The Tracking of Internal and External Training Loads with Next-Day Player-Reported Fatigue at Different Times of the Season in Elite Soccer Players

Abstract

The aim was to assess factor structure of player-reported fatigue and quantify within-subjects correlations between changes in training load measures and next day player-reported fatigue at different time points of an elite football season. Using longitudinal research design, twenty-four professional footballers, mean (SD) age of 25.7 (3.4) years, were monitored during their competitive season, including preseason. Player-reported fatigue data and session ratings of perceived exertion (session-RPE) were collected via a mobile application. Heart rate (HR) and global positioning system (GPS) data were collected daily for each player in field sessions. Principal component analysis (PCA) indicated three components with Eigenvalues above 1.0; “soreness”, “mood, and “hydration”. Within-player correlations between training load values and next day player-reported fatigue values were trivial to moderate (r ≈ -0.42 to -0.04). In-season we observed large correlations between Total Distance (TD) and PlayerLoad with Soreness (r=-0.55, 95% CI: -0.62 to -0.46; r=-.054, 95% CI: -0.62 to -0.46), but during pre-season, correlations were small (r=-0.15, 95% CI: -0.28 to -0.01; r=-0.13, 95% CI: -0.26 to 0.01). The HR TRIMP, TD and session-RPE measures each showed trivial to moderate correlations (r ≈ -0.41 to -0.08) with next day “mood”. Our in-house player-reported fatigue questionnaire was sensitive to the multi-dimensional nature of fatigue, identifying physiological (soreness), psychological (mood and stress) and nutritional (hydration and nutrition) components. We found the in-season correlations with training load to be greater than previously reported in the literature, specifically with next day player-reported “soreness”. Nevertheless, correlations between the items of our scale and pre-season training load were small.

Keywords: athlete monitoring, wellness, training load, performance, football

INTRODUCTION

In professional football, training is designed to prepare players physically, technically and tactically for matches. A training session induces an internal psychophysiological response that provides the stimulus for acute yet transient adaptations while, chronic adaptations rely on the appropriate systematic exposure to training (27). This overall psycho-physiological response may result in acute fatigue and, either desirable chronic adaptations to physiological systems (neuromuscular, metabolic, endocrine etc.) or, undesirable chronic stress-related symptoms (overtraining, injury, etc.) (31). Consequently, the ability to monitor the response to training, both physically and mentally, is important to the coach or practitioner (50). Indeed, the majority of practitioners working in team sports place an equal emphasis on monitoring the training load and the acute fatigue response (47).

Quantifying the response to training is complex and multi-factorial. Objective biomarkers, such as Creatine Kinase, VO_2max, often fail to accurately reflect the holistic response to the training process and recovery (43), and their practical feasibility has been questioned (48). A players' fatigue status is a multi-component construct encompassing several variables that indirectly measure physical and psychological wellness (43). Player (or athlete) self-reported measures have been used to quantify constructs such as; stress, recovery, mood, and anxiety, primarily to detect symptoms of non-functional overreaching or overtraining. These include instruments such as the RESTQ-Sport (28), DALDA (41), POMS (24) which have been shown to be more sensitive to acute changes in training load than objective measures (43), perhaps because they better reflect the complex multifactorial nature of fatigue (32). Unfortunately, the practical application of these scales is limited for daily evaluation of athletes and interpretation generally falls outside of the scope of practice of a physical preparation or conditioning coach. This has led to the popularity of short customized in-house questionnaires within team sport monitoring (47). These questionaires ask players' to report their subjective ratings of constructs such as fatigue, recovery, muscle soreness, mood, stress as well as other factors that may affect the response to training including the quality of sleep and nutrition. Changes in these self-reported outcome measures have been associated with changes in internal load (sRPE, HRex, Cortisol) and external load (Total Distance, High Speed Running) measures in elite soccer players (9). These outcome measures have also shown relationships with in-game technical performances (21) along with self reported decrements in scores the day after a matches in Austrailian Football players (20). These studies provide some evidence for the sensitivity of these athlete-reported measures despite little consistency between the type of scale, bi-polar and uni-polar, or the verbal anchors / number of points used on the scale both in research and, in practice (47).

Previous studies have summed the scores of multiple items (survey questions) from player self-reported questionaires to described higher order constructs such as "wellness" or "wellbeing" (9, 20). These constructs are by definition complex and multi-factoral in nature thus, assuming unimensiality (e.g. Gallo *et al.*, 2016). This practice is questionable from a conceptual standpoint and "wellness" questionaires have been criticised for a lack of either theoretical reference framework or further robust validation (32). However, elite team sport athletes compete weekly / biweekly inducing stress on multiple biological systems (aerobic, anaerobic and neuromuscular) and practitoners require time efficent, non-invasive methods of quantifying the fatigue status of their players (51). Constructs such as fatigue or soreness are known acute responses to demanding exercise and can be influenced by pscyho-physiological factors (30) or lifestyle (sleep and or nutrition). Despite their limitations self-reported outcomes measures appear to have practical value and are recommended for use with caution and, alongside other monitoring strategies (34, 49, 52).

In an ideal world, robust psychometric evaluation of player self-report questionnaires should be conducted before implementation in practice and practitioners can use the COSMIN- COMMET criteria to assist (32). However, in practice self-report questionnaires are often already embedded into athlete monitoring (47) and with turnover of coaching and support staff may even be inherited practices. It is critical practitioners evaluate these instruments within their own environment to understand the structure of the interrelationships (collinearity) amongst items within the questionnaire and determine its validity. A valid survey should be conceptually sound, reflecting the multi-dimensional nature of fatigue (43). Determining the factor structure of a survey is an important first step in evaluating the dimensionality of a questionnaire. Principle component analysis (PCA) provides a method of determining factor structure and reduces data to unique components containing variables which correlate with each other, whilst the principle components themselves do not correlate (55). These statistically derived components should represent constructs that can be explained theoretically. In the context of athlete self-reported measures, it would make sense that PCA would identify both psychological and physiological factors for the reasons outlined above. PCA also provides a rationale for reducing the items of a questionnaire reported whilst maintaining as much of the variation in the data as possible (17). Single-item reports are not without their limitations, particularly when measuring complex constructs, but they have practical value in communicating data between support staff, players and coaches. Indeed, these measures may help practitioners' quickly priorities critical conversations with players which enable a deeper understanding of context.

