# Biomarkers of Craving in Daily-Life: Further Evidence for an Autonomic Craving Signature across Addiction Types Unlocking the Potential for Better Personalized Interventions.

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## INTRODUCTION

**Addiction** is characterized by a loss of control over the persistent use of a reinforcer such as substances (alcohol, tobacco, cannabis, etc.) or behaviors. **Craving** is a clinical phenomenon defined as an irresistible urge to consume (Auriacombe et al., 2018) and appears to play a central role in addiction (Gauld, Baillet et al., 2023).

**Craving** is a dynamic phenomenon that fluctuates in intensity and frequency. The Ecological Momentary Assessment (EMA) method allows the capture of craving episodes in daily life and has shown a prospective link between increased craving intensity and the likelihood of future use (Cleveland et al., 2021; Serre et al., 2015). However, identifying and reporting craving episodes can be difficult for patients (Raftery et al., 2020). Thus, the identification of craving biomarkers could help overcome this difficulty. The main objective was **to identify a transdiagnostic physiological pattern of craving measured in daily life using EMA and physiological sensors.**

## METHODS

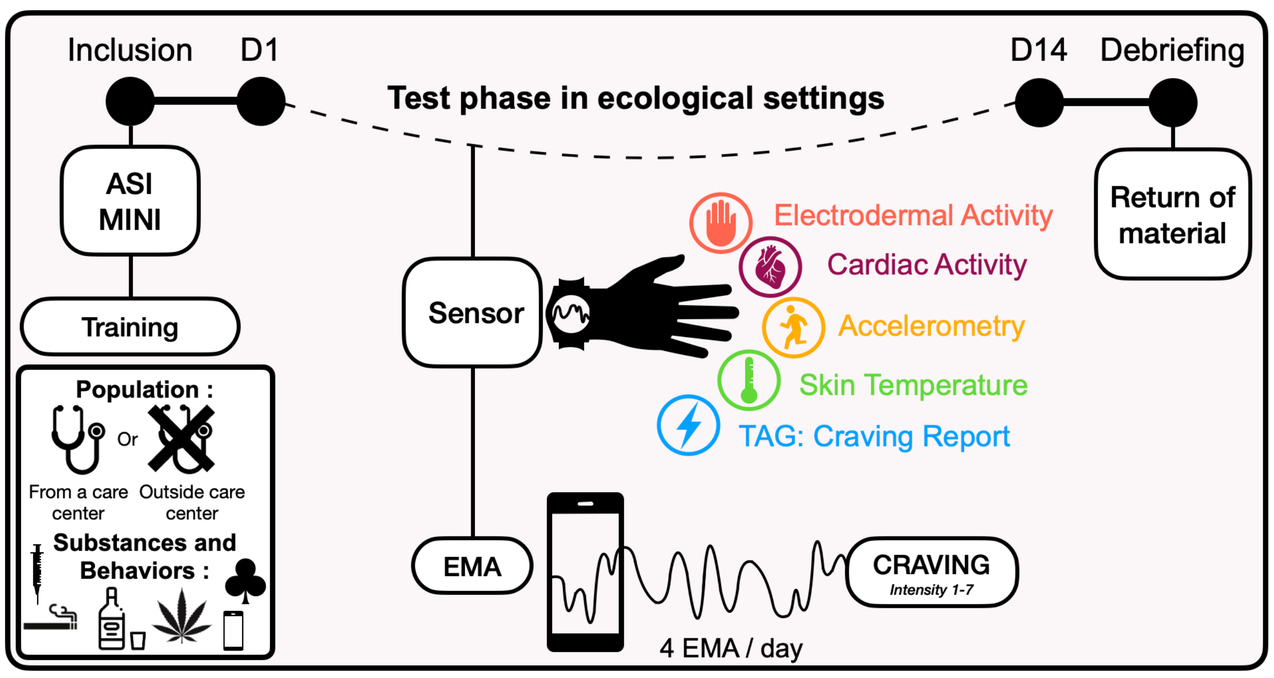


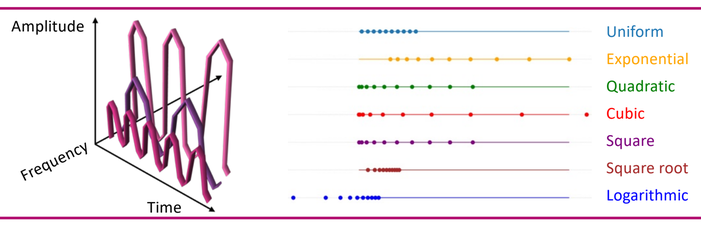

**Figure 1:** BioEMA study protocol diagram

### 1. Sample labelling

Labeling of craving and non-craving data. **Only high-intensity craving periods** (4 or more on a 7-point scale) **were selected.**

