

Information System for Monitoring and Assessing Stress among Medical Students

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Abstract. The severe or prolonged exposure to stress-inducing factors in occupational and academic settings is a growing concern. The literature describes several potentially stressful moments experienced by medical students throughout the course, affecting cognitive functioning and learning. In this paper, we introduce the EUSTRESS Solution, that aims to create an Information System to monitor and assess, continuously and in real-time, the stress levels of the individuals in order to predict chronic stress. The Information System will use a measuring instrument based on wearable devices and machine learning techniques to collect and process stress-related data from the individual without his explicit interaction. A big database has been built through physiological, psychological, and behavioral assessments of medical students. In this paper, we focus on heart rate and heart rate variability indices, by comparing baseline and stress condition. In order to develop a predictive model of stress, we performed different statistical tests. Preliminary results showed the neural network had the better model fit. As future work, we will integrate salivary samples and self-report questionnaires in order to develop a more complex and intelligent model.

Keywords: stress; heart rate variability; wearable devices; big data mining; medical students

1 Introduction

Stress is a huge problem in today's society. Modern lifestyle exerts an enormous burden on individuals by pushing towards increasing productivity and longer working hours. This feeling of persistent underachievement, that modern working conditions exert, leads to burnout and stress-related mental disorders such as anxiety. According to the Aon EMEA Health Survey 2018, stress and mental health are the main concerns affecting the well-being of employees in Portugal [1]. It is well known that an excessive level of stress interferes with productivity and has an impact on the individual's physical and emotional health [2,3,4]. In fact, job stress is responsible for poor work performance, high absenteeism, and several diseases, such as coronary heart disease, as well changes in lifestyle [5].

The stressful environments can be seen everywhere in our daily life, although for some occupations there is an increase in risk factors. So that, it is of the utmost im-

portance to monitor the stress levels of these individuals on a regular basis, in order to anticipate chronic stress and thus to intervene early. Usual stress-assessment methods present some limitations: they cannot be applied continuously, in real-time, and commonly use invasive ways for evaluation, affecting the individual's routine, may skewing the results of the assessment.

In this study, we describe the EUSTRESS project that aims to create an Information System (IS), adapted to the type of stress profile of the individual, to monitor stress levels of the individual, continuously and in real time, and also predict chronic stress. The IS will use a measuring instrument based on mobile/wearable devices and machine learning techniques to collect and process stress-related data from the individual without his/her explicit interaction, and present the results in easily interpretable graphic environment. A predictive model will analyze stress recovery patterns, and a stress-control mechanism will emit alerts in case of excessive levels or cumulative effects (chronic stress).

The remaining of this paper is as follows. Section 2 presents the review of the literature in terms of theoretical and methodological rational for the study of stress among medical students. Following this background, we discuss in the Section 3 our research project called Eustress Solution. Section 4 presents preliminary results of our research, which will be discuss in the Section 5, to conclude and give some advices for future work.

2 Background

In common sense, the term *stress* usually takes a negative connotation. However, stress is a part of human life and the series of organic reactions it triggers can be quite healthy, pushing the human being to a response to a threatening situation (e.g. running away from a ferocious animal or assertively resolving a situation of conflict). Stress affects an individual's cognitive performance in a biphasic mode. Too little stress impairs adequate performance, increasing with physiological levels of acute stress and followed by a decrease in performance again with prolonged or disproportioned levels of stress.

When an individual is exposed to stressful stimuli (physical or psychological), the organism perceives it as a threatening event and mounts an adequate biological and behavioral responses. However, it is very difficult to distinguish between an optimal stress level – it is called *eustress* - and an exacerbated level – it is called *distress*. The first distinction between eustress and distress was made in the 1960s by Selye [6], to refer to a number of physiological and psychological reactions to harmful or unfavorable conditions or effects.

2.1 Methods for stress assessment

Among the different methods to evaluate stress in its different levels, the most common in the literature are in the psychological, physiological and behavioral domains. Usually, the psychological stress assessment is done using self-administered ques-

tionnaires, which are widely used and considered reliable, such as Stress Self-Assessment Scale, Perceived Stress Scale - PSS [7], and Stress Response Inventory – SRI, [8]. However, these questionnaires only provide information on stress levels at the time of evaluation, not covering the stressors or the evolution of stress levels [9].

