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Section: Original Investigation

Article Title: Predicting Future Perceived Wellness in Professional Soccer: The Role of Preceding Load and Wellness

Authors: Arne Jaspers[1], Tim Op De Beéck[2], Michel S. Brink[3], Wouter G.P. Frencken[3], Filip Staes[4], Jesse J. Davis[2], and Werner F. Helsen[#1]

Affiliations: [1]KU Leuven, Department of Movement Sciences, Movement Control and Neuroplasticity Research Group, Leuven, Belgium. [2]KU Leuven, Department of Computer Science, Leuven, Belgium. [3]Center for Human Movement Sciences, University of Groningen, University Medical Center, Groningen, The Netherlands. [4]KU Leuven, Department of Rehabilitation Sciences, Musculoskeletal Rehabilitation Research Group, Leuven, Belgium.

Journal: *International Journal of Sports Physiology and Performance*

Acceptance Date: January 8, 2019

DOI: https://doi.org/10.1123/ijspp.2017-0864

“Predicting Future Perceived Wellness in Professional Soccer: The Role of Preceding Load and Wellness”
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International Journal of Sports Physiology and Performance

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Submission type: Original Investigation

Names of the authors and affiliations:

Arne Jaspers*[1], Tim Op De Beéck*[2], Michel S. Brink[3], Wouter G.P. Frencken[3], Filip Staes[4], Jesse J. Davis#[2], Werner F. Helsen#[1]

* Shared first authorship, in alphabetical order
# Shared last authorship, in alphabetical order

1. KU Leuven, Department of Movement Sciences, Movement Control and Neuroplasticity Research Group, Leuven, Belgium
2. KU Leuven, Department of Computer Science, Leuven, Belgium
3. Center for Human Movement Sciences, University of Groningen, University Medical Center, Groningen, The Netherlands
4. KU Leuven, Department of Rehabilitation Sciences, Musculoskeletal Rehabilitation Research Group, Leuven, Belgium

Corresponding author:
Arne Jaspers
KU Leuven
Department of Movement Sciences
Tervuursevest 101 (box 1501), B-3001 Leuven, Belgium
Mobile: +32496683288
E-mail: arne.jaspers@kuleuven.be

Preferred running head: Machine learning for interpreting load and wellness

Abstract count: 244

Text-only word count: 3734

Number of figures: 6

Number of tables: 0

International Journal of Sports Physiology and Performance

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Abstract

Purpose: The influence of preceding load and perceived wellness on the future perceived wellness of professional soccer players is unexamined. This paper simultaneously evaluates the external and internal load for different time frames in combination with pre-session wellness to predict future perceived wellness using machine learning techniques. **Methods:** Training and match data were collected from a professional soccer team. The external load was measured using global positioning system technology and accelerometry. The internal load was obtained using the RPE multiplied by duration. Predictive models were constructed using gradient boosted regression trees (GBRT) and one naive baseline method. The individual predictions of future wellness items (i.e., fatigue, sleep quality, general muscle soreness, stress levels, and mood) were based on a set of external and internal load indicators in combination with pre-session wellness. The external and internal load was computed for acute and cumulative time frames. The GBRT model's performance on predicting the reported future wellness was compared to the naive baseline's performance by means of absolute prediction error and effect size. **Results:** The GBRT model outperformed the baseline for the wellness items fatigue, general muscle soreness, stress levels and mood. Additionally, only the combination of external load, internal load, and pre-session perceived wellness resulted in non-trivial effects for predicting future wellness. Including the cumulative load did not improve the predictive performances. **Conclusions:** The findings may indicate the importance of including both acute load and pre-session perceived wellness in a broad monitoring approach in professional soccer.

Keywords: football, global positioning system, rating of perceived exertion, athlete monitoring, predictive modelling

Introduction

Monitoring team-sport athletes is considered important for understanding responses to training and match load, and accordingly, for optimizing loads to ensure competition readiness.[1] Consequently, various player tracking tools are employed to continuously monitor training and match load.[2] Furthermore, these loads elicit responses, such as fitness, fatigue and a certain need for recovery.[2, 3] These athletes' responses are often measured by perceived wellness questionnaires.[2, 3] In professional soccer, several studies have provided evidence for using perceived wellness questionnaires to quantify the outcome of a training or match load by assessing players' fatigue statuses.[4-8] It is assumed that changes in perceived wellness influence both on-field performance and injury risk.[9, 10]

Two studies have evaluated the external load in relation to changes in perceived player wellness, and both focused on the distance covered at high speed (HSR; >14.4 km.h^{-1}).[7, 8] Other external load indicators such as total distance, distance covered at very high speed (VHSR; >20.0 km.h^{-1}), accelerations, and decelerations remain unexamined. Most studies examining the relationship between load and perceived wellness use the session rating of perceived exertion (sRPE),[5, 6] which is derived by multiplying the RPE by duration, and is considered a global measure of the internal load.[11]

To date, perceived wellness studies in professional soccer have focused on either external or internal load indicators. A simultaneous evaluation of external and internal load indicators has not been conducted yet. Thus, a combined approach that simultaneously evaluates different load indicators and their relationship with perceived wellness can help identify relevant load indicators. This may improve load management strategies for optimizing perceived player wellness in professional soccer.

Similarly, the impact of loads accumulated over several days on perceived wellness needs further exploration. One study in professional soccer focused on the cumulative external load as measured by HSR over the previous 2, 3, and 4 days.[8] However, considering the cumulative load did not improve the strength of the relationship between HSR and changes in perceived player wellness.[8] Still, evaluating load indicators beyond HSR over different time periods has not been conducted and could help better understand of the influence of cumulative loads on perceived wellness.

