Prediction of Stress Coping Capabilities from Nightly Heart Rate Patterns using Machine Learning

Linda Vorberg[1*], Siri Pflueger[1*], Robert Richer[1], Katharina M. Jaeger[1], Arne Küderle[1], Nicolas Rohleder[2], and Bjoern M. Eskofier[1]

***Abstract*—Stress is related to short- and long-term alterations in stress systems, including the hypothalamic-pituitary-adrenal (HPA) axis and the sympathetic nervous system (SNS). While it is well established that stress experienced during the day can affect sleep quality, less is known about how it affects stress systems during the night. We assume that stress coping strategies can have an impact on how stress carries over into the night and that individuals with bad coping mechanisms show elevated activation of stress systems during sleep. For that reason, we recorded the heart rate (HR) and heart rate variability (HRV) of 21 healthy participants on two consecutive nights during sleep and the first hour after awakening and extracted cortisol and alpha-amylase from saliva samples collected in the first hour after awakening. Stress coping capabilities were assessed using self-reports. We performed backward stepwise multiple regression models to analyze the relationship between HR(V) and stress coping and trained different machine learning-based regression algorithms to predict positive (SVF_{Pos}) and negative (SVF_{Neg}) stress coping capabilities, respectively. Our results show that individuals with higher SVF_{Neg} scores showed higher SNS activity during the night, whereas higher SVF_{Pos} scores indicated lower SNS activity. SVF_{Pos} was predicted with a mean absolute error (MAE) of 1.51 ± 0.73 and SVF_{Neg} with an MAE of 2.79 ± 1.53. Our findings indicate an association between nightly HR(V) and the individual's capability of coping with stress. This provides further information about how stress influences sleep and might be used for tailored intervention and feedback on successful stress coping.**

***Index Terms*—stress coping, sleep, cortisol awakening response, heart rate variability, machine learning**

I. Introduction

Stress can be defined as an emotional experience associated with nervousness, tension, and strain [1]. We experience stress in our daily life and face it with individual coping strategies. The higher the perceived stress levels the more likely it is that the body responds to it by activating the stress system which consists of two major axes: The sympathetic nervous system (SNS) and the hypothalamus-pituitary-adrenal (HPA) axis [2]. The SNS is activated rapidly in the case of stress by increasing heart rate (HR) and blood pressure to prepare the body for a fight-or-flight response [3]. On the other hand, the HPA axis, as a slow operator, regulates the activation of the endocrine glands and leads to the secretion of cortisol.

Generally, cortisol follows a circadian rhythm: After reaching the lowest levels during the first half of the night, the cortisol concentration starts to rise slowly and reaches its maximum peak in the cortisol awakening response (CAR), a strong increase in cortisol levels in the first 30–45 min after awakening in the morning [4]. According to current research, the CAR, as well as heart rate variability (HRV), are reported to be associated with stress-related variables. For example, Stalder et al. examined the CAR's relationship to HR(V) in the context of awakening [5]. In their study, individuals with an elevated CAR exhibited higher levels of HR and lower levels of HRV post-awakening. Associations between HRV and sleep quality were investigated by da Estrela et al. [6], which reported that lower HRV can be linked to a greater risk for stress-related sleep disturbances which can even increase the likelihood of developing depressive symptoms. Similar findings were by Michels et al., where low sleep quality was found to lead to unhealthier HRV patterns measured over five minutes, with stress enhancing this relationship [7].

The effect of stress coping on sleep was investigated by Sadeh et al. [8], indicating that the coping style used to manage a stressor is a key factor in the relationship between stress and sleep. Otsuka et al. showed that negative coping strategies like "giving up on problem-solving" or smoking and drinking are positively correlated with sleeping disorders, such as symptoms of insomnia or nightmares [9]. In contrast, positive coping, like exercising or sharing worries, was inversely correlated with these disorders.

In the context of coping mechanisms, several studies have been conducted concerning HR(V). Positive coping strategies, like tension reduction and positive reappraisal, were correlated with lower levels of HR in a resting state [10]. Moreover, higher low frequency (LF) power of HRV is related to stronger expression of negative emotions, which suggests a relationship between coping style and autonomic cardiac function [11].

