increased compared to the questionnaires published in the literature [51,52].

Since recovery is a critical period between successive training sessions or competitions potentially necessary to improve subsequent performance (i.e., supercompensation, so-called psycho-physiological process for reducing fatigue and regaining vigor) [25], the main objective of the TQR scale is to prevent the onset of fatigue and to find a balance between training and recovery [53]. In this context, Selmi et al. (2018) [54] highlighted that TQR and Hooper Index (HI) (i.e., sleep quality, overall stress, fatigue, and DOMS) are useful to monitor the effects of TL and sensitive to stress and recovery assessment [34]. For example, HI and TQR scores are significant predictors of performance in soccer players [33,55] with increasing HI and TQR scores significantly associated with high TL [33,36,56]. Interestingly, a review carried out by Selmi et al. (2018), reported that HI and TQR recorded before each training session or match were influenced by the variability of TL and influenced the physical and technical soccer performances [57]. However, some authors found no significant association between the TQR, wellbeing status, and the RPE in soccer [1,7,54,57]. These controversial results could be due to the typology of analysis conducted. Indeed, the analytical approach of these studies are mono-dimensional, i.e., the use of only one variable at time without fully manipulating the complex patterns (i.e., TL) inherent the available data. Differently, to the best of our knowledge, only few studies, including the one carried out by Rossi et al. (2019) [58], applied a complex analysis such as machine learning approaches to investigate the relationship between TL, wellness, and recovery. In this perspective, the authors found that it is possible to accurately estimate the wellness status of players based on their workload history [58]. These approaches could help to better understand the implications of TL on players' wellness and recovery status, allowing the development of mathematical models able to give accurate prediction and consequently possible useful insights about injury risks [59–63] and internal TL [64].

Considering that previous studies highlighted the strong mono-dimensional relationship between TL and individuals' wellbeing, the aim of this study was to better understand the complex relationship between IL (using RPE methods), recovery state, and availability (i.e., subjective players' readiness status) using a machine learning approach. With this approach, practitioners could easily simulate players' response to planned training in order to maximize the training effect and possibly to reduce injury risk.

2. Materials and methods

2.1. Experimental approach to the problem

In this cross-sectional study, players from a professional Italian soccer club were monitored using RPE scale [65] to assess IL, and TreS scale [66,67] to detect information about recovery and training/match availability during an entire season (2021–2022).

Fig. 1 provide the research structure process used for this study. First, the data of the TreS scale was recorded every morning at 9:00 a.m. Then, after each training session, the rating of perceived exertion (RPE) was recorded for each player.

In order to detect pattern describing the training mycrocicle an auto-correlation analysis was conducted. Moreover, a cross-correlation analysis was also performed in order to detect a relationship between self-reported recovery/availability and the TL. Finally, based on the results of the previous analyses, a mediational analysis was conducted in order to detect the mediators affecting the relationship between TL and recovery of the next day.

2.2. Participants

Thirty-two-professional soccer players (age: 18.5 ± 0.4 years, height: 177 ± 6 cm, weight: 67 ± 6.7 kg) competing in the U19 Italian Championship were analysed. The selected soccer players had in average 12 years of soccer training experience. Moreover, they carried out 5 training sessions per week plus the official match. The following inclusion criteria were considered: 1) professional male soccer players; 2) no injury in the previous six months. Based on the exclusion criteria, only the goalkeepers were not eligible for the study. The duration of the training sessions was approximately 110 min and mainly included technical-tactical team tasks along with some general physical exercise without ball (e.g., high intensity interval training, HIIT) [21,45]. Strength and conditioning exercises were performed twice a week (i.e., one session in the gym and one session on the pitch).

All participants signed an informed consent before taking part in the data collection. The study, which complies with the principles of the Declaration of Helsinki, was approved by the Bioethics Committee of the University of Palermo (n. 68/2021).

2.3. Procedures

Participants were monitored during training and official matches (OM) performed on a third-generation artificial pitch or natural grass. Data was collected through RPE scale. Internal TL was calculated multiplying training durations and RPE value. To estimate the

players' state of recovery the TreS scale was used.

Soccer players were categorized into six groups according to their role as follows: central back (CB, $n = 5$), external strikers (ES, $n = 5$), fullback (FB, $n = 7$), midfielder (MD, $n = 5$), wide midfielder (WM, $n = 7$), and strikers (S, $n = 3$).

2.4. Measures

Internal load assessment – Internal TL for each participant was calculated according to the session-RPE method by Foster et al. (2001) [68]. In detail, 30 min after each session, the duration (minutes) and each RPE training session were recorded for players using smartphone applications (i.e., through a WhatsApp broadcast list). TL from each session for each player was calculated from the product of the session duration and the player's RPE (Foster et al., 2001) [68]. The training session duration included warm up, cool down, and rest between tasks.

Recovery assessment – To estimate the players' state of recovery the TreS scale [66,67] that includes both Global Quality Recovery (GQR) and Training Intensity Availability (TIA) was used. Global Quality Recovery (GQR) ranging from “I have not recovered at all” (0 points) to “Full recovery” (10 points) presented to the athletes before the daily training session through WhatsApp using the question: “What is your physical recovery condition now?”. Training Intensity Availability (TIA) ranging from “Complete rest” (0 points) to “Ready for competition” (10 points). Athletes answered the following question: “What is your availability to train or compete?”. The questionnaire has been proposed in the morning at the same time period (i.e., 9:00 a.m.). Each player received a graphical imagine scale on WhatsApp including a precise description of the scale values.