Recently, research in Australian rules football,[12] American college football,[13] and professional soccer[14] has provided evidence that perceived pre-training wellness influences the subsequent training output. In view of the model of Impellizzeri and colleagues,[15] the pre-training wellness status may be considered as an individual characteristic that impacts the performed external load but also the main stimulus for the training outcome, the perceived internal load. Following the rationale of the training process model,[15] one can argue that pre-training wellness may also influence the outcome of training or match load. Consequently, it is possible that pre-training wellness, in addition to training and match load, may influence future perceived wellness. However, to our knowledge, the influence of pre-training wellness on future perceived wellness remains unexplored.

Finally, the relationships between load and perceived wellness can be examined for both each individual wellness item on the questionnaire,[3-8] and a global wellness measure computed as the summed score over all items.[3, 6] One limitation of a global wellness measure is the limited capability to identify specific relationships between load indicators and wellness items.[12, 13] Relationships between load indicators and various perceived wellness items have been examined for different season periods in professional soccer. However, except for a frequently observed relationship between higher loads and an increased perceived fatigue, the relationships between load and other wellness items such as sleep quality and general muscle soreness are less clear.[6-8] Furthermore, the relationships between diverse load indicators and wellness items have not been investigated over the course of a full season. Therefore, an explorative examination of relationships between load and wellness items over a longer period can provide additional insights into typical load-wellness response profiles for each wellness item over a season.

It is generally recognized that the relationship between load and perceived wellness may be non-linear.[12, 14] Therefore, linear statistical techniques used in earlier research may be incapable of elucidating these relationships. Non-linear statistical models or machine learning techniques may provide additional insights in relationships between load and training outcomes. Machine learning (ML) techniques are suited for these analyses and corresponding data because they often account for multicollinearity and can model non-linear relationships among large sets of variables.[16]

This study will apply ML techniques to construct individual predictive models for professional soccer players to (1) examine simultaneously the relationship between external (EL) and internal load (IL) indicators on future perceived wellness (FPW) items as measured on the next day; (2) investigate the impact of both acute and cumulative loads on FPW items; and (3) evaluate the influence of pre-session perceived wellness (PPW) on FPW items.

Methods

Subjects

Data from 26 professional male soccer players (mean ± SD age: 23.2±3.7 years, weight: 77.5±7.4 kg, height: 1.82±0.06 m, body fat: 10.4±1.9%) competing for the same team at the highest level in the Netherlands were collected during the 2015-2016 season, both pre-season and in-season. Written informed consent was obtained according to the Helsinki declaration. The study was approved by the ethical committee of KU Leuven (file number: s57732).

Training and match load

External load was measured individually during all field training sessions and matches throughout the season. Data were obtained using an athlete tracking system with an integrated 10 Hz global positioning system (GPS) and accelerometer technology (Optimeye S5, Catapult Sports, Melbourne, Australia). This system is considered a reliable tool for measuring external load that obtains an acceptable level of accuracy for quantifying various locomotor activities.[17] The minimum effort duration to detect velocity was 0.6 seconds, and 0.4 seconds for acceleration with a smoothing filter of 0.2 seconds.[18, 19] The data were processed using the manufacturer's software (Sprint™ version 5.1.7, Catapult Sports, Melbourne, Australia). Based upon earlier research,[20, 21] the included external load indicators were training and match duration, total distance covered, PlayerLoad, distance covered at high speed (>20 $km.h^{-1}$), the number of acceleration efforts >1 $m.s^{-2}$ and deceleration efforts <-1 $m.s^{-2}$.

The internal load was obtained for all players after the training sessions and matches using the sRPE method.[11] In order to ensure that the perceived effort would reflect the session in total, rather than the most recent exercise intensity, each player was separately asked 30 minutes after every training session or match to rate his perceived exertion using a category ratio scale of 0-10 with verbal anchors (with 0 rated as 'rest', 1 rated as 'very, very easy' and 10 rated as 'maximal').[22] All players were familiarized with the scale before the study commenced. Each player's sRPE in arbitrary units (AU) was derived by multiplying the RPE with the training or match duration in minutes.[22] The entire duration of a training session was used including the transition time between drills. For matches, the sum of the warm-up and match time was used. The time between the warming-up and the start of the match as well as the half time break were excluded.

Perceived player wellness questionnaire

The perceived player wellness data were individually collected using a custom-designed iPad-based electronic survey (TopSportsLab™, Leuven, Belgium) each morning prior to any session. Players were not asked to report wellness scores on match and rest days. The survey contained five questions about fatigue, sleep quality, general muscle soreness, stress levels, and mood that were used in earlier research.[3, 4] The responses were reported on a 5-point scale (with 1 and 5 representing poor and very good ratings), with 0.5-point increments.[3] The players were familiarized with the questionnaire before the start of the study.

Data analysis

This study applied a widely used machine learning pipeline to construct individual predictive models for each player.[16] An individual model was constructed by ignoring the data from all other players. The goal was to predict a training session's outcome, which was represented by the future value of a perceived wellness (FPW) item. Specifically, the models predicted what perceived wellness score a player would report for an item prior to the next day's first session. Combinations of three sets of input variables were considered: external load indicators (EL), internal load indicators (IL), and pre-session perceived wellness (PPW) items.

Figure 1 illustrates the input variables that were computed to predict the FPW prior to the first session on day D_{FPW}. Based upon earlier research, the EL and IL variables of training sessions and matches were summed over four different time frames: 1 day (acute), 2 days, 3 days and 4 days.[8] Additionally, because the weekly load is often related to an increased injury risk, the EL and IL variables were summed over the previous 7 days.[23] The PPW was defined as the pre-session perceived player wellness that was reported before the first session on day D_{FPW}-1 (i.e., a time frame of 1 day).

