Physiological signals in daily life among tobacco, alcohol and cannabis users: Discriminating craving from no-craving episodes

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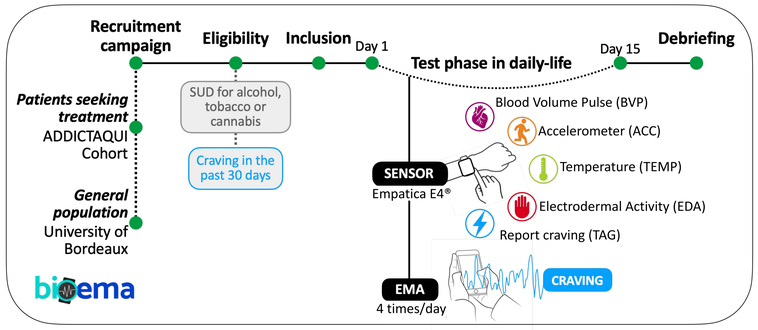
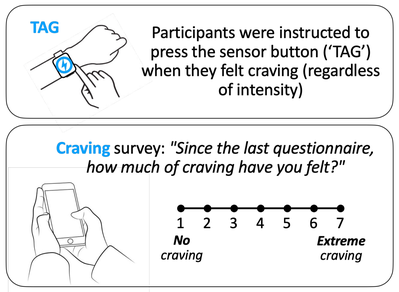
INTRODUCTION

Addiction is characterized by a loss of control over use of reinforcers such as substances (alcohol, tobacco, cannabis…). **Craving** is a clinical phenomenon defined as a strong urge to use (Auriacombe et al., 2018) and plays a central role in addiction (Gauld, Baillet et al., 2023). Craving is a dynamic phenomenon that fluctuates in intensity and frequency and whose daily variations are prospectively associated with use by Ecological Momentary Assessments method (Cleveland et al., 2021; Serre et al., 2015). It is the cause of repeated relapses and yet, identifying/reporting craving episodes can be difficult for some patients (Raftery et al., 2020). The identification of biomarkers of craving could compensate for this. Craving is associated with **changes in autonomic arousal** and **unique neurobiological changes** (Sinha et al., 2009), that would be identified in daily-life (Carreiro et al., 2020, 2021).

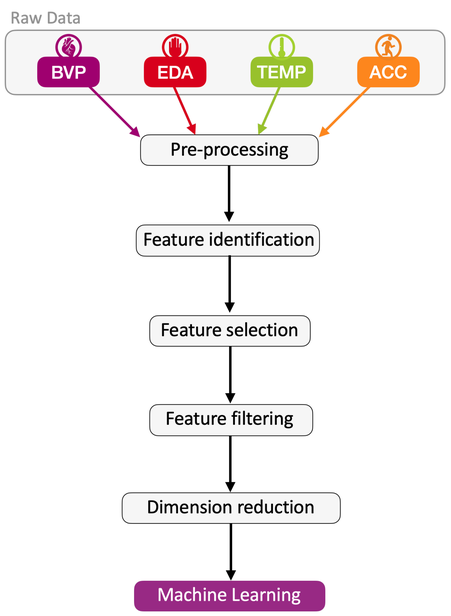
OBJECTIVE To discriminate craving from no-craving episode through the analysis of physiological signals captured in daily-life with Ecological Momentary Assessment and biosensors among participants with addiction.

METHODS





Analysis strategy:



Feature identification Based on features found in the literature (Lutin et al., 2021)

- Time-domain features, Frequency-domain features, Non-linear domain features
- Time-domain features, Frequency-domain features, Spectral-domain features
- Time-domain features, Frequency-domain features, Trough-to-peak features

Feature selection

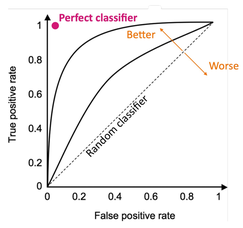
Epochs of **5' before and after** the craving event or randomly in the no-craving period.