2.5. Statistical analysis

An autocorrelation analysis was conducted in order to detect similarity between observations among the variables (i.e., TL, recovery, and availability) time series as a function of the time lag between them. Autocorrelation is the correlation of a signal with a

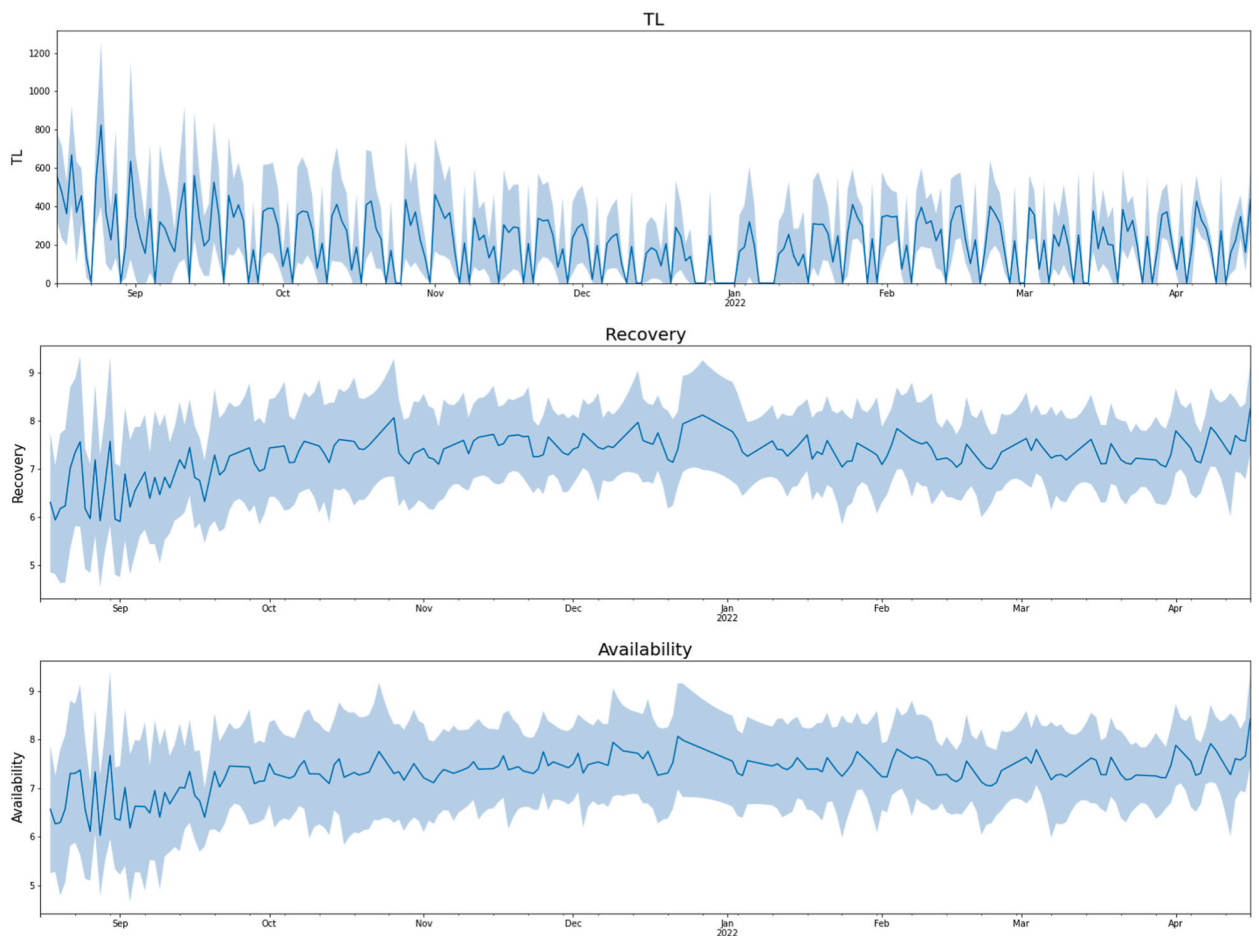


Fig. 2. Time series of TL, Recovery, and Availability. The line reflects the team mean, while the shade is the team variability. Legend. TL, Training Load; Sep, September; Oct, October; Nov, November; Dec, December; Jan, January; Feb, February; Mar, March; Apr, April.

delayed copy of itself as a function of delay. The analysis of autocorrelation is a mathematical tool for finding repeating patterns, such as the presence of a periodic signal obscured by noise or identifying the missing fundamental frequency in a signal implied by its harmonic frequencies. In statistics, the autocorrelation of a real or complex random process is the Pearson correlation (r) between values of the process at different times, as a function of the two times or of the time lag.

A cross-correlation analysis was conducted in order to detect correlations between two time series. Cross-correlation is a measure of similarity of two series of data as a function of the displacement of one relative to the other. The term cross-correlations refers to the correlations between the entries' time series.

Moreover, the magnitude of the auto- and cross-correlation were also reported as the coefficient of determination (r^2).