As coping mechanisms are proven to play a vital role in the relationship between stress and night-time sleep, we focus on the investigation of positive and negative stress coping. In most of the studies, assessing HR(V) and linking them to coping strategies, the physiological measures mostly took place during the day or during task completion. While it is known that stress enhances sleep disturbances, less is known about how it affects stress systems, especially the SNS, during the night, verified by physiological measures. Therefore, this work aims to predict an individual's stress coping capabilities based on HR(V) measures during the night and in the morning. Furthermore, the role of the CAR and salivary alpha-amylase (sAA) is investigated in the context of HPA axis and SNS activity, respectively. Since previous work has shown the promising

*Responsible authors, Email: linda.vorberg@fau.de and siri.pia.pflueger@fau.de

[1]Machine Learning and Data Analytics Lab (MaD Lab), Department Artificial Intelligence in Biomedical Engineering (AIBE), Friedrich-Alexander-Universität Erlangen-Nürnberg (FAU), Erlangen, Germany

[2]Chair of Health Psychology, Friedrich-Alexander-Universität Erlangen-Nürnberg (FAU), Erlangen, Germany

potential of applying machine learning techniques to discover complex psychological patterns [12], we examined the use of machine learning-based regression models besides multiple linear regression models commonly used in literature.

II. METHODS

A. Data Acquisition

We acquired data from $n = 30$ healthy participants aged 18–27 years on two consecutive nights. The exclusion criteria for study participation were smoking, acute or chronic mental illness, or the use of medication (except hormonal contraceptives). All participants provided written informed consent before participating in our study. The study protocol was approved by the Ethics Committee of the Friedrich-Alexander-Universität Erlangen-Nürnberg (number 106_13B).

1) Biomarker: We measured cortisol and sAA levels using Salivettes (Sarstedt AG & Co. KG, Numbrecht, Germany) at six different time points: before going into bed (SA), immediately after awakening (S0), and four other samples in 15 min intervals during the first hour after awakening (S1-S4). Participants were instructed to chew on a polystyrol roll for one minute and to not to consume anything orally except water.

2) ECG: HR(V) parameters were measured by recording an ECG during sleep and the first hour after awakening using a wearable sensor node (Portabiles GmbH, Erlangen, Germany) attached to a chest strap. The sensor node records a 1-channel ECG according to Lead I of Einthoven's Triangle and logs data onto the internal storage with a sampling frequency of 256 Hz for subsequent data processing on a computer.

3) Self-report: Subjective stress coping and processing strategies were assessed using the "Stressverarbeitungsfragebogen (SVF)" (Stress Processing Questionnaire) [13] with 120 items before the first night.

Due to incomplete or corrupted sensor data, a total of $n = 21$ participants (55 % female) with 36 nights remained for further analysis. The mean age of the study population was 22.9 ± 1.8 years with a BMI of 22.1 ± 2.1 $\mathrm{kg\,m^{-2}}$.

B. Data Processing

1) Biomarker: From the raw cortisol samples assessed in the morning we computed the area under the curve with respect to ground (AUC_G) and with respect to increase (AUC_I) for both biomarkers. The AUC_G represents the total cortisol output during the first hour after waking [14]. The AUC_I reflects the changes over time, as the baseline of cortisol or sAA concentration is subtracted. In addition, we computed the slopes of cortisol and sAA between samples S0 and S2 (denoted as a_{S0S2}). We objectively assessed sampling times using the *CARWatch* application [15].

2) ECG: The ECG data were used to calculate HR and HRV based on the RR intervals extracted after filtering and QRS complex detection provided by the *Neurokit2* library [16]. Artifacts in RR intervals were reduced according to previous work (e.g., [17]).

ECG data were divided into two phases: The *sleep phase*, the time between saliva samples SA and S0, and the *wake phase*, the time between S0 to S4. If less than 30 min of data during the wake phase was remaining, these data were excluded from further analysis to reduce the risk of bias of HR(V) features. From the extracted HR data, mean and standard deviation were recorded for sleep and wake phases, respectively (denoted, e.g., $\sigma(\mathrm{HR}^{\mathrm{wake}})$). Furthermore, HRV features like Low Frequency ($\mathrm{HRV_{LF}}$), Very Low Frequency ($\mathrm{HRV_{VLF}}$), High Frequency ($\mathrm{HRV_{HF}}$), Very High Frequency ($\mathrm{HRV_{VHF}}$), Root mean square of successive RR interval differences ($\mathrm{HRV_{RMSSD}}$), and the percentage of successive RR intervals that differ by ≥ 50 ms ($\mathrm{HRV_{pNN50}}$), were calculated using *NeuroKit* library for both sleep and wake phase (denoted, e.g., as $\mathrm{HRV_{LF}^{wake}}$).