Feature filtering

Features were rejected in case of following criteria:
- missing values (not enough physiological data)
- Lack of statistical significance in Student's t test (p-value > 0.05)
- Low variance (Min-Max normalization) (≤0.00025)
- High correlation (≥0.98)

Dimension Reduction

Principal component analysis produces a **linear combination of features** (called principal components (PCs)) ordered according to their ability to explain the total variance of all features, regardless of class.



Machine Learning

Linear Discriminant Analysis & evaluation of classification algorithm with standard metrics: **sensitivity, specificity, accuracy and area under the curve (AUC) of the receiver operating characteristic (ROC) Curve.**

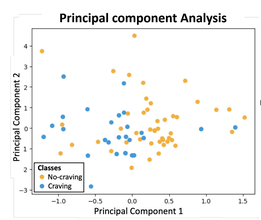
Analyses performed with Python (3.11.2) and R (4.1.0)

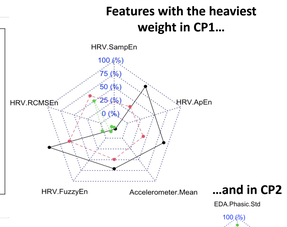
RESULTS

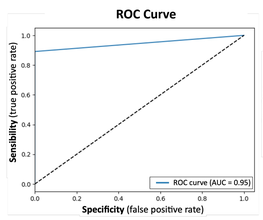
Focus on *one* participant

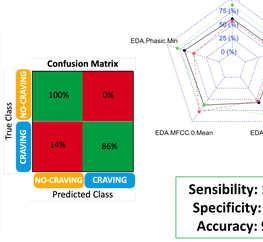
53 y.o.

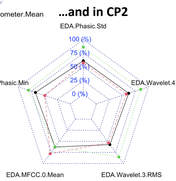
- Feature identification: **187** features extracted
- Feature selection: **46 samples** per class
- Feature filtering: **36** features deleted
- Dimension Reduction: **10 PCs** (66% of variance)









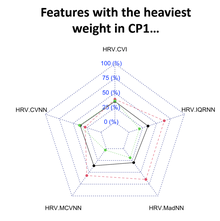


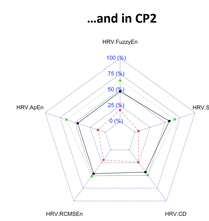
Sensibility: 100%
Specificity: 86%
Accuracy: 93%

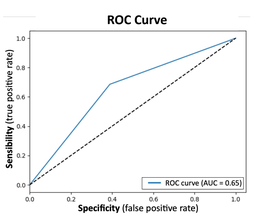
Preliminary results on *all* participants

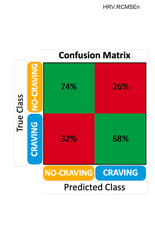
N=29 | 55% n=16 | 32 y.o. (7.7) | 14.5 y. (1.9) | Main inclusion 48% (n=14) | Completion 85% | Sensor port 9.4H/d

- Feature identification: **187** features extracted
- Feature selection: **833 samples** per class
- Feature filtering: **34** features deleted
- Dimension Reduction: **23 PCs** (66% of variance)









Sensibility: 74%
Specificity: 68%
Accuracy: 70%

DISCUSSION

Focusing on one participant: the **accuracy** of model was **93%,** suggesting that this method could be *reliable* to discriminate craving from no-craving episodes.
Preliminary results on all participants: the **low accuracy (70%)** indicates moderate performance. The lack of samples and the lack to minimize inter-individual variability could explain this, and it is necessary to include more participants and standardize each feature to refine the algorithms and the accuracy of model predictions.

CONCLUSION

Better performance of the classification model (good sensibility and specificity), could enable to distinguish craving vs. no-craving episodes from physiologic signals, which may enable the development of relapse prevention interventions in daily life.

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