A mediational analysis was conducted in order to detect the mediators that affect the relationship between TL and recovery of the next day. In order to take in consideration, the assumption of related pairs, a repeated measures mediational analysis was performed. In particular, marginal regression model using generalized estimating equations based on autoregressive covariance structure was used to meet both time series and repeated measures assumptions.

All the analyses were performed by using Python 3.8 programming language.

3. Results

3610 observations were recorded for this study. In total, 191 training sessions (112.81 ± 55.96 trainings per player) were analysed. Players were followed for 10 months (from August 16th 2021 to April 16th 2022), that is during 44 weeks, 191 training days (119 were rest days), and 43 official matches. Fig. 2 shows the timeseries of TL, recovery, and availability. The descriptive statistics for all the features was provided in Table 1.

The autocorrelation analysis indicates that there is a repeating pattern for all the variables (Fig. 3). In particular, TL shows a moderate autocorrelation at 7 days lag ($r = 0.53$, $r^2 = 0.27$, $p < 0.001$). This indicates that there is a repeated weekly microcycle throughout the season. For recovery ($r = 0.64$, $r^2 = 0.41$, $p < 0.001$) and availability ($r = 0.63$, $r^2 = 0.40$, $p < 0.001$), the best lag for both of them is 1 day. It indicates that recovery and availability are related to the past day value. Moreover, an autocorrelation peak is detected at 6–7 days lag for both recovery ($r = 0.58$, $r^2 = 0.34$, $p < 0.001$ and $r = 0.57$, $r^2 = 0.33$, $p < 0.001$, respectively) and availability ($r = 0.58$, $r^2 = 0.34$, $p < 0.001$ and $r = 0.56$, $r^2 = 0.31$, $p < 0.001$, respectively) reflecting the weekly microcycle.

The cross-correlation analysis (Fig. 4) indicates that TL is negatively affected by Recovery ($r = 0.46$, $r^2 = 0.21$, $p < 0.001$) and Availability ($r = 0.42$, $r^2 = 0.18$, $p < 0.001$) of the current day (lag = 0 day). This indicates that TL is modulated by practitioners in accordance with Recovery and Availability status of the players. In particular, the lower the Recovery and Availability are, the lower TL will be.

Moreover, Fig. 4 shows that TL negatively affects recovery ($r = 0.52$, $r^2 = 0.27$, $p < 0.001$) and availability ($r = 0.39$, $r^2 = 0.15$, $p < 0.01$) of the next day (lag = 1 day). It indicates that TL influences recovery and availability status of the players on the next day. Indeed, the higher the TL is, the lower the recovery and availability will be in the next day.

The mediational analysis indicates that there is a direct relationship between TL and recovery in the next day (coefficient = -0.0003 [-0.0004 , -0.0002]; $p < 0.001$). Additionally, this relationship is moderately mediated by availability (coefficient = -0.0001 [-0.0002 , -0.0000]; $p < 0.01$).

4. Discussion

This study aimed to find the complex relationship between TL (i.e., internal training load operationalized using $RPE \times \text{session time}$) and training/match recovery and availability (using TreS scale) through multidimensional analysis. Specifically, autocorrelations, cross-correlation, and mediational analysis have been conducted for this cross-sectional study involving an entire season performed by U19 professional soccer players.

The first main result of this work is that there is a repeating pattern for all the variables considered (TL, recovery, and availability) as shown by autocorrelation analysis (Fig. 3). Specifically, analysis reveals a repeated TL weekly microcycle structure (7 days lag) throughout the season which can be attributed to the training programming scheduled by the technical and physical staff. The same microcycle structure has been found also considering recovery and availability although the strength of their correlations is less evident at 7 days lag. This result could be explained by the complex nature of the recovery (complex and multifactorial phenomenon)

Table 1
Descriptive statistics.

	TL	Recovery	Availability
mean	376.41	7.35	7.36
std	203.95	1.01	1.00
min	20	4	1
25%	240	7	7
50%	360	7	7
75%	480	8	8
max	1620	10	10

Legend: TL, training load; std, standard deviation; min, minimum; 25% percentile; 50% percentile; 75% percentile; max, maximum.