The data was split chronologically to respect its sequential nature: the first 80% of a player's data was used to construct the model (i.e., the learning set). The remaining 20% was used for model evaluation (i.e., the testing set).

For each of the five time frames, seven combinations of variable classes were considered: EL, PPW, IL, EL + PPW, IL + PPW, EL + IL, and EL + IL + PPW. For each of the five FPW items (fatigue, sleep quality, general muscle soreness, stress levels, and mood), one model per player was learned for each of the 35 input variable time frame combinations. The individual predictive models were constructed from the learning set using the Gradient Boosted Regression Tree (GBRT) algorithm in Scikit Learn.[24, 25]

GBRTs can handle both high-dimensional data and mixed variable types. A GBRT model contains a number of decision trees. Decision trees are learned using a top-down stepwise process. Each step selects the single best input variable according to some score criteria and adds it to the model. Then, it partitions the data based on this variable's value, and recursively finds the best variable in each partition. This process helps with multi-collinearity because highly-correlated variables will have similar scores. Therefore, after adding one of these variables to the model, the others are unlikely to be included because they will not help to further partition the data. Additionally, ensembles of decision trees tend to be robust to overfitting.[26] To assess if the learned individual models captured any dependencies between the input variables and the FPW, a naive baseline model was constructed that ignores all input variables. This model simply predicted a player's FPW as the average of all FPW values in his learning set. A learned model only outperforms this baseline if it captures some relationship between the input variables and the FPW.

An individual model's predictive performance was evaluated by making a prediction for each of the player's reported wellness scores in the testing set and then computing the mean absolute error (MAE) for these predictions. The predictive performance for a given set of input variables was computed as the macro average of all the MAEs for the individual models that were constructed using that set of input variables.

Per wellness item, and for each combination of input parameters and time frames, two comparisons were done. First, the macro MAE of the GBRT models was compared to the macro MAE of the baseline models. Second, the effect sizes between the macro MAE of the GBRT models and the macro MAE of the baseline models were calculated to evaluate the meaningfulness of the predictive performances using Cohen's d: d = (macro $MAE_{BASELINE}$ – macro MAE_{GBRT}) / pooled $SD_{BASELINE,GBRT}$. The threshold values for effect sizes were trivial (0.0-0.19); small (0.2-0.59); moderate (0.6-1.19); large (1.2-1.99); and very large (>2.0).[27]

Initially, the dataset contained data collected from 6110 training sessions or matches across all 26 players. Before the above methodology was applied to the dataset, four preprocessing steps were required, as illustrated in igure 2.

First, perceived wellness scores were not reported on most rest and match days. Consequently, these days FPW value was unknown. Hence, these days were excluded from the learning and testing set. However, the EL and IL variables were monitored on these days and were used to calculate the cumulative external and internal loads.

Second, sometimes it was not possible to calculate the 7-day cumulative load for EL or IL due to missing EL and IL data (e.g., the first week after the off-season, international qualifiers, etc.). While these instances did not occur at random, they were excluded because the missing loads could not be realistically imputed.

Third, even if the FPW was known, the PPW was missing sometimes. The PPW was imputed using the last observation carried forward method, and hence set to be the reported perceived wellness score on day D_{FPW}-2.[28] If no scores were reported on D_{FPW-2}, then the session was excluded. While a match or training session on D_{FPW}-2 affects the perceived wellness of the player on D_{FPW}-1, this is a common imputation approach for temporal data because it respects the chronological dependencies present in the data. This necessary imputation step should be taken into account when analyzing the results. Other popular imputation strategies were also considered. However, because the data was not missing at random and its chronological dependencies need to be respected, not enough data instances were available to apply potentially more accurate imputation strategies.

Fourth, models were only learned for players where 80 data instances could be constructed to ensure that sufficient data was available for learning and evaluating the models. After preprocessing, the final dataset contained data from 14 players with an average of 98 data instances per player (range 84-119). On average each player's learning data contained 78 data instances (range 67-95) and testing data contained 20 data instances (range 17-24).

Results

Figures 3, 4, 5, and 6 show graphs for the four wellness items (fatigue, general muscle soreness, stress levels and mood) with at least one small effect size found for one of the five considered time frames. Because only trivial effect sizes were found for sleep quality, no plot is shown for it. A small effect size indicates that the GBRT model obtained better predictive performance than the baseline model. For each wellness item, the plot shows the MAEs for each of the seven combinations of EL, PPW and IL as a function of the time frame. A decrease in the MAE over time indicates a better predictive performance when including the cumulative load over the previous days.

Discussion

This study applied machine learning techniques to evaluate the influence of external and internal load indicators, both for acute and cumulative loads, along with pre-session perceived wellness on changes in future perceived wellness.

When comparing EL and IL by absolute prediction error, EL exhibited a better performance for fatigue, general muscle soreness and stress levels. In general, the combination of EL and IL did not result in better predictive performances than EL alone.

Moreover, none of the predictive performances for EL, IL or EL+IL exhibited effect sizes above the trivial level. These effect sizes indicate that the external load and internal load, separately and in combination, do not have sufficient predictive ability for FPW items. However, in earlier research, these external and internal load indicators were related to changes in perceived wellness items and revealed various results, including non-significant and significant correlations with the magnitude of correlation ranging from trivial to large.[5-8] The difference with earlier findings could arise from the type of analysis performed. Prior work used analyses to quantify the strength of the linear associations among variables. In contrast, our study uses predictive models, that given EL and IL data collected at some future time point would make accurate predictions for that data's FPW values. Therefore, the current study's findings complement the earlier works.