The travel and environmental constraints of Major League Soccer (MLS) constitutes an addition challenge to practitioners and athletes in their preparations for the season. Due to its large geographic area, >3.7 million miles^2, variations in altitude (39' to 5280' above sea level), and seasonal variations in temperature, athlete responses to load should not be expected to be uniform throughout an MLS season due to the added physiologic stresses as compared to most European football leagues. Currently there is a lack of applied research that evaluates existing fatigue monitoring in Major League Soccer. Studies that identify both the factor structure of player-reported questionnaires and their sensitivity to variations in training load over extended periods of time (50) are of practical relevance. Thus, our aims were two-fold; first, we wished to assess the factor structure of our player-reported fatigue questionnaire through PCA (Part A). Second, we aimed to quantify the within-player association between changes in internal and external training load measures, and the player ratings in these key components of player-reported fatigue (Part B).

METHODS

Experimental Approach to the Problem

A retrospective observational study over six-months in a Major League Soccer (MLS) club. Data collection spanned the first six months of the 2018 season (Mid-January to Mid-June) and included a six-week preseason training camp. Six months was selected as the data collection period, so as, to avoid the most congested periods of the season and create a more balanced comparison between the different types of training days in a competitive soccer season.

Participants

Twenty-four professional football players from a single club (Age: 26 ± 3.4 years Height: 171 ± 2.7cm, Body mass: 78 ± 7.1 kg) participated in this study and had played at least one first team match. All players were registered with the same Major League Soccer club, which is the highest level of football in the United States of America. We excluded goalkeepers from the data selection processes. We used data from training sessions and games in the current analysis. Data from on-field rehabilitation sessions and re-integration progressions, in which a player only completed a portion of training due to club's return to play protocols, were excluded from this data set. Athlete consent was obtained for all data collection and use in further research via an informed consent form and the study was approved by Teesside University's School of Health and Life Sciences Ethics sub-committee (Study No 238/18).

Procedures

During all on-field training sessions and games, players wore GPS units sampling at 10-Hz (S5, Catapult Innovations, Australia). Prior to the analysis of sessions, data was expected to comply with the clubs pre-existing data standards which checks for compliance within the metrics of Horizontal Dilution of Precision (HDOP) (<3) and #Sat (>9) set forth in the Catapult user manual. The device was worn by players in the manufacturer's vest, which holds the unit between the scapulae. Validity and reliability of GPS units have been established in previous work, with specific attention to acceleration, deceleration, and constant running (10). The use of GPS and accelerometry was further studied in team sport change of direction and non-linear running (7) and in high intensity efforts (53). Variables selected for analysis were Duration (min), Total Distance (m), Relative Distance (m/min), "Jogging" Distance (9.7 km/hr-13.7 km/hr.) (m), "Running" Distance (13.68km/hr-20.16km/hr.) (m), "Striding" Distance between 20.2 km/hr. and 24.8 km/hr. (m), "Sprinting" Distance above 24.8 km/hr. (m), (15,22). We also selected PlayerLoad (AU) to reflect the accelerative nature of football (11,44). Wundersitz et al. (57) found data of this nature, utilizing acceleration and decelerations, have been shown valid and reliable in team sports when measures exceed 12Hz. The metric "High Speed Running" (HSR) is the sum of the values "Striding" and "Sprinting". The variable Duration was derived via post session analysis and calculated by a summation of all active time periods during the session. Rest periods, transition to other exercises and coaching stops were all eliminated from the total duration of the session during the analysis of the individual session by performance department staff.

The measurement of player internal load was performed via heart rate monitoring and session ratings of perceived exertion (sRPE). HR monitors (T-34 Coded, Polar Electro, OY, Finland) sampling at 5 Hz - either held via the manufacturer's belts or were fed into the built-in holsters on GPS vests - were worn in every session. Raw data were transmitted continuously to the GPS units and then exported from the GPS manufacturer's software (Logan Plus Sprint, Catapult Sports, Australia). A heart rate training impulse (HRtrimp) was calculated using the methods outlined by Stagno, Thatcher and van Someren, (45) with maximum heart rate calculated from the clubs preseason testing, in which players completed a field based intermittent fitness test (Yo-Yo IR 1) to volitional termination of the assessment. Max HR was deemed the highest HR reached in the final 2 minutes of the assessment.

sRPE were collected at the end of each training day, via phone application, to assess how hard players perceived the training session. The players provided rated the overall session exertion on the CR-100 scale using the data collection procedures as per McLaren et l. (32). Data were collected within two hours of the session or match.

Each morning, players reported their perception of "Sleep", "Mood", "Energy", "Recovery", "Soreness", "Nutrition" and "Hydration" on a Likert scale where 1 was "least optimal" and 10 "most optimal", via a phone application. These measures were selected based on their effectiveness in monitoring acute changes in athlete well-being (43). All athletes were familiarized with the scales and questionnaires in a formal meeting prior to the beginning of the data collection period. Though, many of the athletes in the current study had been a part of this club's data collection processes for years prior. Wording on the scale were selected to emulate a normal conversation, utilizing colloquialisms and "emojis" to help guide the athlete's decision-making process.

Players were also asked to complete this questionnaire on any "Off Day" following a match, upon waking to capture next day player-reported fatigue post-match loading. When completing the surveys, the initial view of the questions showed the scale utilized in this survey and/or anchors were utilized in each question to give players reference to the scale again. Both surveys were completed via personalized messages on player's phones and social media communications (Facebook/Slack messenger) to simplify the data collection process for both players and researchers. Players were asked to fill the survey out upon waking up, before arriving in the facility each morning, as well as on any “off days” following a match. Supplemental Digital Content (see Text Supplemental Digital Content 1- Player Reported Fatigue) shows the player-reported fatigue questionnaire, anchors and the interface as seen by athletes when completing the scale.

Statistical Analyses

Part A: Principle Component Analysis

The distribution of player-reported fatigue data are visualised in Figure 1. The internal consistency of the player-reported fatigue was evaluated by Cronbach’s alpha (0.84; 95% CI 0.82 to 0.86). We are aware that this Chronbach’s alpha has been calculated by pooling the time-points for each participant. To control for any influence of pseudoreplication, we also analysed the data after averaging across time-points for each participant in line with Bland and Altman (5). The Cronbach’s alpha following this adjustment was 0.86 (95% CI 0.74-0.93). To determine the factor structure, a PCA was performed using SPSS version 26 (SPSS Inc., Chicago, IL, USA). The Chi-sqaured value for Bartlett’s test of sphericity was 2258 ($p < 0.0001$) and Kaiser-Meyer-Olkin (KMO) values were greater than 0.5 for each test (0.62 to 0.90) thus, meeting the requirements previously established for the performance of a PCA in sport science research (55). PCA is a method that can be used for data reduction for example, Williams, et al. (5) as it reduces data to unique components containing variables which correlate with each other, whilst the principle components themselves do not correlate (55).