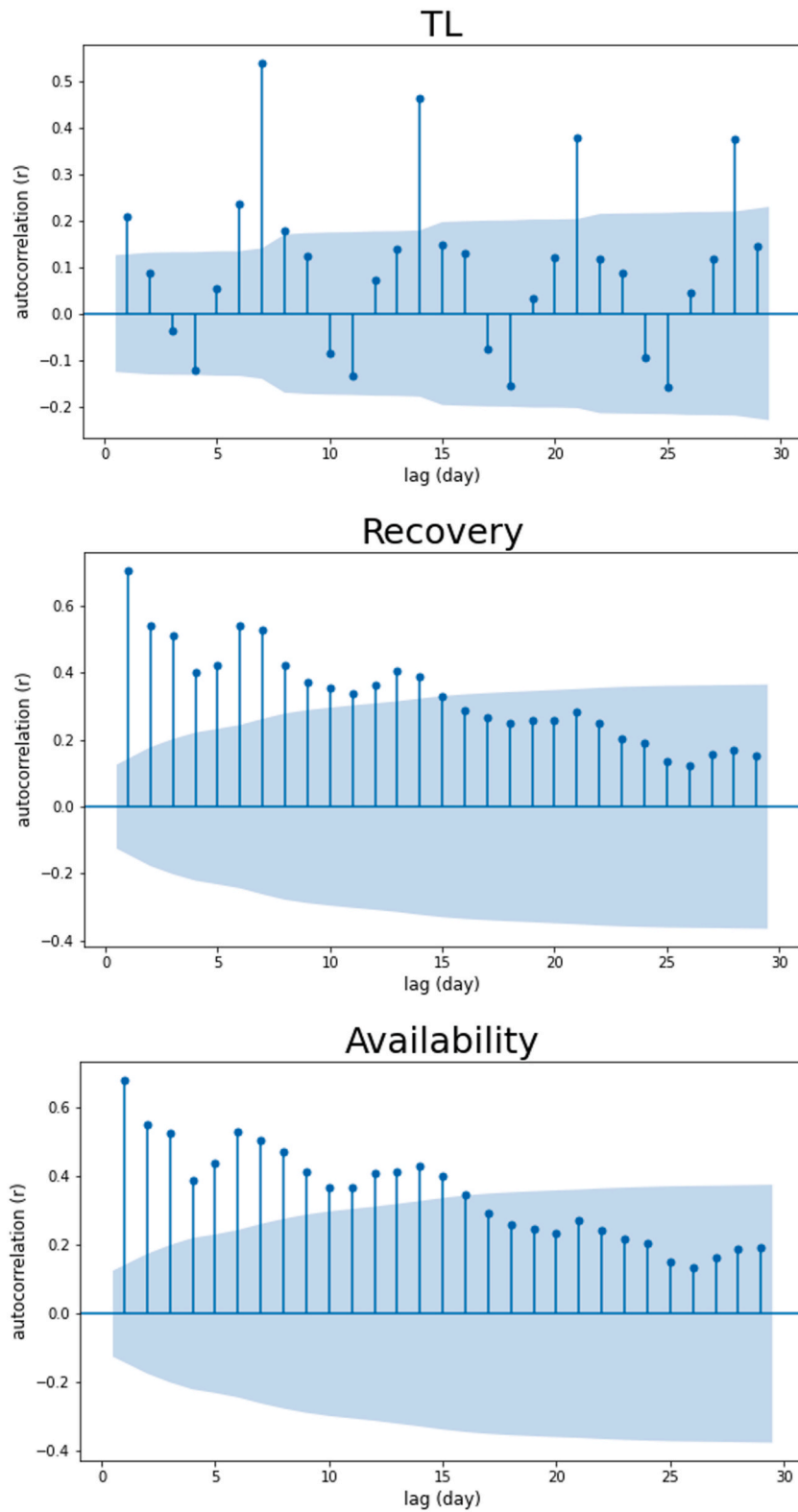


Fig. 3. Autocorrelation plot of TL, Recovery, and Availability. The bars reflect the autocorrelation coefficient of a specific lag, while the shadow shows the range of statistical significance. Legend. TL, Training Load.

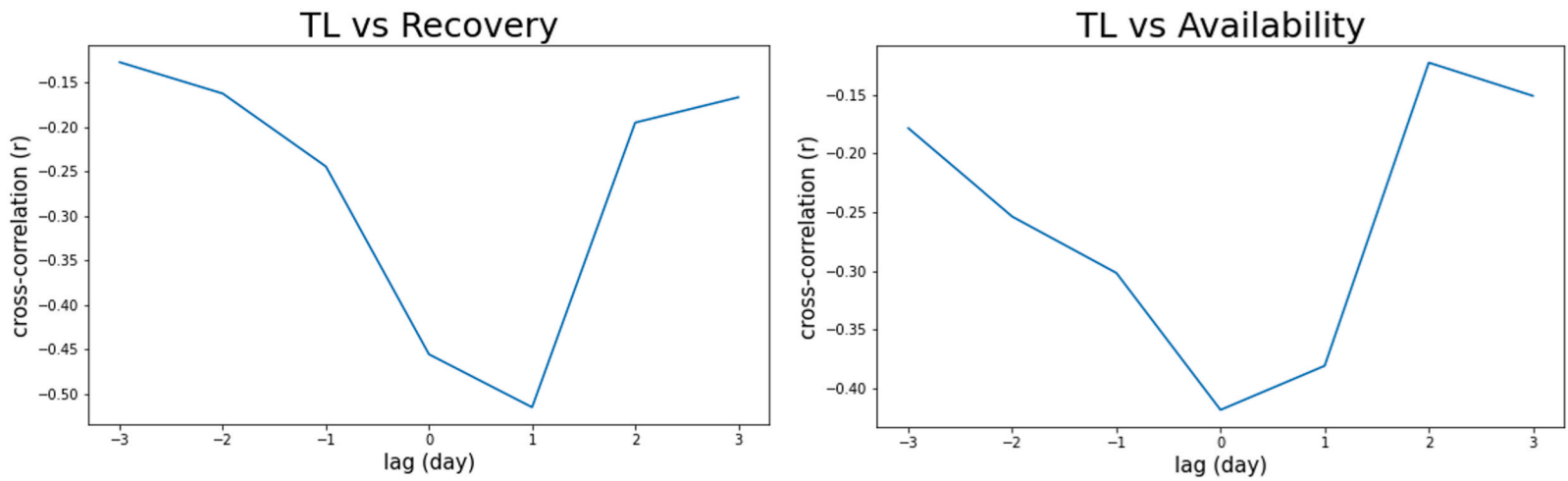


Fig. 4. Cross-correlation analysis of TL vs Recovery and TL vs Availability. Legend. TL, Training Load.