3) Self-report: From the SVF items we computed the subscales $\mathrm{SVF_{Pos}}$, which is a measure for positive coping strategies to reduce stress, like distraction or stressor devaluation, and $\mathrm{SVF_{Neg}}$, which is associated with strategies that enhance stress, like escape or social distancing. Both SVF subscores range from 6 to 30 with higher scores indicating stronger expression of the respective coping strategy.

All processing steps were performed using *BioPsyKit*, an open-source Python library for the analysis of biopsychological data [18].

C. Statistical Analysis

To find the best combination of explanatory or causal variables, we performed a stepwise backward multiple regression (SBMLR) on our dataset. This regression builds a prediction model in which the prediction variables are selected using an automatic process. In the beginning, all HR(V) features were z-normalized and then entered into the backward elimination. Step by step, the least significant regressor is removed from the model until all variables have a p-value below the significance level $\alpha = 0.05$. We used different HR and HRV features as regressors and predicted the dependent variables of the SVF questionnaire and the cortisol and sAA features. We use the following notation to indicate statistical significance: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

TABLE I
PARAMETERS AND CORRESPONDING VALUES FOR HYPERPARAMETER OPTIMIZATION (GRID SEARCH AND RANDOMIZED SEARCH). THE PARAMETER NAMES ARE GIVEN AS SPECIFIED BY SCIKIT-LEARN [19]

Classifier	Parameter	Values
SVR	`C`	{0.1, 1, 10, 100}
	`kernel`	{linear, radial basis function, polynomial}
	`gamma`	{auto, scale, 0.1, 0.01, 1e-4}
	`k (n_features)`	{2, 3, 4, 5}
RF	`max_depth`	{10, 30, 50, 100, none}
	`max_features`	{auto, sqrt, 0.3}
	`min_samples_leaf`	{1, 2, 3}
	`n_estimators`	{100, 200, 400, 1000, 2000}
AB	`base_estimator`	{SVR, DecisionTreeRegressor, KNeighborsRegressor}
	`learning_rate`	{0.001, 0.01, 0.05, 0.1, 0.5, 1,1.5}
	`loss`	{linear, square, exponential}
	`n_estimators`	{10, 30, 50, ..., 300}

TABLE II
BACKWARD STEPWISE REGRESSION RESULTS BASED ON HR(V) FEATURES. REGRESSION MODELS WITH MORE THAN ONE PREDICTOR ARE SHOWN TOGETHER IN ONE TABLE CELL.

Independent variable	**Dependent variable**	β	**p**	$\mathbf{r^2}$
$\sigma(\mathrm{HR}^{\mathrm{wake}})$	$\mathrm{AUC_G(sAA)}$	-405.915	0.034*	0.110
$\mathrm{HRV}^{\mathrm{wake}}_{\mathrm{LF}}$	$\mathrm{AUC_G(sAA)}$	-1210.215	0.016*	0.113
$\mathrm{HRV}^{\mathrm{wake}}_{\mathrm{VLF}}$		1174.014	0.016*	0.113
$\mathrm{HRV}^{\mathrm{wake}}_{\mathrm{LF}}$	$\mathrm{AUC_I(sAA)}$	1383.476	0.025*	0.159
$\mathrm{HRV}^{\mathrm{wake}}_{\mathrm{VHF}}$		-1464.262	0.018*	0.159
$\mathrm{HRV}^{\mathrm{wake}}_{\mathrm{LF}}$	$\mathrm{a_{S0S2}(sAA)}$	0.818	0.026*	0.165
$\mathrm{HRV}^{\mathrm{wake}}_{\mathrm{VHF}}$		-0.902	0.015*	0.165
$\mu(\mathrm{HR}^{\mathrm{wake}})$	$\mathrm{AUC_G(cort)}$	75.708	0.038*	0.103
$\mu(\mathrm{HR}^{\mathrm{sleep}})$	$\mathrm{AUC_G(cort)}$	84.618	0.022*	0.128
$\mathrm{HRV}^{\mathrm{sleep}}_{\mathrm{HF}}$	$\mathrm{AUC_G(cort)}$	93.040	0.040*	0.152
$\mathrm{HRV}^{\mathrm{sleep}}_{\mathrm{RMSSD}}$		-107.959	0.018*	0.152
$\mathrm{HRV}^{\mathrm{sleep}}_{\mathrm{LF}}$	$\mathrm{AUC_I(cort)}$	-90.211	0.017*	0.137

