Random Forest as a promising tool to investigate links between factors leading to mental fatigue build-up

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Introduction

Since the **COVID-19 pandemic**, both mental and physical fatigue have shown a significant increase in their prevalence, even in healthy individuals[1]. Still, it is not clear what are the factors that could underlie this phenomenon.

- Aim: using machine-learning methods (**random forest,** RF) to predict and explore **relations** between various predictors of fatigue symptoms during the 2020 Belgium lockdown.

Dataset

The CONFIN dataset contains **554 participants** (46.79 ± 16.24 y.o., 423♀).

- Predictors: work-related variables, affective state, sleep metrics & mental load, considering condition **before and during lockdown**.
- Targets: **fatigue symptoms** during lockdown on **mental & physical** subscales of the Multidimensional Fatigue Inventory (MFI) :
  - Low fatigue = 0 – 10
  - High fatigue = 11 - 20

Methods & Results

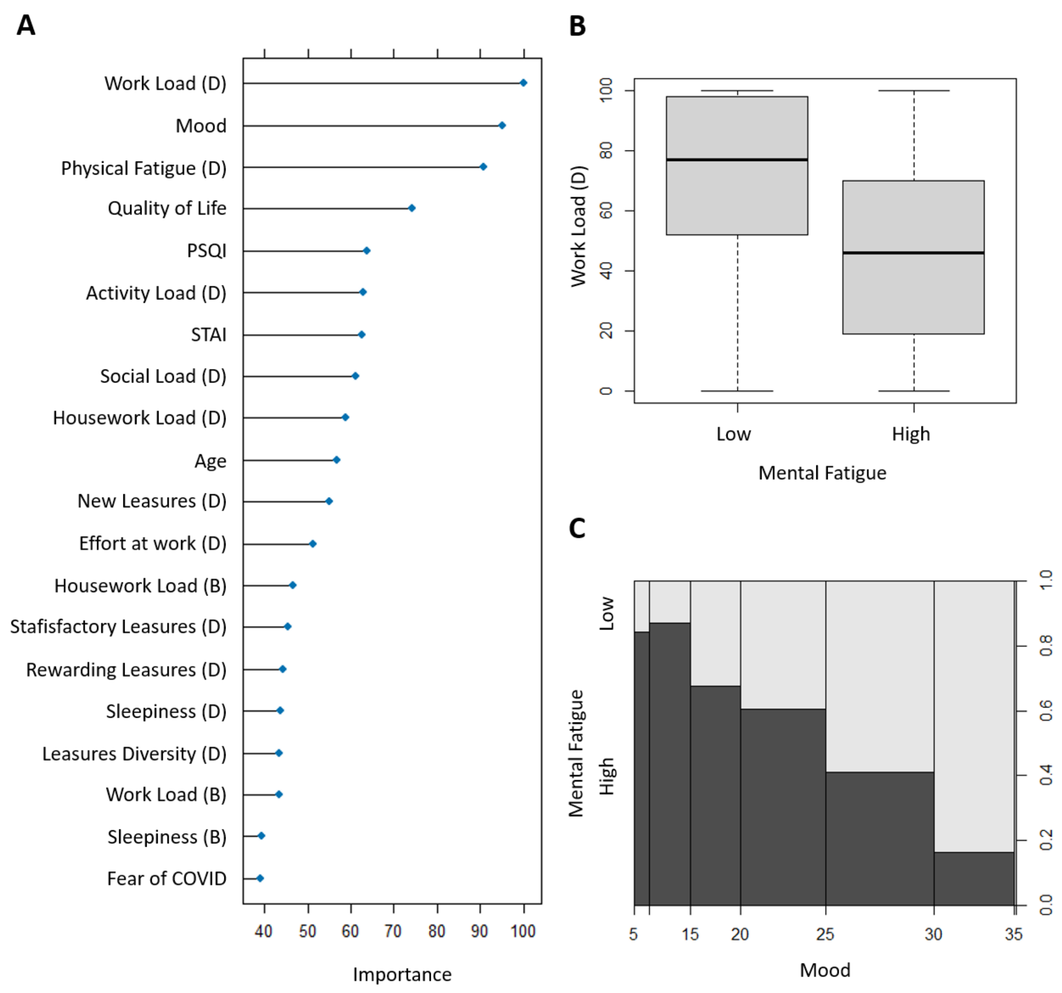
RF classification models were implemented in R (RStudio) using the **randomForest** and **caret** packages.

We split our dataset into training and testing set, the former accounting for 90% of the initial dataset. We then implemented **two distinct RF models** to predict mental and physical fatigue. A **10-fold cross-validation** was used to validate our algorithms.

Main **parameters** were as follows:

- Number of predictors = 44
- Number of trees used in the forest (**ntree**) = 500
- Number of random predictors selected at each split (**mtry**) = 2

	Mental Fatigue	Physical Fatigue
Accuracy	0.73	0.75
Sensitivity	0.77	0.89
Specificity	0.71	0.62



(A) Top 20 most important variables used to predict mental fatigue. **(B)** Higher mental load at work seems to predict lower mental fatigue severity. **(C)** Lower mood seems to predict higher mental fatigue severity.

Conclusion

Performance metrics suggest that RF are a **promising tool to predict fatigue** severity with good accuracy. In addition, our results showed the importance of **mental load at work** and **general mood** to predict mental fatigue during the lockdown. Higher load seems associated with lower fatigue while the inverse pattern is observed for the mood.

Intriguingly, CONFIN participants with higher mental load at work also exhibit a better mood (not shown). One hypothesis could be that increased commitment at work would help remain motivated despite important changes in work life[2]. It may be seen as a coping mechanism to preserve well-being, thus alleviating lockdown fatigue effect[3].

[1]T. Field et al., *Am J Psychiatr Res and Rev*. **27**, (2021); [2]Chung, *J Appl Psych.* **107**, (2022); [3]Charonitis et al., *Psych Belg*., in rev. (2023)

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