compared to the load. In fact, the recovery registered on a given day depends on the recovery of the previous ones (and therefore on the fatigue conditions of the player) [1,2,5,6]. Moreover, the recovery is subjective and is closely linked to individual factors of the players. The differences in stimuli and load represent a critical aspect to achieve physiological adaptations within the context of elite soccer [7–9]. Moreover, training programming is a fundamental strategy to potentially increase performance and, at the same time, trying to reduce the risk of injury [7,10,11,13–25]. For example, a study suggests quantifying loads relative to competition demands as it represents an advantageous strategy for training periodization models [23,26]. In order to optimize the training effects [12,24] and the consequent adaptations deriving from them, some programming practices have been suggested such as tapering with particular interest to recovery strategies (as for example in MD+1 for players who have played more than 60 min) [23,27,28]. Given the high psycho-physical stress involved in the soccer activity, especially in official matches, monitoring both the player's recovery and training load is essential for optimizing performance and reducing the likelihood of injury occurrence [4,5,29–31].

The player's physical, technical, tactical, and psychological responses to a training stimulus can be influenced by a number of factors such as an imbalance between the training-recovery process, an increase in TL, an accumulation of fatigue, and the player's fitness status [33–36]. Recovery has been described as the vital period between successive training sessions or competitions with the potential to improve performance later (psycho-physiological process for reducing fatigue and regaining vigour) [4,38]. The relationship between loading and recovery has been investigated by several studies which have shown conflicting results [4,38]. Some studies found that HI and TQR scores are significant predictors of performance in soccer athletes [33,39,40] and significantly associated with heavy training loads (i.e., high HI and TQR scores associated with high TL) [25,34,41,42]. However, other studies showed no significant association between TQR, wellbeing status, and training load in soccer [1,43]. This contrast results could be explained by the different statistical analyses used. In fact, authors performed a correlation analysis, although, in these studies, the assumption of the absence of repeated measures was not met. While, in our study we use an analysis for detecting association between time series. The cross-correlation analysis shows that TL is negatively affected by recovery and availability of the current day (lag = 0 day). In particular, lower recovery and availability will result in following lower TL. We speculate that this result can depend on the appropriateness of training scheduling during microcycle planning as the physical trainer staff strongly considers the modulation of the loads based on the players' recovery conditions in order to increase performance (supercompensation) and reduce the possibility of overload (and consequent non-contact injuries). Moreover, we found that TL also negatively affects recovery and availability of the next day (lag = 1 day). Accordingly, the higher the TL in a current day will determine, a lower recovery and availability in the next day, although different factors could affect the psychophysiological player's recovery such as fitness level, individual characteristics, individual training responses based on players profiles [4,30,44]. We speculate that the player's ability to recover depends mainly on the quantity and quality of the load (typology such as metabolic or neuromuscular stimuli) [30,45] performed in the previous day.

Moreover, through the mediational analysis we found that there is a direct relationship between TL and recovery in the next day. Indeed, this relationship is moderately mediated by availability. This means that the relationship between an independent factor (i.e., TL) and an outcome (i.e., recovery) or vice versa is fully or partially explained by a mediator (i.e., availability). In this case, it could be possible that availability explains a component of the relationship between TL and recovery strengthening the existing relationship between the two components. We also underline that our analysis approach does not allow to find any causal link between the complex and multifactorial components such as TL and recovery. However, our analysis confirms that there is a relationship between TL and recovery and that these components influence each other both on the same day and on the next day. Several studies confirm that from a physiological point of view, fatigue after a match or intense training requires 48–72 h of recovery. The rationale that explains the relationship between TL and recovery seems logical since training stimuli, known as psychophysical stress, requires recovery, as suggested by applied physiology studies. Articles found no relationship between TL and recovery, that are in contrast with our findings, used a different statistical approach, i.e., through simple correlations authors analysed measurements repeated over time. For example, Haddad et al. (2013) reported no relationship between well-being indices (i.e., sleep, stress, fatigue, and DOMS) recorded before the training sessions and the RPE during a submaximal effort [1]. It is worth noting that this result may be related to indicators used as authors have considered the relationship between RPE and wellbeing, which has a different meaning than TL (which includes time) used in our analysis. Also, Osiecki et al. (2015) showed no significant association between TQR and RPE [7]. Conversely, in the same study, authors showed a significant correlation between TQR and CK in professional soccer players during an official competition. These results indicate that TQR can be used in the monitoring of the recovery state of professional soccer players [7]. Nedelec et al. (2014) reported that HI and TQR obtained before the match, and 24, 48, and 72 h after the match were significantly correlated with the number of sprints (5 m) performed during the match at 48 and 72 h [13]. These results suggested that HI and TQR can assist practitioners to modify TL after an official match.

5. Conclusion

The complex relationship between TL (i.e., RPE*session time) and training/match recovery and availability (using TreS scale) has been found applying a multidimensional analysis approach. Autocorrelations, cross-correlations, and mediational analysis on repeated measures were used than the simple one-dimensional approach such as Pearson's product moment correlation coefficients.

