# Modelling the effect of cumulative training load on the risk of injury

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## Background

In recent years, researchers have attempted to assess the effect of training load on the risk of sports injuries (Griffin et al., 2019, Andrade et al., 2020). Relationships between risk factors and sports injuries are often complex (Bittencourt et al., 2016), and assessing training load poses additional challenges (Windt and Gabbett, 2017, Kalkhoven et al., 2021). Firstly, training load is a time-varying exposure (Nielsen et al., 2019), with long-term effects likely to differ depending on distance in time from the current day (Williams et al., 2017). Secondly, in addition to direct effects of activity exposure, training load may also indirectly affect injury risk through development of athlete fitness and fatigue (Gabbett, 2016). Finally, both the magnitude of training load (i.e. distance run) and the relative training load (i.e. distance run this week relative to distance run previous week) is thought to have an effect on injury risk (Gabbett, 2016, Tysoe et al., 2020), and both may act non-linearly upon the risk of injury (Bache-Mathiesen et al., 2021). While some methods have been recommended to handle some of these challenges in isolation (Nielsen et al., 2019, Bache-Mathiesen et al., 2021), it is unclear how to deal with them in symphony.

## Aim

The aim is to determine how to model the cumulative effect of training load when assessing its (causal) effect on the risk of sports injury in a cohort study.

## Study assumptions and target audience

We assume that the modeling methods developed in this study are to be applied primarily to:  
- Studies focused on causal inference, rather than prediction (Nielsen et al., 2020).   
- Studies where the goal is to identify risk factors, using epidemiological methods relevant for observational cohort studies. In other words, a study without randomization (Vandenbroucke, 2004).  
- Studies with access to a data analyst / data scientist with advanced statistical tools available (Sainani et al., 2021, Casals and Finch, 2017).

### Research questions

1. Is it possible to assess the effect of the long-term training load pattern without subjectively aggregating the training load data?
2. If so, can it be done in a manner that lends itself to clinical interpretation?
3. Can “change in training load” and “amount of training load” be modelled in the same model without losing interpretive value?

## Study Design

Experimental simulation study. Simulations will be based on a real cohort of longitudinal sports data.

We will simulate data with long-term effects of training load and relative training load on the risk of injury, and see how methods are able to uncover different functions of training load and time. Then, we see how these methods compare when used on a real sports dataset, by measuring model fit and interpretability. This will illustrate that the methods used on the simulated data can be used on a real dataset.

### Simulation process

We will use the same sample size for all analyses. We imagine that we have a study where sample size is sufficient: a scenario of 3 football teams (75 players) followed meticulously for a season (300 days), altogether 22 500 training load values, measured by sRPE. This will be sampled from the real dataset to ensure a realistic distribution. We will include a figure in the supplementary with the distribution.   
  
Using the observed sports data, we will simulate a time-to-event relationship between training load as a time-varying exposure and time-to-injury. We will assume that the first injury is the final event. Recurrent injury will not be addressed in this article.   
  
Different scenarios of potential long-term effects of absolute and relative training load will be simulated.

For amount of training load, we will assume the risk shape is J-shaped (Bache-Mathiesen et al., 2021). Under this assumption, the lowest point of risk is intermediate levels of training load. The highest is under high levels of training load.

For change in training load, we will assume that higher loads current day compared to load previous day increases risk, whilst loads lower current day than previous day reduces risk (Gabbett, 2016). This means we will assume a linear relationship between change in training load and injury.

In addition, we will create the following time-lag scenarios for amount of training load and change in exposure of training load:

1. **Constant.** Across 4 weeks, the effect of training load has a constant effect each day. Thereafter, training load has no effect. This is an overly simplistic base scenario.
2. **Decay.** Across 4 weeks, the effect of training load gradually decays for each day (Williams et al., 2017). Thereafter, training load has no effect. This was hypothesized as a likely scenario if past training load has a direct effect on injury risk.
3. **Exponential decay.** On the current day, training load has the highest risk of injury. The affect of training load drops markedly during the past 3 days, and decays gradually across the past 4 weeks. Thereafter, training load has no effect. This is a likely scenario if past training load has an indirect effect on injury risk.
4. **Direct, then inverse.** Training load values on the current week (acute) increases risk of injury, whilst the training load values three weeks before the current week (chronic) decreases risk of injury (Blanch and Gabbett, 2016). Thereafter, training load has no effect. This hypothesis has recently been critiqued and thought unlikely (Wang et al., 2020, Impellizzeri et al., 2020), we will nevertheless see if our methods can reveal this relationship should it be the case. Analysis will only be run on the amount of training load (not change), the relationship between the amount and the injury risk will be assumed linear, and results will be in the supplementary.