[Figure 1 about here]

There are various approaches for extracting principle components, based on thresholds for eigenvalues (for example greater than 1) or visual inspection of the scree plot (12) (see Text, Supplemental Digital Content 1, which displays the produced scree plot and component analysis). It is also important to consider practitioner expertise within statistical models (52). Based upon our data we decided to extract three principle components (Eigenvalues 3.82, 1.44 and 0.97) explaining 78% of the variance (see Text, Supplemental Digital Content 2- PCA). Varimax rotation revealed the factors weighing heaviest on each component were "soreness" on component 1, "stress" on component 2, and "hydration" on component 3 (see Text, Supplemental Digital Content 2- PCA).

Part B: Within-player associations between internal and external training load and physical, psychological and nutritional components of wellbeing.

All model residuals were explored for parity with a Gaussian distribution and, deemed appropriate. A general linear model was used to quantify within-player correlations between next-day player-reported fatigue and collected internal and external training loads (5,6). We did not select predictors on the basis of statistical significance in a step-wise fashion. Rather, expert knowledge was used to select independent variables of practical interest, while also selecting variables which have shown to be important in previous research (52). We then quantified univariate within-subject correlations between outcome and predictor variables according to the approach reported by Bland and Altman (5,6). The following thresholds were used to interpret the magnitude of the correlation between variables: <.1 Trivial, .1 to .3 Small, .3 to .5 Moderate, .5 to .7 Large, .7 to .9 Very Large, and .9 to 1.0 Almost Perfect. All results are shown with Confidence Intervals of 95%, as required. The statistical analysis software, SPSS (SPSS Inc., Chicago, IL, USA) was used for the statistical calculations.

RESULTS

Descriptive data are presented for the current study in Table 1. Within-player association between player-reported fatigue and internal and external training loads are presented as a correlation coefficient with 95% confidence interval for soreness (figure 2), mood (figure 3), and hydration (figure 4) for all observations and separately for pre- and in-season (Overall n= 534, in-season n= 310, pre-season n= 224).

[Table 1 about here]

We observed small to moderate relationships with soreness overall, with the strongest associations in-season. For example, moderate to large negative associations were observed for three variables that include training volume Total Distance (-0.55, 95% CI -0.62 to -0.46), PlayerLoad (-.54, 95% CI -.62 to -.46) and session RPE (-.46, 95% CI -.54 to -.36) as well as high-speed running (-.43, 95% CI -0.52 to -0.33). We also observed small but clear negative relationships between Total distance (-.40, 95% CI -.49 to -.30) and PlayerLoad (-.41, 95% CI -.50 to -.31) and mood for in-season but not pre-season associations between internal and external load and next day hydration were generally trivial or small (-0.16 to 0.16).

Associations between our load measures and all player-reported fatigue can be viewed in Supplementary Digital Content 3- Partial Correlations).

[Figure 2 about here]

[Figure 3 about here]

[Figure 4 about here]

DISCUSSION

We aimed to assess the factor structure of our player-reported fatigue questionnaire and to quantify the within-player associations between changes in internal and external training load measures, and changes in next day player-reported fatigue. A key finding was that our questionnaire represented three distinct components, with Eigenvalues close to or above 1 reflecting the multi-factorial nature of fatigue. Trivial to moderate within-player correlations were found between the next day player-reported fatigue measures and training load variables when considering the data set as a whole. However, when we separated data into "in-season" and "Pre-Season" subgroups, associations were strongest in the in-season period, rather than the pre-season period. (figures 3-5) and tended to be of a moderate to large magnitude for items loading on component 1 (e.g. soreness). Associations tended to be of small to moderate magnitude for component 2 and trivial for nutrition or hydration (component 3).

We extracted three principle components explaining 78% of the variance in the data. The item with the highest loading on component 1 was "soreness" (0.82) followed by "recovery" (0.80) and "energy" (0.77). Soreness is a well-known acute perceptual response to exercise that can be attributed to microdamage within the muscle (19) or damage to nervous system (e.g. at the neuromuscular junction) (14,27). We should expect a valid measure of "soreness" to be sensitive to changes in loads as shown in previous research (36,48,51,42) and we observed moderate to large associations with load "in-season". Item's such as "recovery" and "energy" are more difficult to conceptualize and could be criticized for lacking in any clear definition. In their review on athlete reported outcome measures, Jefferies et al. (2020) reported that single items, "may possess acceptable face validity."(29), which parallels our rationale for utilizing PCA to analyse the current player reported outcome measures. Of note, constructs must be "unidimensional" and "unambiguous" to ensure quality responses, which seems to have been met by the three components we derived from the PCA (29).

Despite the above observations, the items loaded strongly on component 1 with similar moderate-to-large associations with changes in load suggesting they represent, at least to an extent, physiological fatigue and share collinearity with "soreness". Fava et al. (2012) noted in their work on Clinimetrics, that responsiveness should be defined as "able to detect clinically relevant changes in [health] status over time" (16) Considering both our data and the criticisms of some player-reported outcome measures for lacking clear definitions or any theoretical reference framework to support their use (32), practitioners may wish to consider the rationale for including items such as "recovery" and "energy" in their monitoring questionnaires. Indeed, “energy” loaded on two principle components (component 1: 0.77 and 2: 0.45) suggesting it may be multi-factorial and difficult to assess within a single-item (16,23,29).

The items that loaded strongest on principle component 2 were “mood” (0.87) and “stress” (0.86) which represent psychological constructs associated with fatigue (18,21). Measures of psycho-social wellbeing remain a necessary part of fatigue assessment, as noted changes in measures like “sleep quality”, “stress”, “wellbeing” were effected by loading and general sporting conditions (i.e. wins/losses), which is an important consideration in applied sport science (18,21,51). Sleep loaded relatively equally on both principal components 1 and 2 which, given the importance of sleep to both physical and psychological recovery makes intuitive sense (42). Acute physiological responses such as delayed onset of muscular soreness have been shown to contribute to poor sleep quality (50) while poor sleep quality is known to affect psychological factors such as “mood” or “stress” (4).

Thorpe et al (48,49,50,51,52) utilized “soreness”, “fatigue” and “sleep” as player reported outcome measures in elite football players. Our findings would broadly support these choices but would suggest the inclusion of item(s) addressing psychological wellness such as mood or stress in subsequent questionnaires. The final component represented nutrition or hydration status with strong factor loadings for both of these items (0.94 and 0.95, respectively). We observed trivial associations between load and either of these items, which is not surprising given there is no conceptual reason to expect load to affect nutrition status. However, nutrition can support recovery and or adaptation to training, and has been shown to be effected by over-training and thus the inclusion of one or both of these items maybe informative to staff working with players on a daily-basis to reiterate good practices (13,26,38).