D. Machine Learning-based Regression Models

To predict subjective stress coping capabilities from HR(V) data, we trained three different machine learning-based regression models on the feature set: Support Vector Regression (SVR), Random Forest (RF), and AdaBoost (AB). We evaluated the different regression models using an outer five-fold cross-validation (CV). Within each fold of the cross-validation, we optimized hyperparameters using an inner five-fold CV with the coefficient of determination r^2 as the target metric. A grid search was performed for SVR and AB, and randomized search for RF. All parameters and value ranges for optimization are presented in Table I.

For both SVR and AB, we normalized features using z-score normalization. For each regressor and each outer CV fold, we selected the hyperparameter combination yielding the highest r^2 value. We then retrained the model on the entire training data of the respective fold before evaluating it on the test data to compute the metrics r^2 and mean absolute error (MAE). All classifiers were implemented using *scikit-learn* [19].

III. RESULTS

A. Statistical Analysis

Overall, the regression analysis based on the normalized HR and HRV data shows a relationship between the HR(V) and both psychological variables and biomarkers.

SBMLR analyses show a significant relationship between $\mu(\mathrm{HR}^{\mathrm{sleep}})$ and $\mathrm{SVF_{Neg}}$ ($\beta = 1.403, p = 0.006, r^2 = 0.198$), as well as between $\mu(\mathrm{HR}^{\mathrm{wake}})$ and $\mathrm{SVF_{Neg}}$ ($\beta = 1.626, p = 0.001, r^2 = 0.267$). In addition, $\mu(\mathrm{HR}^{\mathrm{wake}})$ significantly predicted $\mathrm{SVF_{Pos}}$, ($\beta = -1.002, p = 0.005, r^2 = 0.236$). These relationships show that higher HR during sleep is related to higher negative coping strategies and higher HR during the first hour after awakening is associated with higher negative and lower positive stress coping strategies. Furthermore, regression analysis revealed significant relationships between HR(V) parameters and biomarkers (Table II). While HR(V) parameters during sleep significantly predicted the cortisol reaction in the following morning, parameters during the first hour after awakening predicted the amylase reaction.

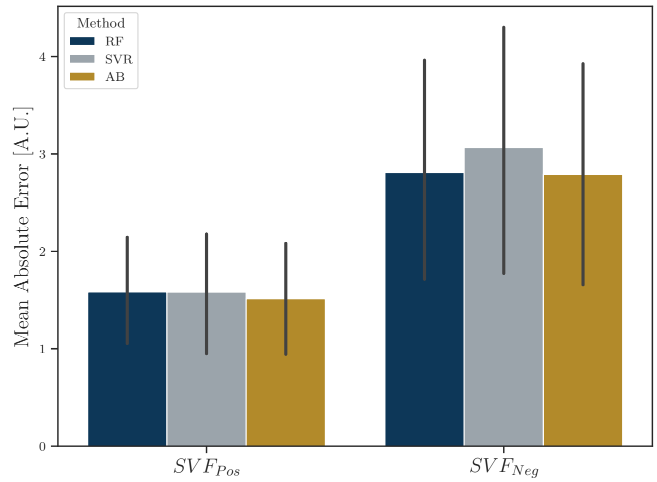

Fig. 1. Mean absolute error of $\mathrm{SVF_{Pos}}$ and $\mathrm{SVF_{Neg}}$ score prediction with RF, SVR and AB, averaged over all folds of the CV.

B. Machine Learning Approach

Figure 1 shows the mean absolute error for all machine-learning based regression models, averaged over all folds of the CV. All three models reached similar MAE values for predicting positive and negative stress coping strategies. The lowest error was reached by AB with a MAE of 1.51 ± 0.73 for $\mathrm{SVF_{Pos}}$ and 2.79 ± 1.53 for $\mathrm{SVF_{Neg}}$. The range of the scores in the examined population was 11.10–22.70 for $\mathrm{SVF_{Pos}}$ and 10.30–24.80 for $\mathrm{SVF_{Neg}}$. For SVR and RF we additionally examined the most important features selected by the regression model. $\mathrm{SVF_{Pos}}$ was mainly predicted by $\mu(\mathrm{HR}^{\mathrm{sleep}})$ and $\sigma(\mathrm{HR}^{\mathrm{sleep}})$ as well as $\mu(\mathrm{HR}^{\mathrm{wake}})$ for both SVR and RF. $\mu(\mathrm{HR}^{\mathrm{sleep}})$ and $\mu(\mathrm{HR}^{\mathrm{wake}})$ were the most important features when predicting $\mathrm{SVF_{Neg}}$ with SVR, whereas the prediction with RF was dominated by $\mathrm{HRV_{RMSSD}}$ and $\mathrm{HRV_{pNN50}}$ besides $\mu(\mathrm{HR_{sleep}})$, $\mu(\mathrm{HR}^{\mathrm{wake}})$ and $\sigma(\mathrm{HR}^{\mathrm{sleep}})$.