In accordance with a training programming schedule, a repeated TL weekly microcycle structure was detected throughout an entire season. Moreover, recovery and availability show a similar microcycle pattern. Actually, an association between TL and recovery and consequently availability was found. First, the lower the recovery and availability in the current day are, the lower the TL of the current day training is. Secondly, TL of the current day negatively affects the recovery and availability of the next one (i.e., the higher the TL in a current day is, the lower the recovery and availability in the next day are). Finally, we found that the direct relationship between TL and recovery in the next day is moderately mediated by availability.

In conclusion, our analysis strengthens the presence of a relationship between TL and recovery and that these components influence each other both on the same day and on the next day.

In order to improve the strength and rationale affecting recovery and its implications, future research should include other factors such as the athlete's fitness status, physique assessment (e.g., aerobic and strength test, and individual physical characteristics and players profile). Above all, it would be advisable to associate the data derived from the monitoring of the external load (e.g., global positioning system, GPS) together with the IL as well as the use of some derived indices (e.g., EL/IL ratio). Further indices should be included in the future research such as the acute chronic workload ratio (ACWR) or any performance or load scores calculated with machine learning approaches.

5.1. Practical implications

Given the relationship between TL, injuries, and performance, training/match monitoring represent a fundamental and essential practice that involves practitioners. Athlete monitoring allows to increase the positive effects (e.g., fitness, readiness, and performance) and minimize the negative ones (e.g., excessive fatigue and injury) of training. In this way, practitioners should collect and manage a large amount of data through the analysing and interpreting process. In accordance with the "monitoring cycle" proposed by Gabbett et al. (2017) [5], practitioners should monitor both training and competitions to better understand the training effect considering the following factors: 1) the workload performed by the athlete (i.e., EL); 2) the athlete's response to workload (i.e., IL); 3) the athlete's ability to tolerate workload (i.e., perceptual well-being and recovery); 4) if the athlete is physically and/or mentally prepared for exposure to another training stimulus (e.g., readiness and availability to train/compete). In this way, practitioners could optimize decision-making process on training prescription in order to provide appropriate training stimuli within the microcycle. We suggest of using the RPE and TreS scale to evaluate TL and recovery/availability of players to better adjust and schedule training within the microcycle.

Author contribution statement

Guglielmo Pillitteri, Valerio Giustino, Giuseppe Battaglia conceived and designed the experiments; Guglielmo Pillitteri performed the experiments; Guglielmo Pillitteri, Alessio Rossi analysed and interpreted the data; Carlo Simonelli, Ignazio Leale contributed reagents, materials, analysis tools and data; Guglielmo Pillitteri, Alessio Rossi, Valerio Giustino wrote the paper.

Data availability statement

Data will be made available on request.

Declaration of interest's statement

The authors declare no competing interests.

Acknowledgements

This work is supported by the European Community's H2020 Program under the Funding Scheme H2020-INFRAIA-2019-1 Research Infrastructures Grant Agreement 871042, www.sobigdata.eu, SoBigData++: European Integrated Infrastructure for Social Mining and Big Data Analytics. The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.

References

- [1] M. Haddad, et al., Influence of fatigue, stress, muscle soreness and sleep on perceived exertion during submaximal effort, *Physiol. Behav.* 119 (2013) 185–189.
- [2] M. Kellmann, et al., Recovery and performance in sport: consensus statement, *Int. J. Sports Physiol. Perform.* 13 (2) (2018) 240–245.
- [3] M. Mohr, P. Krstrup, J. Bangsbo, Match performance of high-standard soccer players with special reference to development of fatigue, *J. Sports Sci.* 21 (7) (2003) 519–528.
- [4] O. Selmi, et al., Monitoring psychometric states of recovery to improve performance in soccer players: a brief review, *Int. J. Environ. Res. Publ. Health* 19 (15) (2022).
- [5] T.J. Gabbett, et al., The athlete monitoring cycle: a practical guide to interpreting and applying training monitoring data, *Br. J. Sports Med.* 51 (20) (2017) 1451–1452.
- [6] T.J. Gabbett, S. Ullah, Relationship between running loads and soft-tissue injury in elite team sport athletes, *J. Strength Condit Res.* 26 (4) (2012) 953–960.
- [7] R. Osiecki, et al., The Total Quality Recovery Scale (TQR) as a proxy for determining athletes' recovery state after a professional soccer match, *J. Exercise Physiology Online* 18 (2015) 27+.
- [8] D. Fransson, et al., Skeletal muscle and performance adaptations to high-intensity training in elite male soccer players: speed endurance runs versus small-sided game training 118 (1) (2018) 111–121.
- [9] T. Soligard, et al., How much is too much? (Part 1) International Olympic Committee consensus statement on load in sport and risk of injury, *Br. J. Sports Med.* 50 (17) (2016) 1030–1041.
- [10] A. Coutts, T. Kempton, S. Crowcroft, A.J. Coutts, S. Crowcroft, T. Kempton, Developing athlete monitoring systems: theoretical basis and practical applications, in: M. Kellmann, J. Beckmann (Eds.), *Sport, Recovery and Performance: Interdisciplinary Insights*, Routledge, Abingdon, 2018, pp. 19–32.
- [11] F.M. Impellizzeri, S.M. Marcora, A.J. Coutts, Internal and external training load: 15 Years on, *Int. J. Sports Physiol. Perform.* 14 (2) (2019) 270–273.
- [12] A.C. Jeffries, et al., Development of a revised conceptual framework of physical training for use in research and practice, *Sports Med.* 52 (4) (2022) 709–724.