Several studies have highlighted relationships between internal and external training loads in player-reported wellness (1,18,56). We observed similar or slightly higher magnitude associations between player-reported "soreness" and "mood" and internal and external training loads (figures 2 & 3), particularly in the in-season period, compared to those previously reported (36,42,43). With respect to comparing correlations, it should be noted that due to the within player nature of this analysis, these comparisons are purely participantive. The moderate and large magnitude correlations could be attributed to the inclusion of match data, which has been shown to be a large percentage (roughly 40%) of weekly training loads (46,50). Of note, Total Distance, PlayerLoad and the session-RPE all tended to have larger correlations to player-reported soreness when compared to other independent variables (Figure 2, 3, 4) which aligns with previously published work (1,39,40). Major League Soccer provides unique challenges with regards to playing matches across time zones, climates and at different altitudes which may increase the response to loading in players in comparison with other leagues (37,54). Indeed, future research should look to investigate the effects of these environmental challenges on both load, and response to football matches.

In contrast, during the "preseason" period, the associations between training load and all player-reported items were either trivial or small with the exception of RPE measures which tended to be small to moderate (see Figures 2-4). McMahon et al. reported in their study of a week leadup to World Cup Qualifying matches in international elite women's football players that their player-reported items were not sensitive enough to detect changes in lower load training days, which would correspond with our study's small magnitude correlations in the pre-season sub group (33). Practitioners should account for musculoskeletal fatigue that may be present in "preseason" which may affect both performance in session and responses to that load acutely (27). The weaker associations in the "preseason" data may be caused by other contextual variables (examples: temperature, fitness levels, previous loading, or other variables) which have effects on responses to loading. Indeed, Buchheit et al. have noted the importance of context in understanding training data, specifically in preseason, as there are many contextual variables which must be understood to connect the relationship to "response" (9). Potentially, a combination of these factors could explain the lack of associations observed here in pre-season.

We observed that Total Distance and PlayerLoad had similar magnitude of associations with "soreness" (see Figure 2). These measures are comparable values when discussing load monitoring in the applied setting and have been used interchangeably to discuss the concept of volume previously in the research (3) These two external training load variables show the strongest relationships with both mood and soreness, high speed running and sprint distance (see Figures 2 and 3). The measure of session-RPE had a moderate correlation with "soreness" during the in-season period (Figure 2). Bartlett et al. (3) found that the measure, total distance, most strongly associated with RPE in their study, but also noted the importance of select intensity measures, such as high-speed running, as important in the relationship with RPE. Thus, it is unsurprising that RPE, in this study had moderate magnitude correlations with "soreness" as all measures of external load were shown to have moderate to large correlations with "soreness". Volume based metrics such as Total Distance and PlayerLoad will tend to give the best understanding of the amount of work done, and thus, in a sport such as soccer, be representative of muscular damage, more so than some of the intensity based metrics such as High Speed Running, which could represent tactical or environmental changes (2,8,25). These similarities may indicate a potential combination effect of the external load measures which is identified through participantive assessments.

A potential limitation of this study lies in the questionnaire, which did not undertake the thorough selection and psychometric validation recommend by others (32). However, the questionnaire was developed in practice and based upon previous literature (50,51,52), through requirements of the coaching and support staff and, conversations with players. Validated questionnaires such as the POMS, RESTQ-s and DALDA are time consuming and impractical for daily monitoring therefore short-format or single-item measures have practical value (50,51,42). Further research could investigate the validity of our single-items against these multi-item scales, perhaps at certain points throughout a season, particularly for items in component 2 such as "stress" or "mood". Despite these limitations our study provides an important first step in evaluating and refining practice.

A further limitation of this study, which consistently occurs in the applied setting, is compliance in player-reported fatigue and session-RPE questionnaire completion. While reminders for the athletes were established throughout the process by the researchers, there are times where gaps in the data occurred. Non-compliance occurred particularly around travel and off days. A difficulty of the next day player-reported fatigue is off days, due to the fact that players and staff are away from their normal routines. This together with the long and physically demanding season meant we observed ebbs and flows in survey compliance. Within normal schedules, there are imbalanced counts in training sessions and games, and between in-season and pre-season sessions. Compliance issues can potentially magnify these discrepancies, creating shifts in correlation magnitudes due to the imbalanced counts in session data (in-season n=310, pre-season n=224). Despite this, we were able to track a substantial number of observations for both pre-season and in season. Finally, it should be noted that these data are taken from one squad playing in the MLS and caution should always be taken when extrapolating findings more broadly. Standardizing player monitoring practices across leagues would enable larger multi-site evaluations in the future.

Conclusions

Our in-house player-reported fatigue questionnaire was sensitive to the multi-dimensional nature of fatigue identifying physiological (soreness), psychological (mood and stress) and nutritional (hydration and nutrition) components. In-season correlations from the current study were greater than previously reported in the literature, specifically with next day player-reported "soreness" however, the items of our scale were not associated with pre-season training load.

Future Considerations

In-season correlations from the current study were greater than previously reported in the literature, specifically with next day player-reported “soreness”. This may be related to the specific challenges within the MLS and other North American sport leagues as it pertains to travel, scheduling, and environmental issues and further research to evaluate these contextual factors is warranted. Furthermore, it is recognized this is a first step in assessing the validity of our player reported fatigue questionnaire and deeper psychometric evaluation of these scales and their ability to measure complex constructs is required. Indeed, further research may wish to investigate players coach and clinician perceptions of these constructs in greater detail and work towards a consensus on their measurement.

PRACTICAL APPLICATIONS

In the current sport science environment, many data points are collected throughout a training period, and thus ensuring the utility of these measures is of key importance. Practitioners must continually evaluate their current practices to ensure the data they are collecting can answer important performance questions. Player-reported “soreness” and “mood” were sensitive to changes in load and may be useful as part of a player-monitoring strategy to understand portions of multifactorial fatigue. The context of pre-season and in-season showed varying levels of relationships, displaying the importance of further context in data collection. We would advise sports scientists and strength and conditioning practitioners view these as crude but potentially useful tools for monitoring large teams however, they should not be viewed as the only measure of fatigue in a program without further research into their utility and added contextual variables in collection.