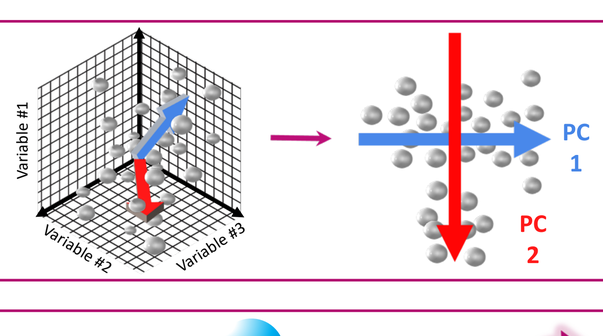

### 2. Extraction of characteristics

**191 features** extracted from the 4 physiological signals. Data normalization, scaling, and filtering.



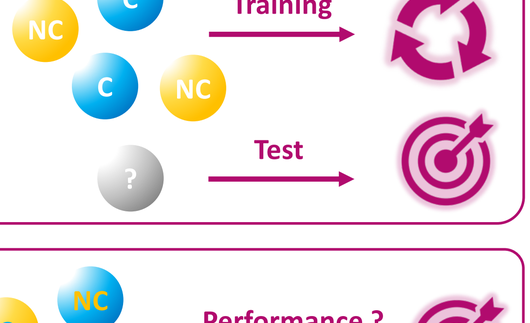

### 3. Reduction of dimensions

Principal Component Analysis (PCA) was used to reduce the number of dimensions in order to improve **interpretability and analysis.**




### 4. Binary classification and cross-validation

**Machine learning** was used to obtain classifiers for our samples. The classifiers used were: **Linear Discriminant Analysis** (LDA), **Support Vector Machine** (SVM), and **Minimum Distance to Mean** (MDM).




### 5. Permutation test

Random shuffling of the labels was performed to **ensure that the classifier's performance was indeed driven by the craving variable.**

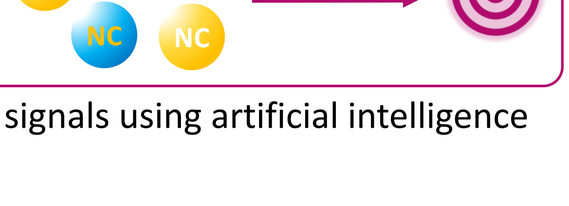
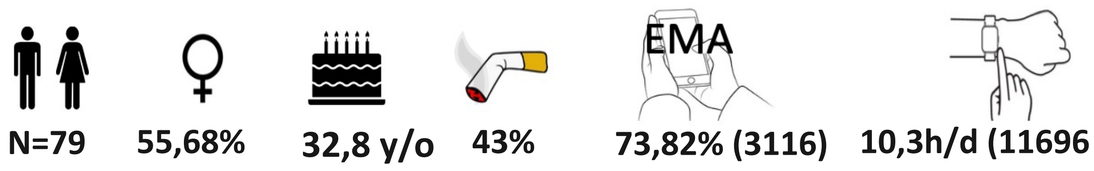



**Figure 2:** Analysis process of physiological signals using artificial intelligence

## RESULTS




N=79 | 55,68% | 32,8 y/o (±11,16) | 43% | 73,82% (3116) | 10,3h/d (11696 h)

**88 physiological features were selected and normalized.** Principal Component Analysis (PCA) was performed on 8 participants who had at least 20 episodes in both the "craving" and "non-craving" labels. PCA showed that 33 principal components (PCs) were sufficient to explain 99% of the total variance. **The first principal component alone explained 56,7% of the total variance and was composed of features related to electrodermal activity.**