- [13] M. Nedelec, et al., The influence of soccer playing actions on the recovery kinetics after a soccer match, *J. Strength Condit Res.* 28 (6) (2014) 1517–1523.
- [14] F.M. Clemente, et al., Weekly load variations of distance-based variables in professional soccer players: a full-season study, *Int. J. Environ. Res. Publ. Health* 17 (9) (2020).
- [15] F.M. Impellizzeri, E. Rampinini, S.M. Marcora, Physiological assessment of aerobic training in soccer, *J. Sports Sci.* 23 (6) (2005) 583–592.
- [16] B. Guerrero-Calderón, et al., Analysis of the Competitive Weekly Microcycle in Elite Soccer: Comparison of Workload Behavior in Absolute and Relative Terms, 2022.
- [17] S.J. McLaren, et al., The relationships between internal and external measures of training load and intensity in team sports: a meta-analysis, *Sports Med.* 48 (3) (2018) 641–658.
- [18] J. Vanrenterghem, et al., Training load monitoring in team sports: a novel framework separating physiological and biomechanical load-adaptation pathways, *Sports Med.* 47 (11) (2017) 2135–2142.
- [19] F.M. Clemente, F.M.L. Martins, R.S. Mendes, Periodization Based on Small-Sided Soccer Games: Theoretical Considerations 36 (5) (2014) 34–43.
- [20] J.D. Bartlett, et al., Relationships between internal and external training load in team-sport athletes: evidence for an individualized approach, *Int. J. Sports Physiol. Perform.* 12 (2) (2017) 230–234.
- [21] M. Buchheit, P.B. Laursen, High-intensity interval training, solutions to the programming puzzle: Part I: cardiopulmonary emphasis, *Sports Med.* 43 (5) (2013) 313–338.
- [22] T.J. Gabbett, et al., The relationship between workloads, physical performance, injury and illness in adolescent male football players, *Sports Med.* 44 (7) (2014) 989–1003.
- [23] A. Martín-García, et al., Quantification of a professional football team's external load using a microcycle structure, *J. Strength Condit Res.* 32 (12) (2018) 3511–3518.
- [24] G. Kenttä, P. Hassmén, Overtraining and recovery. A conceptual model, *Sports Med.* 26 (1) (1998) 1–16.
- [25] O. Selmi, et al., Influence of intense training cycle and psychometric status on technical and physiological aspects performed during the small-sided games in soccer players, *Res. Sports Med.* 26 (4) (2018) 401–412.
- [26] A. Silva, et al., Psychological, biochemical and physiological responses of Brazilian soccer players during a training program, *Sci. Sports* 23 (2008) 66–72.
- [27] A.L. Owen, et al., A contemporary multi-modal mechanical approach to training monitoring in elite professional soccer 1 (3) (2017) 216–221.
- [28] M. Nédélec, et al., Stress, sleep and recovery in elite soccer: a critical review of the literature, *Sports Med.* 45 (10) (2015) 1387–1400.
- [29] S. Verstappen, et al., The association between training load and injury risk in elite youth soccer players: a systematic review and best evidence synthesis, *Sports Med Open* 7 (1) (2021) 6.
- [30] S.L. Halson, Monitoring training load to understand fatigue in athletes, *Sports Med.* 44 (Suppl 2) (2014) S139–S147.
- [31] M. Gleeson, Biochemical and immunological markers of over-training, *J. Sports Sci. Med.* 1 (2) (2002) 31–41.
- [32] B. Guthrie, et al., Ready or Not, Here I Come: a Scoping Review of Methods Used to Assess Player Readiness via Indicators of Neuromuscular Function in Football Code Athletes, 2022.
- [33] H. Nobari, et al., Association between training load and well-being measures in young soccer players during a season, *Int. J. Environ. Res. Publ. Health* 18 (9) (2021).
- [34] W. Moalla, et al., Relationship between daily training load and psychometric status of professional soccer players, *Res. Sports Med.* 24 (4) (2016) 387–394.
- [35] M. Buchheit, et al., Monitoring fitness, fatigue and running performance during a pre-season training camp in elite football players, *J. Sci. Med. Sport* 16 (6) (2013) 550–555.
- [36] C.R. Bellenger, et al., Monitoring athletic training status through autonomic heart rate regulation: a systematic review and meta-analysis, *Sports Med.* 46 (10) (2016) 1461–1486.
- [37] M. Buchheit, et al., Monitoring changes in physical performance with heart rate measures in young soccer players, *Eur. J. Appl. Physiol.* 112 (2) (2012) 711–723.
- [38] R. Meeusen, et al., Prevention, diagnosis, and treatment of the overtraining syndrome: joint consensus statement of the European College of Sport Science and the American College of Sports Medicine, *Med. Sci. Sports Exerc.* 45 (1) (2013) 186–205.
- [39] M.S. Fessi, et al., Changes of the psychophysical state and feeling of wellness of professional soccer players during pre-season and in-season periods, *Res. Sports Med.* 24 (4) (2016) 375–386.