References

1. Abbott, W. *et al.* (2018) ‘The independent effects of match location , match result and the quality of opposition on participantive wellbeing in under 23 soccer players : a case study’, *Research in Sports Medicine*. Routledge, pp. 1–14. doi: 10.1080/15438627.2018.1447476.
2. Arruda, A. F. S. *et al.* (2014) ‘Effects of a Very Congested Match Schedule on Body-Load Impacts , Accelerations , and Running Measures in Youth Socce ....’, *International Journal of Sports Physiology and Performance*, (August). doi: 10.1123/ijspp.2014-0148.
3. Bartlett, J. D. *et al.* (2016) ‘Relationships Between Internal and External Training Load in Team Sport Athletes: Evidence for an Individualised Approach’, *International Journal of Sports Physiology and Performance*. doi: : http://dx.doi.org/10.1123/ijspp.2015-0791.
4. Benjamin, C. L. *et al.* (2020) ‘Sleep Dysfunction and Mood in Collegiate Soccer Athletes’, *Sports Health*. SAGE Publications Inc., 12(3), pp. 234–240. doi: 10.1177/1941738120916735.
5. Bland, J. M. and Altman, D. G. (1995) ‘Calculating Correlation Coefficients with Repeated Observations: Part 1- Correlation within Participants’, *British Medical Journal*, 310, p. 446.
6. Bland, J. M. and Altman, D. G. (1996) ‘Measurement Error and Correlation Correlation’, *British M*, 313, pp. 41–42. doi: 10.1002/anie.201005078.
7. Boyd, L. J., Ball, K. and Aughey, R. J. (2011) ‘The reliability of minimaxx accelerometers for measuring physical activity in australian football’, *International Journal of Sports Physiology and Performance*, 6(3), pp. 311–321. doi: 10.1123/ijspp.6.3.311.
8. Buchheit, M. *et al.* (2011) ‘Physiological and performance adaptations to an in-season soccer camp in the heat: Associations with heart rate and heart rate variability’, *Scandinavian Journal of Medicine & Science in Sports*, (June). doi: 10.1123/IJSPP.2013-0284.
9. Buchheit, M. *et al.* (2013) ‘Monitoring fitness, fatigue and running performance during a pre-season training camp in elite football players’, *Journal of Science and Medicine in Sport*, 16(6),

pp. 550–555. doi: 10.1016/j.jsams.2012.12.003.

10. Chambers, R. *et al.* (2015) 'The Use of Wearable Microsensors to Quantify Sport-Specific Movements', *Sports Medicine*, 45(7), pp. 1065–1081. doi: 10.1007/s40279-015-0332-9.
11. Colby, M. *et al.* (2017) 'Multivariate modelling of participantive and objective monitoring data improve the detection of non-contact injury risk in elit ....', *Journal of Science and Medicine in Sport*. Sports Medicine Australia, (May). doi: 10.1016/j.jsams.2017.05.010.
12. Costello, A. B. and Osborne, J. W. (2005) 'Best practices in exploratory factor analysis: Four recommendations for getting the most from your analysis', *Practical Assessment, Research and Evaluation*, 10(7).
13. Djaoui, L. *et al.* (2017) 'Monitoring training load and fatigue in soccer players with physiological markers', *Physiology and Behavior*. Elsevier, 181(November), pp. 86–94. doi: 10.1016/j.physbeh.2017.09.004.
14. Drew, M. K. and Finch, C. F. (2016) 'The Relationship Between Training Load and Injury, Illness and Soreness: A Systematic and Literature Review', *Sports Medicine*. Springer International Publishing, 46(6), pp. 861–883. doi: 10.1007/s40279-015-0459-8.
15. Dwyer, D. B. and Gabbett, T. J. (2012) 'Global Positioning System Data Analysis: Velocity Ranges and a New Definition of Sprinting for Field Sport Athletes', *Journal of Strength and Conditioning Research*, 26(3), pp. 818–824.
16. Fava, G. A., Tomba, E. and Sonino, N. (2012) 'Clinimetrics: The science of clinical measurements', International Journal of Clinical Practice, 66(1), pp. 11–15. doi: 10.1111/j.1742-1241.2011.02825.x.
17. Federolf, P. *et al.* (2014) 'The application of principal component analysis to quantify technique in sports', *Scandinavian Journal of Medicine and Science in Sports*, 24(3), pp. 491–499. doi: 10.1111/j.1600-0838.2012.01455.x.

18. Fessi, M. S. and Moalla, W. (2018) ‘Post-match Perceived Exertion, Feeling and Wellness in Professional Soccer Players’, *International Journal of Sports Physiology and Performance*, 13, pp. 631–637. doi: 10.1123/ijspp.2017-0725.

19. Fletcher, B. D. *et al.* (2016) ‘Season Long Increases in Perceived Muscle Soreness in Professional Rugby League Players: Role of Player Position, Match Characteristics and Playing Surface’, *Journal of Sport Sciences*, 34, pp. 1067–1072.

20. Gallo, T. F. *et al.* (2016) ‘Pre-training perceived wellness impacts training output in Australian football players’, *Journal of Sports Sciences*, 34(15), pp. 1445–1451. doi: 10.1080/02640414.2015.1119295.

21. Gastin, P., Meyer, D. and Robinson, D. (2013) ‘Perceptions of Wellness to Monitor Adaptive Responses to Training and Competition in Elite Australian Football’, *Journal of Strength and Conditioning Research*, 27(9), pp. 2518–2526.

22. Gaudino, P. *et al.* (2013) ‘Monitoring training in elite soccer players: Systematic bias between running speed and metabolic power data’, *International Journal of Sports Medicine*, 34(11), pp. 963–968. doi: 10.1055/s-0033-1337943.

23. Govus, A. D. *et al.* (2018) ‘Relationship between Pre-Training Participantive Wellness Measures, Player Load and Rating of Perceived Exertion Training Load in American College Football’, *International Journal of Sports Physiology and Performance*, 13, pp. 95–101. doi: 10.1123/ijspp.2015-0012.

24. Grant, C. *et al.* (2012) ‘The Profile of Mood State (POMS) questionnaire as an indicator of Overtraining Syndrome (OTS) in Endurance Athletes’, *African Journal for Physical, Health Education, Recreation and Dance*, March, pp. 23–32.

25. Gregson, W. *et al.* (2010) ‘Match-to-Match Variability of High-Speed Activities in Premier League Soccer’, *International Journal of Sports Medicine*, 31, pp. 237–242.

26. Halson, S. L. (2014) ‘Monitoring Training Load to Understand Fatigue in Athletes’, *Sports Medicine*, 44, pp. 139–147. doi: 10.1007/s40279-014-0253-z.

27. Hills, S. and Rogerson, D. (2018) ‘Associatons between Self-Reported Wellbeing and Neuromuscular Performance During a Professional Rugby Union Season’, *Journal of Strength and Conditioning Research*. doi: 10.1519/JSC.0000000000002531.

28. Impellizzeri, F. M., Marcora, S. M. and Coutts, A. J. (2019) ‘Internal and external training load: 15 years on’, *International Journal of Sports Physiology and Performance*, 14(2), pp. 270–273. doi: 10.1123/ijspp.2018-0935.

29. Jeffries, A. C. et al. (2020) ‘Athlete-Reported Outcome Measures for Monitoring Training Responses: A Systematic Review of Risk of Bias and Measurement Property Quality According to the COSMIN Guidelines’, International Journal of Sports Physiology and Performance, 15(9), pp. 1203–1215. doi: 10.1123/ijspp.2020-0386.

30. Kellmann, M. and Kallus, W. (2001) *Recovery-Stress Questionnaire for Athletes*. Edited by H. Kinetics. Champaign, IL.