Cumulative loads alone did not result in better predictive performances, which is in accordance with earlier findings that loads beyond the previous day's training are not meaningfully linked to wellness responses.[8] As Thorpe and colleagues suggest,[8] professional soccer's periodization of training and match load with an alternation between demanding sessions and easy or recovery sessions, may be responsible for the large influence of the previous day's training or match load.

Including PPW in combination with EL, IL and EL+IL clearly showed small effect sizes for most time frames for fatigue, general muscle soreness, and stress levels. For mood, the results were more ambiguous and only the combination of acute load for EL and PPW and EL+PPW+IL resulted in a small effect size. To date, no research in professional soccer has focused on the relationship between load and mood, therefore, little information is available to compare results. Additionally, other factors such as match result, match location and quality of opposition may influence mood.[29] Potentially, mood is influenced after prolonged overload and therefore it might be interesting to study periods longer than 7 days. In conclusion, the findings reveal that PPW along with EL and/or IL resulted in the best predictive performances for FPW, thereby indicating the usefulness of monitoring perceived wellness. Therefore, PPW in combination with training and match load may be considered for a broad monitoring approach to improve training prescription and evaluation.

The perceived wellness items fatigue, general muscle soreness and stress levels were predicted by the input variables. For the perceived wellness items sleep quality and mood, almost all predictive performances exhibited trivial effect sizes. Some studies found small to large positive correlations between sRPE and sleep quality,[5, 6] while other studies revealed trivial relationships between HSR and sleep quality.[7, 8] This may indicate that factors beyond load and PPW have a greater impact on these items. Recent research in professional soccer has indicated that the match result, location and quality of opposition impact sleep quality and mood.[29, 30] Nevertheless these items can be useful for assessing a player's status and to support decision-making regarding load management.

A strength of the current study is the using of GBRT machine learning technique, which can capture non-linear relationships, to construct an individual predictive model per player. [31] Furthermore, GBRTs can handle long tailed distributions, outliers and are robust to the presence of irrelevant input variables.[24] Furthermore, GBRTs allowed evaluating a broad monitoring approach by examining simultaneously the impact of EL, IL and PPW on FPW. These techniques and corresponding findings complement the statistical methods used in earlier research[5-8] and help to evaluate the usefulness of perceived wellness in monitoring strategies.

The analysis revealed that individual predictive models are more accurate than average player thresholds, which are commonly used. Therefore, such models could improve monitoring strategies, by comparing the reported wellness to the predicted player wellness after each practice. If the reported wellness and predicted wellness differ substantially (i.e., higher or lower scores), this may be a sign to zoom in on the load and responses of a player for detailed interpretations. Moreover, it may aid in individualizing a training program as the models can simulate how a player with a certain wellness status will respond to a given external load.

Some limitations should be acknowledged. First, a large part of the data could not be used to construct and evaluate the predictive models because the wellness scores were not reported on match and rest days. Since these days do not occur at random, an imputation strategy was necessary to examine the impact of past wellness. This solution provides a reasonable estimation while respecting the data's chronological ordering. Moreover, using this imputation outperformed,the baseline method (i.e., small effect sizes were found) which can be considered as the current state of the art when predicting wellness scores for held-aside data samples. Currently, the applied models are not designed to make predictions when the previous three days only contain a combination of match and rest days. However, they do support all combinations of match, rest -and practice days, when at least one of the previous three days is a practice day. Thus, these models are already versatile enough to be practically useful and the results underscore the importance of daily wellness monitoring. Second, the load of strength training sessions was not included and may influence the perceived wellness. However, besides the normal injury prevention programs, there were only a small number of separate strength training sessions, and therefore, their influence on the results may be limited. Third, the perceived wellness questionnaire used in the current study was previously examined in various studies, revealing relationships between load and the wellness items.[3, 4] The custom items of this perceived wellness questionnaire have not been extensively studied concerning their reliability and validity.[32] Therefore, there possibly exists a more adequate composition of perceived wellness items for a questionnaire to monitor fatigue and recovery status.[32] Finally, the direction of the relationship between input variables (i.e., EL, IL, and PPW) and FPW is not presented in the current study. In earlier research, higher loads were related to lower perceived wellness.[5-8] The correlation and interactions of input variables complicate the interpretation of non-linear models.[33] Nevertheless, the findings indicate that a combination of EL and/or IL together with PPW resulted in the best predictive performances of FPW. As presented by Bittencourt and colleagues,[34] a complex interaction among a web of determinants may be related to injury occurrence and adaptation. Similarly, this may be the case for perceived wellness. In future research, more extensive analyses using partial dependence plots[33] and including other mediating or moderating factors[35] may provide additional insights in the direction of relationships between EL, IL, PPW, and FPW.

Practical applications

The current study's findings indicate the importance of including both load and preceding perceived wellness in a broad monitoring approach. Additionally, the wellness items fatigue, general muscle soreness and stress levels are the most useful items for assessing the combined impact of load and current wellness status on future wellness. These insights may improve load management strategies in professional soccer. Machine learning techniques may have added value for analyzing load-wellness relationships and daily practice by the comparison of predicted/expected versus actual wellness scores. Meaningful differences between these scores may be used for load management strategies. However, more research is warranted to indicate the direction of relationships and the influence of specific load indicators.

Conclusion

The current study focused on predicting future perceived wellness based on preceding load and perceived wellness in professional soccer using individual machine learning models. It was found that the external and/or internal load in combination with preceding perceived wellness resulted in the best predictive performances, indicating the importance of daily wellness status assessment. Including cumulative load for previous days did not improve the predictive performances.