Concerning the physiological data, biological markers include acute phase response hormones/mediators (cortisol, interleukins, ferritin) that are released during the stress response. For physiological assessment, there are several types of bio-signals that can be used, such as hormone levels (e.g. cortisol). The limitation of this assessment is the need for equipment and interaction with the individual, such as saliva, urine, or blood samples. Stress affects also another physiological process, in specific, the exposure to a stressor triggers the autonomic nervous system activating the sympathetic nervous system and inhibiting the parasympathetic nervous system [10, 11]. As a result, there are changes in heart rate – HR – and in heart rate variability – HRV, which can be assessed through an electrocardiogram, for example [12]. Other examples of tests that require specialized equipment are electroencephalogram, electrodermal activity, electromyogram, pupil diameter, speech analysis, and functional magnetic resonance imaging. However, again, this test does not monitor continuously, nor do they detect patterns related to the initial stages of stress. They also require moving to a place with equipment and are usually expensive. To bridge this gap, recent focus on mobile / wearable devices equipped with physiological signal sensors can be an effective way for continuous and non-invasive assessment.

Behavioral assessment, although it is fewer studied, has as its main advantage the possibility of being carried out without affecting the daily life of the individuals. As an example, we can analyze the dynamics of computer keyboard and mouse use, posture and facial expressions.

2.2 Stress among medical students

Higher education is a transition period before students reach the working environment. Students are subjected to increasing periods of work with a progressive focus on autonomy and continuous assessment. The increasing workload is perceived as stressful and commonly leads to mental disorders and perception that their cognitive performance is belowered their expected standards.

Previous works describe several potentially stressful moments experienced by medical students throughout the course. In addition to medical preparation and activity being considered as having a high potential for stress, there are other factors, such as: the student's first contact with the patient, the fact that he or she often lives alone and away from home, long hours of study, and the concerns about professional performance at the end of the course. Typically, most medical schools follow a traditional model that does not address a focus on emotions, which ultimately does not prepare the students to deal emotionally with events such as caring for patients seriously ill, with suffering and with death situations [13].

The period of university studies is commonly associated with a time of anxiety, stress, and even depression. There are several reasons, including the pressure for success in exams [13]. A study in the United States, comparing medical students and

students from other courses, found there was a greater dependence or abuse of alcoholic beverages on medical students [14]. In Portugal, previous works have shown that among medical students, stress is a prevalent risk factor, affecting the decision-making process and altering the activity of brain networks [15, 16].

Academic exams are potential sources of stress for college students. Although it is a fundamental phase in the training and certification process, it is also one of the strongest stress factors due to the high-stake implications in the academic progress and self-perceived image. In particular, in medical students, there is an increase in levels of anxiety, salivary cortisol and stress in the pre-examination period compared to the post-exam period [17,18]. Regarding stress recovery time, an empirical study with medical students [19] indicated that the fatigue levels started to decrease on the day after the examination, and most of the sample of the students needed, on average, six days to recover completely.

For these reasons, understanding the causes of the stress of medical students has also been a privileged topic in research, so that university institutions can adopt measures of prevention and stress management. In this study, we analyzed HR and HVR metrics from a sample of Portuguese medical students in two moments – without the stress induced from evaluations (baseline condition), and during university exams (stress condition). These data have been collected regarding to build a big database, in order to evaluate stress levels and predict chronic stress. Thus, the Eustress Solution has been developed in order to give a contribution in this field and help to understand this phenomenon.

3 The Eustress Solution

The research project named “EUSTRESS – Information system for the monitoring and evaluation of stress levels and prediction of chronic stress” aims to evaluate and develop an IS that monitors and evaluates in real-time the stress levels of an individual in order to develop a predictive model of stress response and chronic stress. For that, it assesses several kinds of information: salivary cortisol samples as a biological marker of stress reaction, self-report measures of experienced stress and coping strategies, physiological data evaluated through a wearable device – smartband and data from an e-assessment management system used for academic exams (MeddQuiz®).

Concerning the physiological data, it was used an application named “EUSTRESS”. This application, specially developed for this project, was implemented in Android on a Samsung Galaxy 3/5 phone and received data from the wearable device – *Microsoft Smartband 2*. This Smartband evaluates skin conductance, body temperature, heart rate variability, calorie intake and expenditure, sleep patterns, and quality [20]. All of these data was sent to the mobile application via Bluetooth.

The MedQuiz is an e-assessment collaborative tool that provides several layers of information on students’ performance during an exam. Basic data includes student’s score, time to completion and number of correct/incorrect/avoid answers in order to understand their stress levels. Metadata obtained concerns behavioral data of the student, pertaining performance (e.g., time spent reading a question) and decision-

making (e.g., number of visits to a question and of times an answer is changed). Additionally, the MedQuizz allows for the collection of direct human-machine interaction data to assess tension during an exam, such as mouse movement patterns or keystroke dynamics, and provides the possibility to test impulsivity (time lag between question) or affect environmental conditions (dim/brighten screen light) in user's experience.