31. Kiely, J. (2018) ‘Periodization Theory : Confronting an Inconvenient Truth’, *Sports Medicine*. Springer International Publishing, 48, pp. 753–764. doi: 10.1007/s40279-017-0823-y.

32. McLaren, S. J., Coutts, A. J. and Impellizzeri, F. M. (2020) ‘Chapter 9i: Perception of Effort and Participantive Monitoring’, in French, D. N. and Torres-Ronda, L. (eds) *NSCA’s Essentials of Sport Science*. Champaign, IL: Human Kinetics.

33. McMahon, G. *et al.* (2018) ‘Relationship between match week load, perceived load and markers of wellness during the FIFA World Cup 2018 Qualifying Stage’, in *European College of Sport Science*.

34. Le Meur, Y. *et al.* (2013) ‘Evidence of parasympathetic hyperactivity in functionally overreached athletes’, *Medicine and Science in Sports and Exercise*, 45(11), pp. 2061–2071. doi:

10.1249/MSS.0b013e3182980125.

35. Noon, M. *et al.* (2018) 'Next Day Participantive and Objective Recovery Indices Following Acute Low and High Training Loads in Academy Rugby Union Players', *Sports*, 6(2), p. 56. doi: 10.3390/sports6020056.
36. Noon, M. R. *et al.* (2015) 'Perceptions of Well being and Physical Performance in English Elite Youth Footballers across a season', *Journal of Sport Sciences*.
37. Nuccio, R. P. *et al.* (2017) 'Fluid Balance in Team Sport Athletes and the Effect of Hypohydration on Cognitive, Technical, and Physical Performance', *Sports Medicine*. Springer International Publishing, 47(10), pp. 1951–1982. doi: 10.1007/s40279-017-0738-7.
38. Peterson, K. D. and Evans, L. C. (2019) 'Decision Support System for Mitigating Athletic Injuries', *International Journal of Computer Science in Sport*, 18(1), pp. 45–63. doi: 10.2478/ijcss-2019-0003.
39. Rabbani, A. *et al.* (2018) 'Monitoring collegiate soccer players during a congested match schedule: Heart rate variability versus participantive wellness measures', *Physiology and Behavior*. Elsevier, 194(July), pp. 527–531. doi: 10.1016/j.physbeh.2018.07.001.
40. Rabbani, A., Kargarfard, M. and Twist, C. (2018) 'Fitness Monitoring in Elite Soccer Players: Group vs. Individual Analyses', *Journal of Strength and Conditioning Research*, pp. 1–8.
41. Rushall, B. R. (1990) 'A tool for measuring stress tolerance in elite athletes', *Journal of Applied Sport Psychology*, 2, pp. 51–66.
42. Saw, A. E., Halson, S. L. and Mujika, I. (2018) 'Monitoring Athletes during Training Camps: Observations and Translatable Strategies from Elite Road Cyclists and Swimmers', *Sports 2018, Vol. 6, Page 63*, 6(3), p. 63. doi: 10.3390/SPORTS6030063.
43. Saw, A. E., Main, L. C. and Gastin, P. B. (2016) 'Monitoring the athlete training response: Participantive self-reported measures trump commonly used objective measures: A systematic

review', *British Journal of Sports Medicine*, 50(5), pp. 281–291. doi: 10.1136/bjsports-2015-094758.

44. Sawczuk, T. *et al.* (2018) 'The influence of training load, exposure to match play and sleep duration on daily wellbeing measures in youth athletes', *Journal of Sports Sciences*. Routledge, 36(21), pp. 2431–2437. doi: 10.1080/02640414.2018.1461337.
45. Stagno, K. M., Thatcher, R. and van Someren, K. A. (2007) 'A modified TRIMP to quantify the in-season training load of team sport players', *Journal of Sports Sciences*, 25(6), pp. 629–634. doi: 10.1080/02640410600811817.
46. Stevens, T. G. A. T. G. A. *et al.* (2017) 'Quantification of in-season training load relative to match load in professional Dutch Eredivisie football players', *Science and Medicine in Football*. Routledge, 1(2), pp. 117–125. doi: 10.1080/24733938.2017.1282163.
47. Taylor, K. *et al.* (2012) 'Fatigue monitoring in high performance sport: a survey of current trends', *J Aust Strength Cond*, 20(1), pp. 12–23.
48. Thorpe, R. T. *et al.* (2015) 'Monitoring fatigue during the in-season competitive phase in elite soccer players', *International Journal of Sports Physiology and Performance*, 10(8), pp. 958–964. doi: 10.1123/ijspp.2015-0004.
49. Thorpe, R. T. (2015) 'Monitoring Fatigue Status in Elite Soccer Players Moores University for the degree of', (December).
50. Thorpe, R. T. *et al.* (2016) 'Tracking morning fatigue status across in-season training weeks in elite soccer players', *International Journal of Sports Physiology and Performance*, 11(7). doi: 10.1123/ijspp.2015-0490.
51. Thorpe, Robin T. *et al.* (2017) 'fatigue status in elite team sport athletes : Implications for practice', *International Journal of Sports Physiology and Performance*, 12(S2), pp. 27–34. doi: 10.1123/ijspp.2016-0434.

52. Thorpe, Robin T *et al.* (2017) 'The Influence of Changes in Acute Training Load on Daily Sensitivity of Morning-Measured Fatigue Variables in Elite Soccer Players', *International Journal of Sports Physiology and Performance*. Human Kinetics Publishers Inc., 12, pp. 107–113. doi: 10.1123/ijspp.2016-0433.

53. Varley, M. C. et al. (2017) 'Methodological considerations when quantifying high-intensity efforts in team sport using global positioning system technology', International Journal of Sports Physiology and Performance, 12(8), pp. 1059–1068. doi: 10.1123/ijspp.2016-0544.

54. Watanabe, N., Wicker, P. and Yan, G. (2017) 'Weather conditions, travel distance, rest, and running performance: The 2014 fifa world cup and implications for the future', *Journal of Sport Management*, 31(1), pp. 27–43. doi: 10.1123/jsm.2016-0077.

55. Weaving, D. *et al.* (2014) 'Combining internal- and external-training-load measures in professional rugby league', *International Journal of Sports Physiology and Performance*, 9(6), pp. 905–912. doi: 10.1123/ijspp.2013-0444.

56. Williams, S. *et al.* (2017) 'Evaluation of the Match External Load in Soccer: Methods Comparison', *Journal of Science and Medicine in Sport*. Sports Medicine Australia, 2(3), pp. 550–555. doi: 10.5604/20831862.1127284.

57. Wundersitz, D. W. T. *et al.* (2015) 'Validation of a Trunk-mounted Accelerometer to Measure Peak Impacts during Team Sport Movements', *International Journal of Sports Medicine*, 36(9), pp. 742–746. doi: 10.1055/s-0035-1547265.