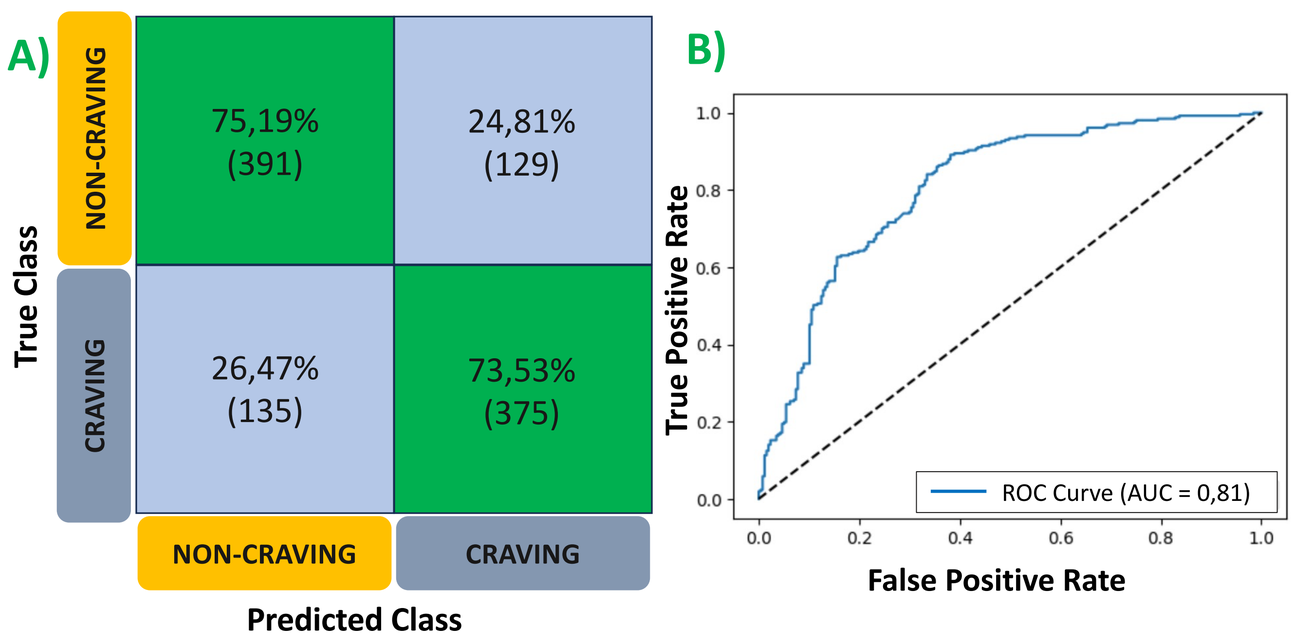



**Figure 3: A)** Confusion matrix and **B)** ROC curve of the SVM classifier.

## DISCUSSION

The use of the SVM classifier made it possible to discriminate between craving and non-craving episodes with a cross-validation accuracy score of 74,37%. This result informs us about the general state of craving and the specific response to craving. **These biomarkers could be used during a biofeedback intervention to help participants identify and control their craving.**

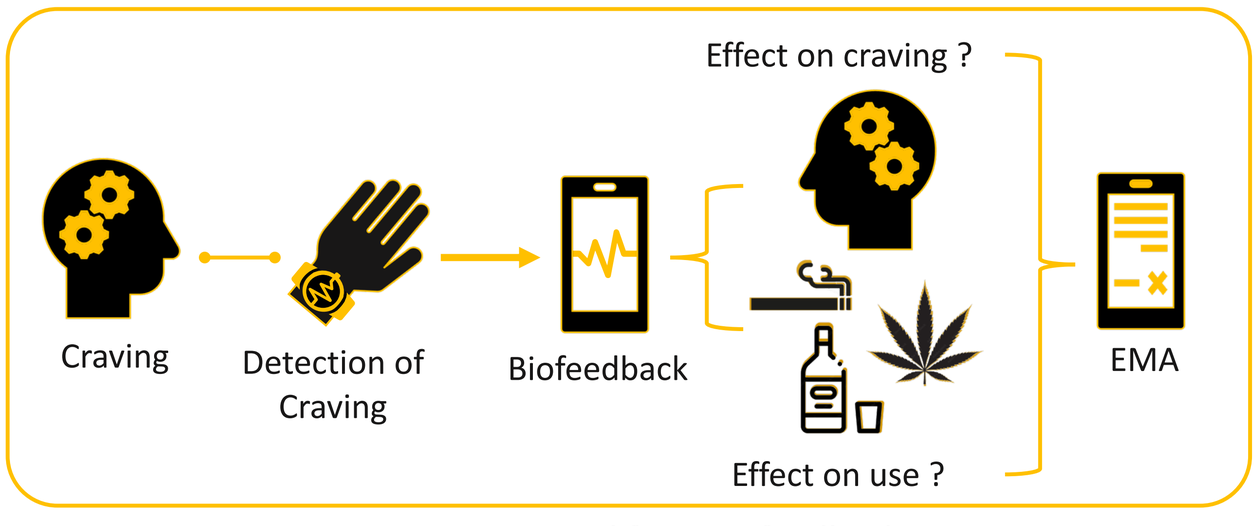



**Figure 4:** Prototype protocol for a Biofeedback intervention.

**Limitations:** Several data could not be analyzed due to the lack of participants who had at least 20 episodes of craving and non-craving periods and the physiological pattern was detected in 8 out of 79 participants. This result needs to be replicated with new datasets.

## CONCLUSION

The identification of craving from physiological data could be an important step in the development of prognostic biomarkers for relapse. **This autonomous craving signature opens the way for everyday life protocols targeting craving regulation through an adaptive and just-in-time intervention (JITAI).**

### Partners

Grand Programme de Recherche BRAIN_2030 | Bordeaux Région Aquitaine Initiative for the future of Neuroscience — Université de Bordeaux — cnrs — Institut National du Cancer — IReSP Institut pour la Recherche en Santé Publique

***No conflict of interest to declare.***

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