And the final, combined scenario, to see if absolute and change in training load can be modelled simultaneously. For this scenario, we will use lag-function number 3) exponential decay.

All in all, this amounts to 7 different scenarios where training load affects injury probability in the main article + the direct, then inverse for supplementary.

After simulation, we will model the cumulative effect without aggregation (Menaspà, 2017) and see if our methods are able to explore and uncover our thresholds and different training load effects. If it does, it should be able to uncover similar, yet real, effects in future populations.

### Methods for comparison

**Summary of chosen methods**

We will simulate time-to-event data, and model the risk of injury with a cox proportional hazards model. We will vary the methods used to handle the time-varying effect of training load, but for the effect of the amount itself, we will model the relationship using a polynomial to the 2nd degree, so that all these methods are compared under the same condition. The following three methods will be used to model the time-varying effect:

1. Rolling average (RA)
2. Exponentially weighted moving average (EWMA), using same lambda as in (Williams et al., 2017, Sedeaud et al., 2020).
3. Distributed lag non-linear model

Likewise, for change in load, we will use a linear model for the relationship between change in load and injury risk. The following methods will be used to handle the time-lag:

1. Week-to-week change
2. Acute:chronic workload ratio (7:28), coupled, RA
3. Distributed lag non-linear model

Methods will be compared by the root-mean-squared error (RMSE), coverage of 95% confidence intervals, average width of confidence intervals, and model fit with the AIC, which has been shown to be the best method of assessing model fit for distributed lag non-linear models (Gasparrini, 2014). Average width is included, as good coverage can be a sign of broad (uncertain) confidence intervals, and the average width will uncover this. In addition, visualizations of the cumulative risk on the current day (day 0) for each method will be assessed.

In summary:  
6 methods \* 7 scenarios = 49 permutations of combinations of method and scenario  
3 performance measures \* 49 permutations = 147 cells with results in one or more tables

In addition, for scenario number 4, 6 methods \* 3 metrics = 18 cells in a table for the supplementary.

**Detailed information about the choice of methods**

In environmental epidemiology, modelling long-term effects, such as pollution or radon-exposure, are a common challenge. Although not entirely applicable to the challenges with training load, they do share the complexities of being long-term, weak-to-moderate time-varying effects. These may be immediate effects, or the effects may occur with some lag, known as time-lagged effects. For example, cold weather can affect patient mortality both on the concurrent days and on the next day. In that case, the effect of cold weather on any day's mortality would be the sum of the effect on that day and the previous day. This is further complicated by a phenomenon known as protracted time-lagged effects, where the health effect measured at any given time is the result of multiple exposure events of different intensities sustained in the past (Gasparrini, 2014). We hypothesize that training load may be such an exposure.

Bhaskaran et al. (2013) suggest using a so-called distributed lag model, a method initially developed in the field of econometrics (Almon, 1965) and later applied to epidemiology (Armstrong, 2006). This approach is intuitive and can be implemented into any regression model (Schwartz et al., 1996). The cumulative effect of training load would be estimated by summing the effect sizes of the lags. The downside is the data-driven exploration of cut-offs, and that exploring too many lag structures risks identifying non-causal relationships that have occurred by chance (Schwartz et al., 1996).

To account for these issues, Bhaskaran et al. (2013) suggest using polynomial or splines constraints to explore the long-term pattern. This has been applied to time-to-event data in medicine (Abrahamowicz et al., 2012, Sylvestre and Abrahamowicz, 2009). Gasparrini (2014) explores distributed lag non-linear models in Cox regression by implementation on real cohort data, in addition to simulated data. The research group has performed more simulations studies since (Gasparrini, 2016, Gasparrini et al., 2017). The main author has developed an R package for performing distributed lag non-linear models that has been updated along with these studies (Gasparrini, 2011). The package has implemented various functions of splines. Splines are better at identifying local shifts in relationship direction, although fractional polynomials are better suited for causal inference (Bache-Mathiesen et al., 2021).