Figure 1: Distribution and individual data points for all items of the wellness data with mean and 95% confidence intervals (black dots and error bars).

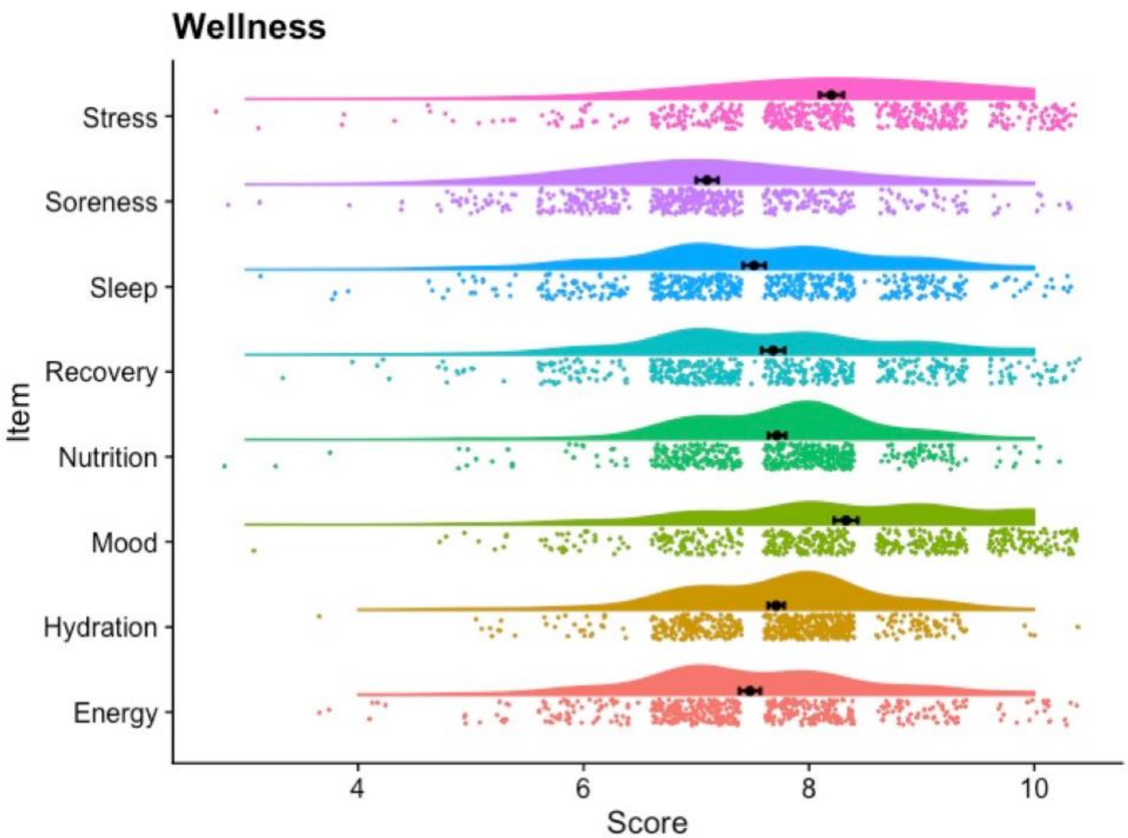


Figure 2: Partial Correlations (95%, CI) for the relationship between Next Day reported Soreness and selected independent variables for Overall, In-Season and Pre-Season periods.