IV. DISCUSSION

This study aimed to investigate the potential prediction of stress coping strategies from physiological data, especially from HR and HRV as two electrophysiological markers describing the activity of the SNS. Furthermore, we examined the relation between HR(V) and the CAR as part of the HPA axis. As shown in the results, we were able to establish a link between HR and the magnitude of the CAR. In line with Stalder et al., we can show that individuals with a higher CAR exhibit a higher HR in the post-awakening period. Additionally, our study can even show this relation for HR during sleep. Similar to the findings of Stalder et al., LF-HRV is inversely related to the magnitude of the CAR [5]. This indicates that there is a link between SNS activity and activation of the HPA axis in the morning. Contrary to cortisol, which mainly correlates with HR and HRV during sleep, sAA shows a significant relationship with HR and HRV in the morning during the wake phase.

Our results show that our main goal, the prediction of coping strategies with HR(V) parameters, is possible. Positive coping strategies can be predicted by assessing $\mu(\mathrm{HR}^{\mathrm{wake}})$. Individuals with a higher HR in the morning cope less with stress in a positive manner. This goes in line with the findings of Fontana et al., who report that lower baseline HR levels are associated with positive coping strategies [10]. Our results add up to the literature by proving this link in a domestic setting with longer periods of HR monitoring. Negative coping strategies were predicted by the mean HR in both the sleep and wake phases. Individuals with higher HR exhibit more negative behavior in response to stress. This is contrary to the findings of Ramaekers et al., who reported lower HR in association with negative emotions and anger [11]. The discrepancy between these results could be explained by different study designs, as Ramaekers et al. recorded HR for 24 hours and also assessed negative coping differently.

Using machine learning-based regression algorithms, we were also able to reliably predict $\mathrm{SVF}_{\mathrm{Pos}}$ and $\mathrm{SVF}_{\mathrm{Neg}}$. All three algorithms performed equally well which emphasizes the stability of the results. Negative coping strategies could be predicted with a relative error of 19.2 % compared to the range in the examined population. Predicting positive coping strategies performed better with a relative error of 13.6 %. Regarding the most important features for regression, $\mu(\mathrm{HR}^{\mathrm{sleep}})$, $\mu(\mathrm{HR}^{\mathrm{wake}})$, and $\sigma(\mathrm{HR}^{\mathrm{sleep}})$ had the biggest impact on the prediction of $\mathrm{SVF}_{\mathrm{Pos}}$. In comparison to SBMLR, machine learning models involved more variables for predicting positive coping strategies, which hints at their complexity. For negative coping strategies, however, SVR utilized the same variables, $\mu(\mathrm{HR}^{\mathrm{sleep}})$ and $\mu(\mathrm{HR}^{\mathrm{wake}})$, as SBMLR. Compared to SBMLR, the prediction with RF involved more variables, including the HRV features RMSSD and pNN50. Overall, the results from machine learning regression models support the findings from SBMLR and extend the relationship between SNS activity and stress coping as a personality trait.

Due to the limited amount of study participants, future work needs to include more subjects from a more heterogeneous group and should control for the overall level of chronic stress, to generalize these preliminary findings.

V. Conclusion and Outlook

Our findings showed that positive and negative stress coping capabilities can be predicted with HR and HRV parameters recorded during the night and the first hour after awakening. Both linear regression and machine learning regressors can forecast the expression of different coping strategies. Machine learning models could establish more complex relationships, but overall it was found that the manifestation of positive stress coping correlates with lower SNS activity, especially lower HR. This hints at a strong influence of stress coping on stress systems during sleep. With this insight, the importance of positive stress coping strategies to foster better sleep quality and cardiovascular health becomes clear once more.

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