Acknowledgements

The authors would like to thank the players and both physical and medical staff for their participation in this study.

Arne Jaspers is supported by a research grant from the Agency for Innovation by Science and Technology–IWT, Belgium (IWT 130841). Jesse Davis and Tim Op De Beeck are partially supported by the KU Leuven Research Fund (C22/15/015) and the Interreg V A project NANO4Sports. The authors have no conflicts of interest to declare.

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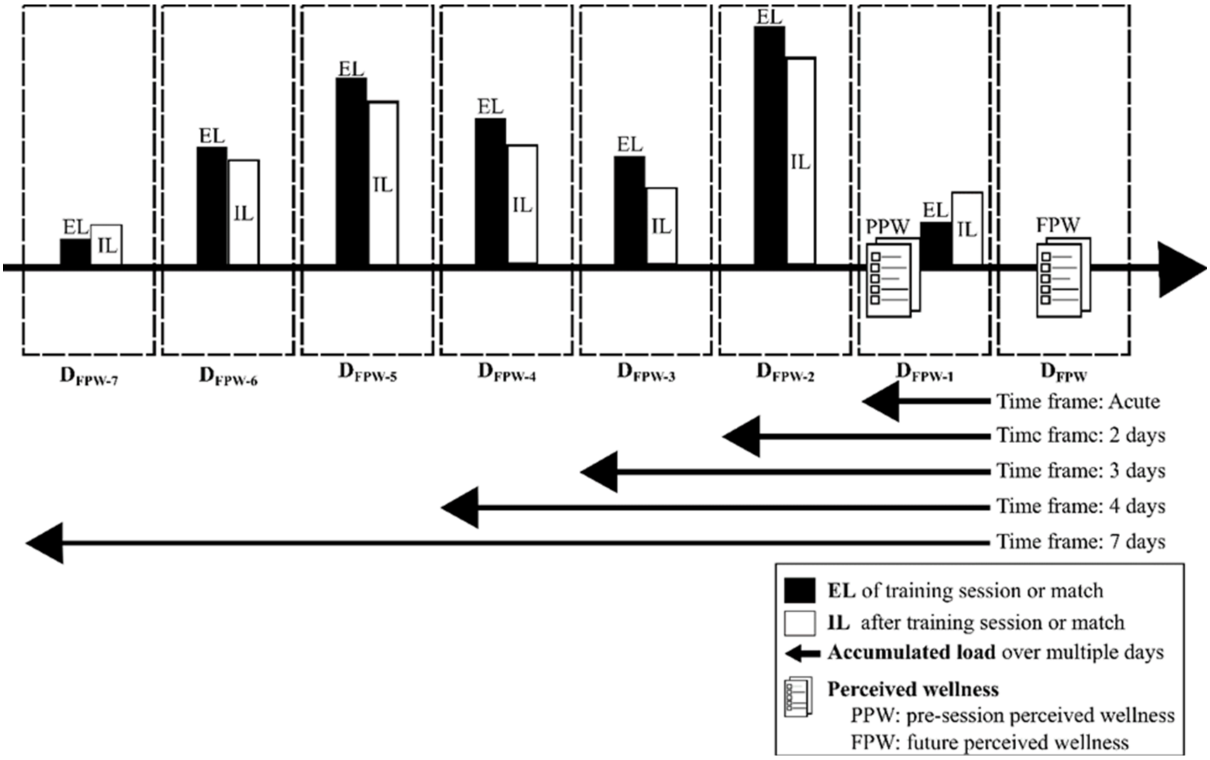

Figure 1. Overview of the parameters that are computed to predict future perceived wellness.

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by Jaspers A et al.
International Journal of Sports Physiology and Performance