- [40] H. Gabriel, et al., Overtraining and immune system: a prospective longitudinal study in endurance athletes 30 (7) (1998) 1151–1157.
- [41] R. Fernandes, et al., In-Season Internal Load and Wellness Variations in Professional Women Soccer Players: Comparisons between Playing Positions and Status 18 (23) (2021), 12817.
- [42] M. Kellmann, Preventing overtraining in athletes in high-intensity sports and stress/recovery monitoring, *Scand. J. Med. Sci. Sports* 20 (2) (2010) 95–102.
- [43] M. Buchheit, Monitoring training status with HR measures: do all roads lead to Rome? *Front. Physiol.* 5 (2014) 73.
- [44] G.N. Sandford, P.B. Laursen, M. Buchheit, Anaerobic speed/power reserve and sport performance: scientific basis, current applications and future directions, *Sports Med.* 51 (10) (2021) 2017–2028.
- [45] M. Buchheit, P.B. Laursen, High-intensity interval training, solutions to the programming puzzle. Part II: anaerobic energy, neuromuscular load and practical applications, *Sports Med.* 43 (10) (2013) 927–954.
- [46] S.L. Curran, M.A. Andrykowski, J.L.J.P.a. Studts, Short form of the profile of mood states (POMS-SF): psychometric information 7 (1) (1995) 80.
- [47] A.J. Coutts, et al., Practical tests for monitoring performance, fatigue and recovery in triathletes 10 (6) (2007) 372–381.
- [48] H. Davis IV, et al., Psychometric item evaluations of the Recovery-Stress Questionnaire for athletes 8 (6) (2007) 917–938.
- [49] S. Kölling, et al., Validation of the Acute Recovery and Stress Scale (ARSS) and the Short Recovery and Stress Scale (SRSS) in three English-speaking regions 38 (2) (2020) 130–139.
- [50] T. Bestwick-Stevenson, et al., Assessment of fatigue and recovery in sport: narrative review, *Int. J. Sports Med.* 43 (14) (2022) 1151–1162.
- [51] K.-L. Taylor, et al., Fatigue monitoring in high performance sport: a survey of current trends, *Journal of Australian Strength and Conditioning* 20 (2012) 12–23.
- [52] T.F. Gallo, et al., Self-reported wellness profiles of professional Australian football players during the competition phase of the season, *J. Strength Condit Res.* 31 (2) (2017) 495–502.
- [53] A. Nässi, et al., Development of two short measures for recovery and stress in sport, *Eur. J. Sport Sci.* 17 (7) (2017) 894–903.
- [54] O. Selmi, et al., Influence of stress, fatigue, sleep and delayed onset muscle soreness on perceived physical enjoyment exertion during small sided games, *Iran. J. Public Health* 47 (3) (2018) 449–450.
- [55] F.M. Clemente, et al., Accelerometry-workload indices concerning different levels of participation during congested fixture periods in professional soccer: a pilot study conducted over a full season, *Int. J. Environ. Res. Publ. Health* 18 (3) (2021).
- [56] S.L. Hooper, et al., Markers for monitoring overtraining and recovery, *Med. Sci. Sports Exerc.* 27 (1) (1995) 106–112.
- [57] O. Selmi, et al., Influence of well-being variables and recovery state in physical enjoyment of professional soccer players during small-sided games, *Res. Sports Med.* 26 (2) (2018) 199–210.
- [58] A. Rossi, et al., Wellness Forecasting by External and Internal Workloads in Elite Soccer Players: A Machine Learning Approach, 13, 2022.
- [59] A. Rossi, et al., Effective injury forecasting in soccer with GPS training data and machine learning, *PLoS One* 13 (7) (2018) e0201264.
- [60] L. Pappalardo, et al., Explainable Injury Forecasting via Multivariate Time Series and Convolutional Neural Networks, 2019.
- [61] E. Vallance, et al., Combining Internal- and External-Training-Loads to Predict Non-Contact Injuries in Soccer 10 (15) (2020) 5261.
- [62] H. Van Eetvelde, et al., Machine learning methods in sport injury prediction and prevention: a systematic review, *J Exp Orthop* 8 (1) (2021) 27.
- [63] A. Rossi, L. Pappalardo, P. Cintia, A Narrative Review for a Machine Learning Application in Sports: An Example Based on Injury Forecasting in Soccer 10 (1) (2022) 5.
- [64] A. Rossi, et al., GPS Data Reflect Players' Internal Load in Soccer, 2017.

- [65] C. Foster, J.A. Rodriguez-Marroyo, J.J. de Koning, Monitoring training loads: the past, the present, and the future, *Int. J. Sports Physiol. Perform.* 12 (Suppl 2) (2017) S22–s28.
- [66] R. Izzo, M. Giovannelli, Ergonomics for the game: internal and external load analysis for problem solving in training soccer”, in: *Ph. D in Science of Physical Exercise and Healthcare*, Urbino University Library, 2018.
- [67] M. Giovannelli, *Ergonomics for the Game: Internal and External Load Analysis for Problem Solving in Training Soccer*, 2017.
- [68] C. Foster, et al., A new approach to monitoring exercise training, *J. Strength Condit Res.* 15 (1) (2001) 109–115.