We will compare the distributed lag nonlinear model with commonly used alternatives in the field. Both in environmental epidemiology, and in the training load field, researchers have identified considerable downsides of using rolling averages to deal with time-lagged effects (Menaspà, 2017, Gasparrini, 2016). The exponentially weighted moving average (EWMA) has been proposed as a more suitable alternative, assuming that training load exposure further back in time is of less importance than observations closer in time (Williams et al., 2017). It has been compared with the rolling average (Murray et al., 2017), and its downsides have been explored mathematically (Wang et al., 2020). EWMA has been used in measuring absolute training load (Sedeaud et al., 2020), but more commonly, before calculation of change in training load (Nakaoka et al., 2021, Hamlin et al., 2019, Dalen-Lorentsen et al., 2021). Although EWMA has been advocated for, studies commonly use rolling averages (Malone et al., 2020, Moreno-Pérez et al., 2020, Albrecht et al., 2020, Hildebrandt et al., 2020), and those who calculate EWMA do so in addition to rolling averages – analyzing both (Nakaoka et al., 2021, Arazi et al., 2020, Enright et al., 2019).

The Acute:Chronic Workload Ratio (ACWR) was invented to address the specific hypothesis that training load closer to the current day increases injury risk, while those further back in time decrease injury risk, depending on whether the current training load is higher or lower than that further back in time (Blanch and Gabbett, 2016). It was an attempt at measuring change in training load while accounting for the effect of time-lag. The most common calculation of the ACWR in football studies was a 1-week absolute:4-week average rolling average ACWR (Wang et al., 2021), equation shown in Lolli et al. (2019). This method of calculation calculates ACWR in weekly blocks. It risks that individuals injured early in the week appear to have low loads, because they were injured, which can give the illusion that low acute loads increases injury risk. The calculation in Carey et al. (2017) calculates daily ACWR loads, with 7-day mean:28-day-average rolling average ACWR. It therefore uses each day for assessing injury risk, improving sample sizes, and does not falsely show increased risk with low acute loads. The disadvantage is that it does not adjust for the activity exposure on day 0 (Wang et al., 2020). “This formula calculates the workload ratio each day by taking the average daily workload in the previous a days (ie, not including what was done on that day) and dividing it by the average daily load in the previous c days.”

Two alternatives to EWMA and ACWR have been proposed: the Robust Exponential Decreasing Index (REDI, Moussa et al., 2019), and the differential load (a measure of relative training load) (Tysoe et al., 2020). Neither have seen widespread use after introduction. The REDI has been used in a single study (Sedeaud et al., 2020). The differential load, to our knowledge, has not been used since its introduction.

### Comparing methods on the observed sports dataset (Optional: will do if decent data available)

We will run our methods on a real, observed sports dataset collected for the purpose of assessing training load and injury risk. In this analysis, we will, for simplicity’s sake, discard events after the first event and run our models on time to first event. A frailty term will be added to the Cox regression to account for within-subject correlation. Any collected potential confounders will be adjusted for (e.g. age, sex). We will model absolute and relative training load in the same model, and compare the same methods as in the simulation study. They can be compared by the model fit (AIC). We can also visualize predictions from the best-fitting model. We have to be clear that we have not accounted for recurrent events, or the multidimensional nature of training load (internal + external measures), this analysis was done first and foremost to compare methods; the results can be used for hypothesis-generation, but nothing more.

## Limitations

Time-varying exposures is a complicated phenomenon that merits in-depth investigation. To limit our study, we cannot compare every scenario and condition that is relevant to training load and sports injury research.

We will not explore the following:

* Recurrent and subsequent injury events (Meeuwisse et al., 2007). This is the topic for our next study.
* Dealing with measurement error.
* Dealing with time-varying confounders (Wang et al., 2020).
* Dealing with multiple risk factors and potential interactions between them (Bittencourt et al., 2016).
* Dealing with multiple measures of training load which may or may not be strongly correlated with each other (Impellizzeri et al., 2019, Kalkhoven et al., 2021).

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