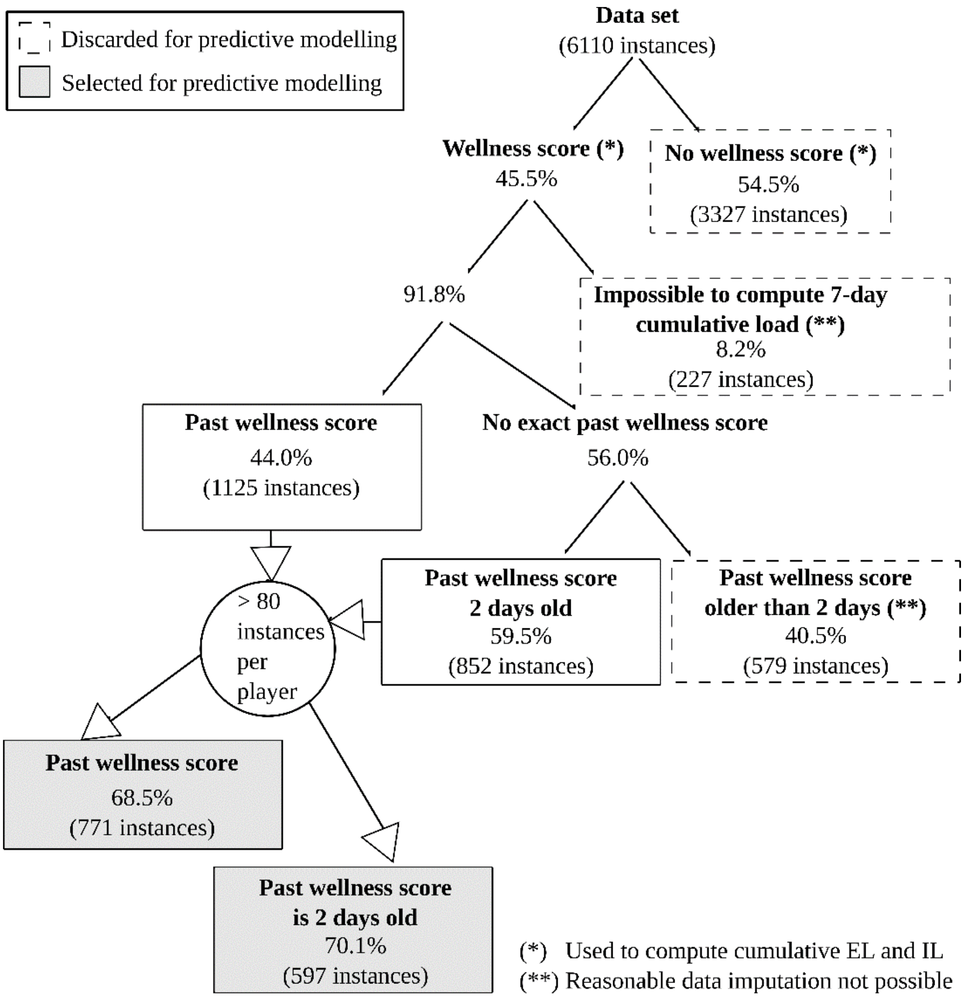

Figure 2. Overview of the preprocessing steps before application of GBRT.

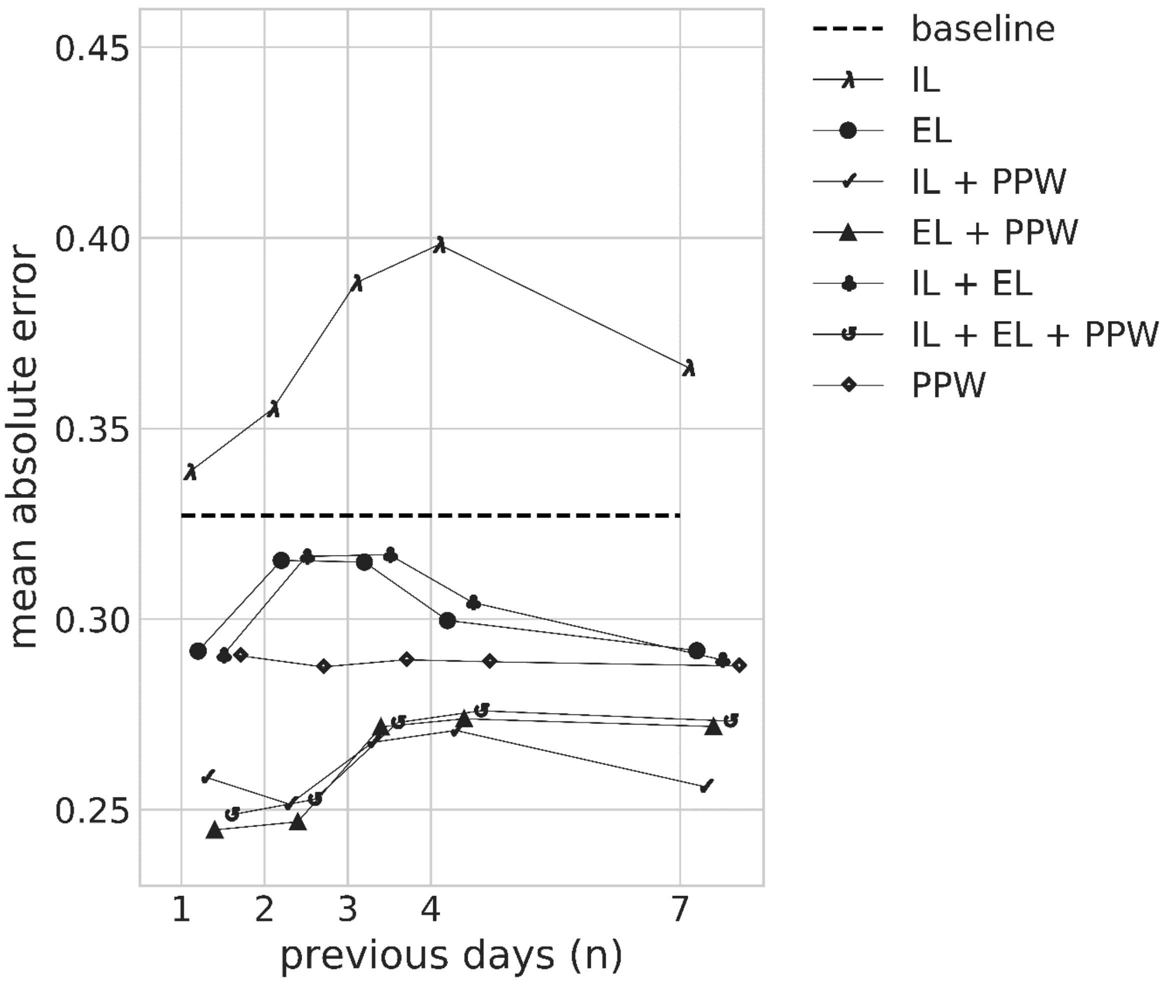

Figure 3. Mean absolute errors for each of the combinations per time frame for perceived wellness item 'fatigue'.

