USOPC Athlete Wellness and Load Interview Report

Perry Battles

May 2025

1 Key Takeaways

- EDA demonstrated that average session heart rate and practice load likely express much of the same information. If collecting both is logistically intractable or difficult, not much is lost by sacrificing one. Because of the familiarity with heart rate data and zones, it may be more useful to present heart rate data to coaches and athletes.
- Sleep has by far the most outsized effect in mitigating athlete wellness by reducing fatigue and stress and increasing mood and motivation.
- Workload does not appear to affect sleep quality within the ranges in which it has been administered, with the exception of a potential slight effect for practice load.
- Soreness was negatively associated with sleep to a much greater degree than with any other variable. Competition load did positively influence soreness.
- Athletes that performed more strength and conditioning in a given week experienced less stress and fatigue. However, these effects are likely very slight and possibly confounded by the positions of players engaging in the most strength and conditioning also performing less other training.

Each of these points is treated much more extensively in the extensive report, submitted alongside this document. For a more complete treatment of the analytical methods and results, please refer to it.

2 Introduction

This report is intended to be read by a sports science team to provide an overview of key trends in the data and directions for further action to facilitate athlete health and wellness and, by extension, performance.

First glances at the data provoked several interesting questions. Firstly, since the athletes were aggregated into different position groups, were any differences in workload or wellness data simply a function of group? This question hasn't been answered extensively enough by the present analysis, but my tentative conclusion is that, while there are likely strong position-based trends as demonstrated by the exploratory data analysis, there are probably also some outlier cases in different positions in which a more nuanced model of workload and wellness is useful, and also some conclusions that apply across groups.

3 Methods

3.1 Exploratory Data Analysis

EDA proceeded in several steps. The first consisted of simply visualizing distributions of the data to determine what models and transformations might be needed to make inferences on the basis of the data with some conviction that the assumptions of the analysis are well-met. From there, I looked at distributions of the variables by position group.

3.2 Gamma Generalized Linear Modeling

Because none of the wellness variables were normally distributed according to the Shapiro-Wilk test, I moved forward with a generalized linear model, which loosens some of the statistical assumptions of standard linear regression. Because the outcome variables seemed to be approximately gamma-distributed, I chose the gamma generalized linear model. I selected some feature subsets that I thought would be informative in modeling each outcome based on known physiological principles and relationships, and moved forward.

4 Challenges

The primary challenge I ran into in analyzing these data was the fact that there were matrix multiplication errors in the underlying `NumPy` and R `glm` code that caused fits of the gamma generalized linear model to fail. Getting around this took some doing; after reading a bit on StackOverflow, it seemed to me that the primary issue was some large numbers being produced in one or more steps of the math underlying the model fit. After being uncertain how to address this in Python, I pivoted over to using R's `glm` package, initially did not have much luck, but ultimately stumbled upon the log linking function as the appropriate choice. This allowed the models to converge and get a proper fit.

5 Conclusions

The greatest conclusion I've drawn from this analysis is that workload is tremendously secondary to sleep for most intents and purposes. If we're carefully trying to monitor athlete loading but we aren't attending to sleep, we're probably not taking care of the big pillars supporting performance. I could see this becoming particularly relevant during travel, particularly where international competition is concerned.

6 Directions for Future Work

Originally, I wanted to have a pure Python analytical pipeline that performed a grid search across several different models and hyperparameter combinations. Some of these models (e.g., random forest regressors) don't produce coefficient estimates in the traditional sense or may not necessarily make assumptions that fit the data very well, but could still be very predictive. Others, like the multilayer perceptron, could do a great job predicting values of the outcome variable but might not necessarily be very readily interpretable. However, there are ways around this: a few solutions that come to mind are Shapley values, as well as visualizing outcome variable surfaces when varying two inputs at a time while we hold the other predictors constant. One can also use principal component analysis to find eigenvectors in the inputs, reduce the input to be two-dimensional, and then visualize changes in the outcome variable that way.

Another question I would like to more extensively answer is how much of the variation in the wellness and workload variables simply depends upon player position group. Although this may not change much from a modeling standpoint, it could have some important practical applications, since a player's position could be a good heuristic for how we need to approach managing their workload. That being said, it could be that there are underlying player positions that do not correspond to the given groups, and discovering those could give us more insight into how to coach these players.