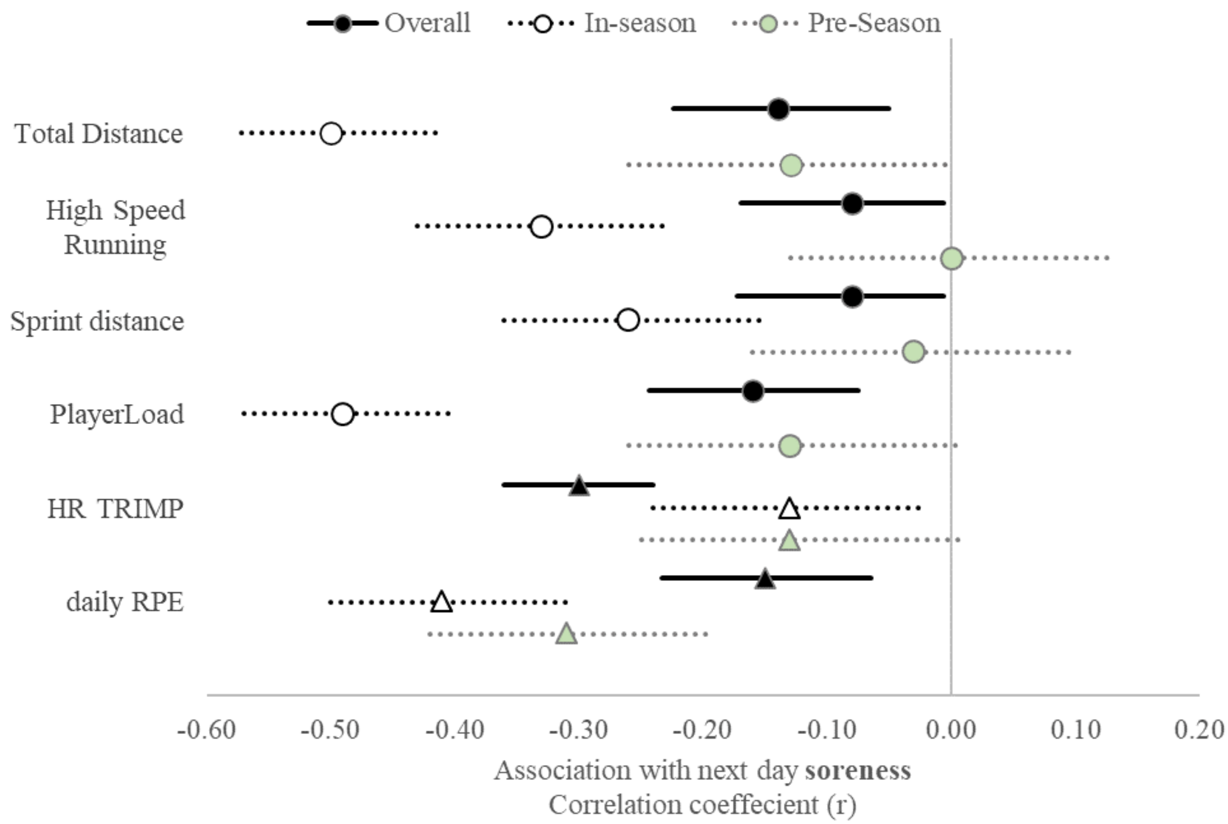
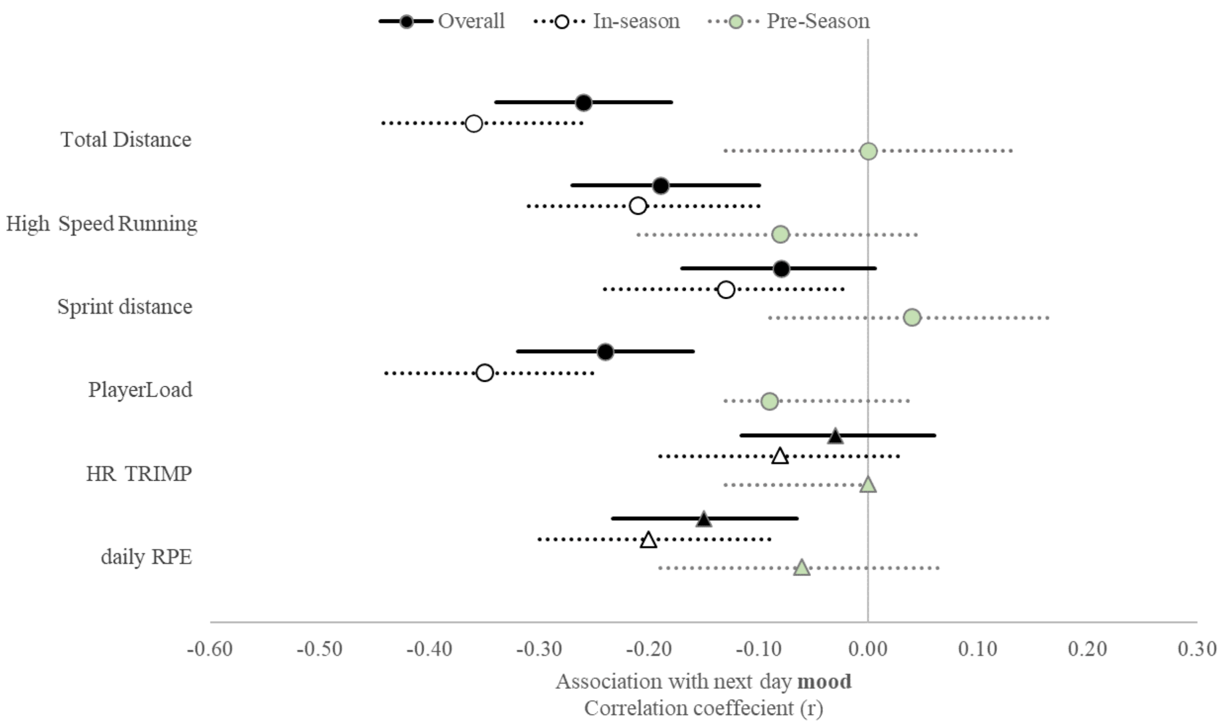
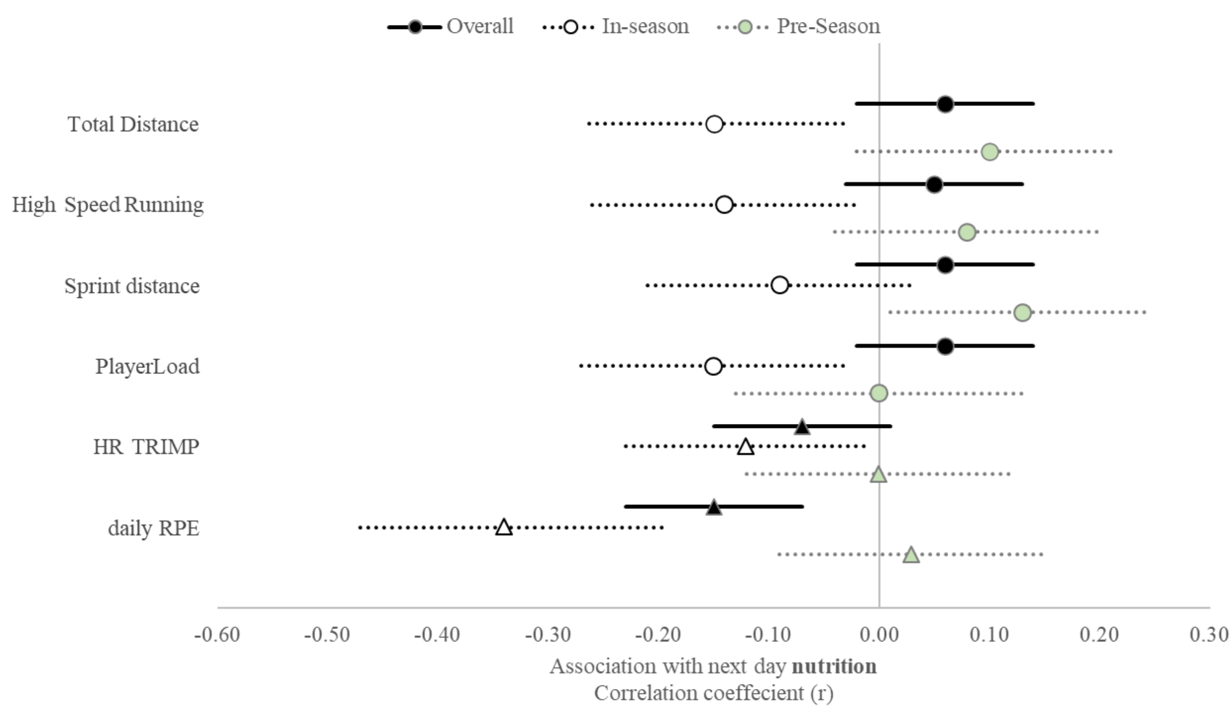


Figure 3: Partial Correlations (95%, CI) and Magnitude for the relationship between Next Day Measured Perceived Mood and selected independent variables for Overall, In-Season and Pre-Season periods



569 Figure 4: Partial Correlations (95%, CI) for the relationship between Next Day Measured
570 Perceived Nutrition and selected independent variables for Overall, In-Season and Pre-Season
571 periods



572

Table 1: Descriptive Statistics (Mean ± Standard Deviation, Range) are shown for training load variables.

Metric	Mean ± Standard Deviation	Range
Total Distance (m)	4872 ± 2351	609-11493
High-speed running distance (m)	190 ± 151	0-738
Sprint distance (m)	55 ± 69	0-415
Player Load (AU)	497 ± 217	60-1078
HR trimp (AU)	78 ± 67	28-316
session RPE (AU)	61 ± 21	10-100

Supplemental Digital Content List

1. Supplemental Digital Content 1, Text, .docx
2. Supplemental Digital Content 2, Text, .docx
3. Supplemental Digital Content 3, Text, .docx