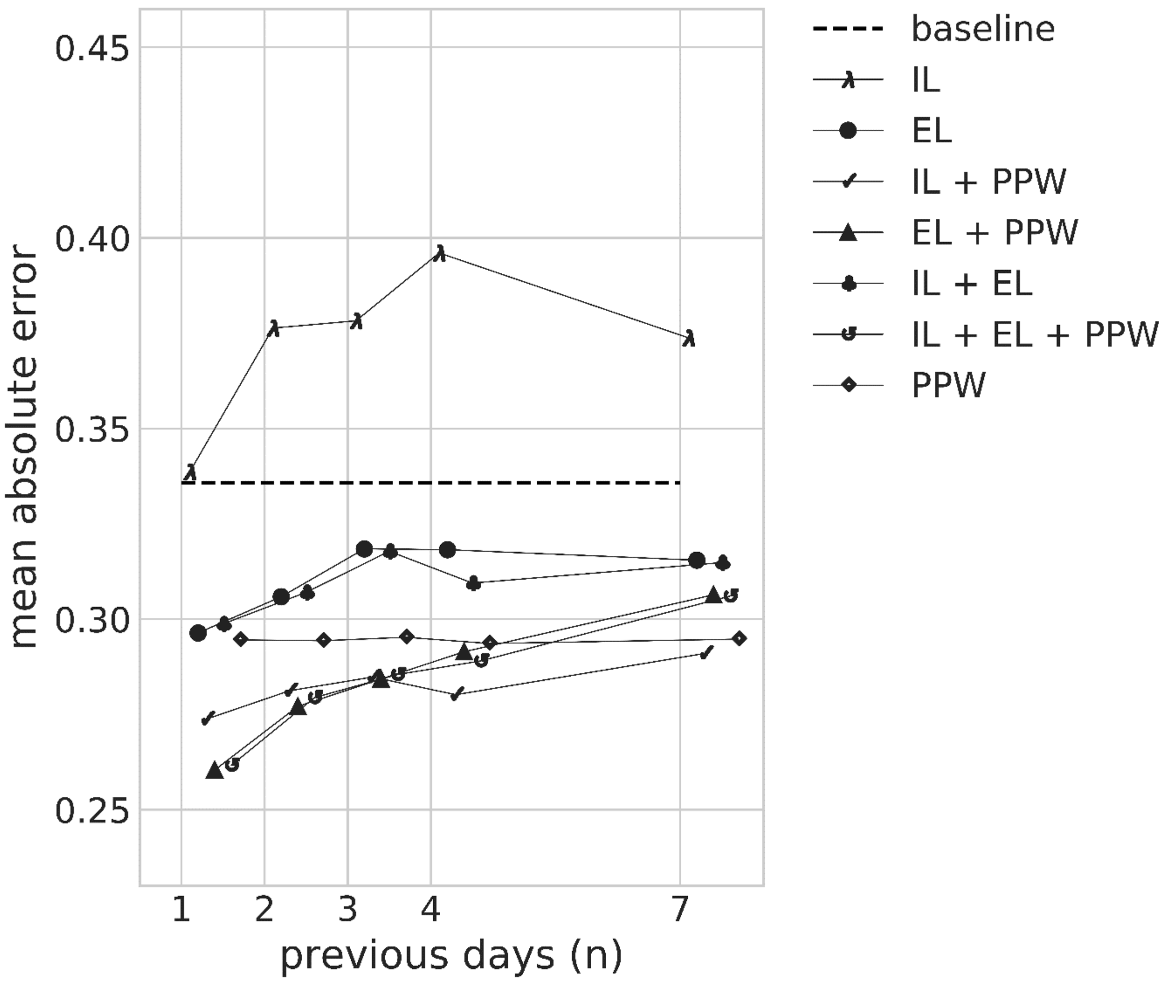

Figure 4. Mean absolute errors for each of the combinations per time frame for perceived wellness item 'general muscle soreness'.

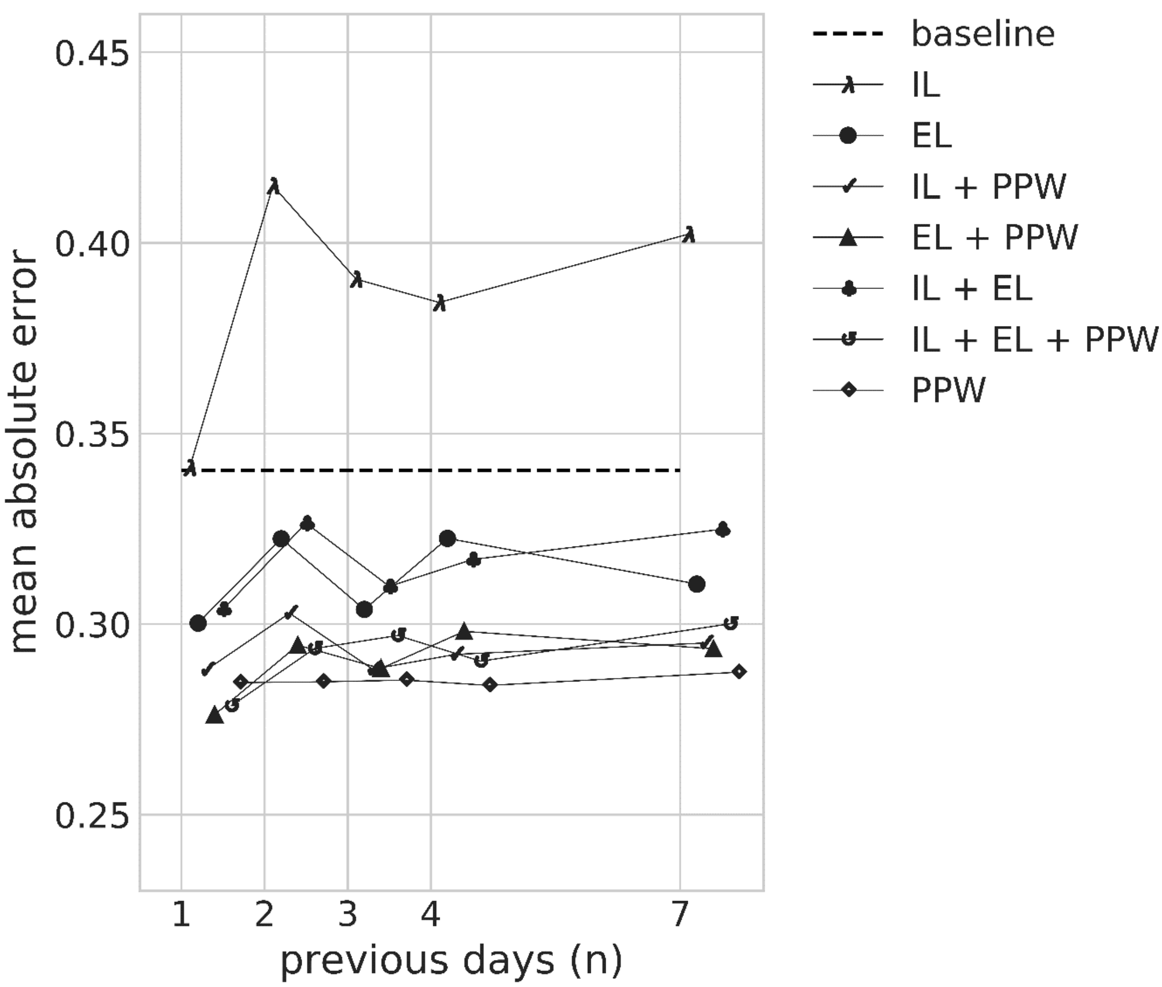

Figure 5. Mean absolute errors for each of the combinations per time frame for perceived wellness item 'stress levels'.

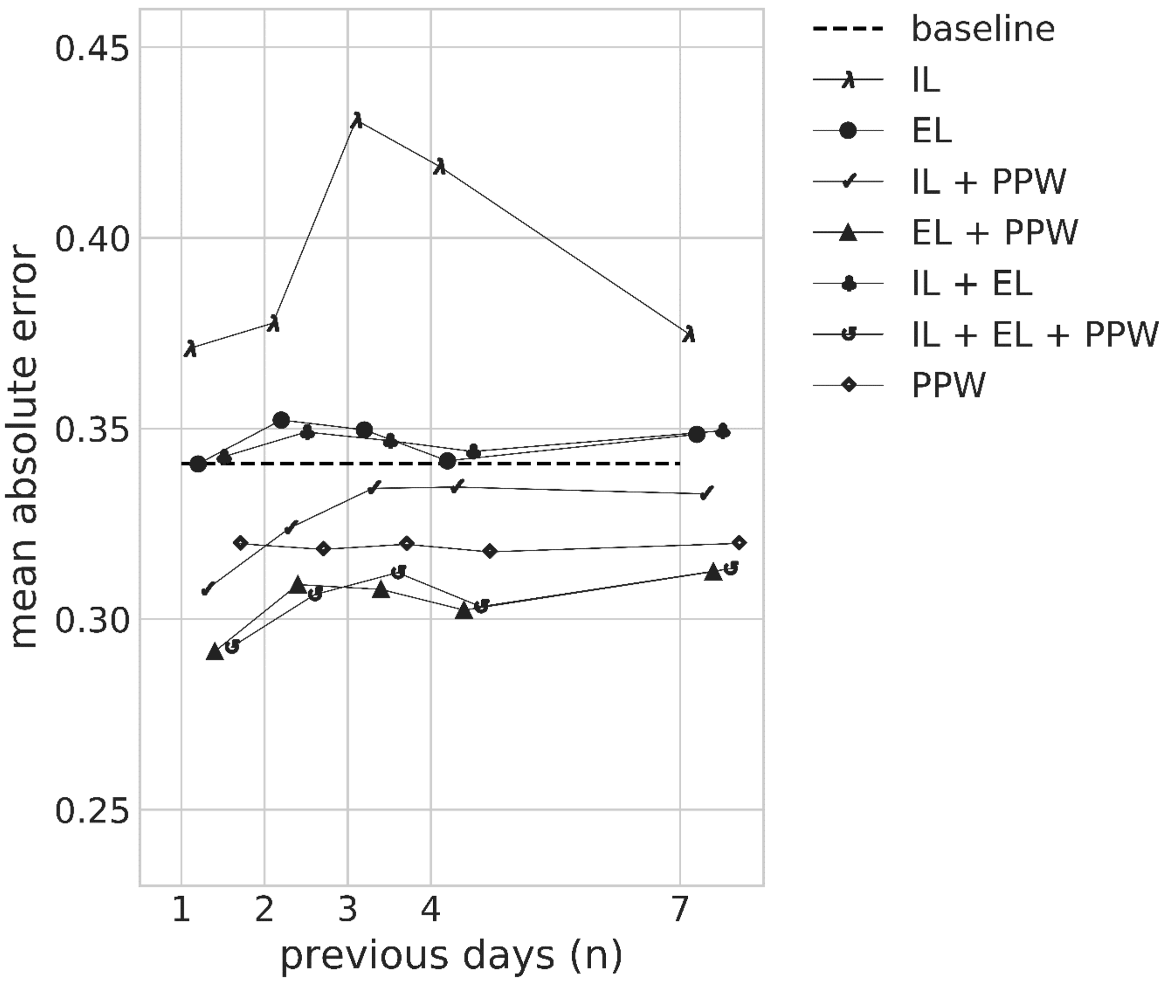

Figure 6. Mean absolute errors for each of the combinations per time frame for perceived wellness item ‘mood’.