Data provided from all of these sources will be integrated through statistical models in order to develop stress profiles (by baseline stress patterns and stress and reactivity patterns) to consequently predict stress states of individuals. In the architecture of this project, a set of proprietary and OpenSource technologies, linked and exchanging data, allow the collection and storage of biometric data. Figure 1 shows the architecture of this information system.

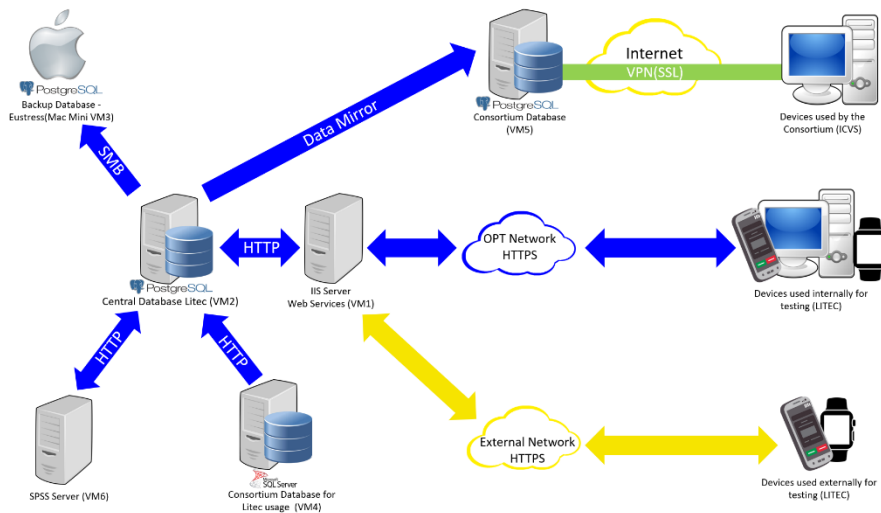


Fig. 1. Architecture of EUSTRESS Solution

The solution has three main goals. The first of them is to determine stress profiles (by baseline levels of stress and by patterns of reactivity and stress recovery) to classify individuals, making the IS adaptable to any individual. The second goal is to build a bigdata using psychological, physiological and behavioral assessments. Finally, the third goal is to interpret the stress reactivity patterns of the individual and predict stress states, cumulative effects of stress, and chronic stress.

3.1 Data collection and ethical procedures

This project was reviewed and approved by the ethical committee of the Life and Health Sciences Research Institute at the University of Minho (Portugal) and the National Data Protection Commission. All participants were informed about the objectives of the study and provided written informed consent. Data were collected from September 2017 to October 2018. Participants were medical students at the Life and

Health Sciences Research Institute at the University of Minho. All students received an informative email about the project and during classes the researcher explained the purpose of their participation, inviting collaboration.

Data were collected in two different conditions for each participant: the first condition was at the beginning of the academic year, a time without the stress induced from evaluations (baseline condition), and the second was during university exams (stress condition) that occurred at three different times. At baseline, participants completed some global self-reported measures (e.g., sociodemographic questionnaire evaluating gender, age, nationality, and academic year; the PSS Portuguese version [21] Brief-COPE Portuguese version [22]) and used the Smartband during a week. In the baseline condition, physiological data were collected at 5 minutes each hour. At the end of each day participants answered the PSS 4 Items [21] and during three days they provided salivary cortisol (in the morning, in the afternoon, and in the evening).

In the stress condition, participants used the Smartband during multiple choice computer-based exams. Physiological data were continuously evaluated during the time of the exam. Participants provided samples of salivary cortisol before and after their exam. Salivary cortisol was collected through *Salivettes*. They also answered the questionnaires concerning stress perception (PSS and Brief-COPE) at the end of their exam. The participants did not receive any compensation for their participation.

These data (i.e., salivary cortisol sample, physiological data, data from the e-assessment management system, and self-report measures) were part of the broad project. However, in accordance with the purposes of the present study and for preliminary analyses, we only presented and analyzed HR and HRV metrics.

3.2 Data analyses

Thirteen HR and HRV time domain indices [11] that quantify the “amount of variability in measurements of the interbeat interval” were calculated from the heartbeat interval data of Smartband sensors. Some examples of these indices were: mean heartbeat intervals (Mean RR), minimum (Min RR) and maximum values of RR (Max RR), median value of RR (Median RR), standard deviation of the RR intervals between normal beats (SDNN), root mean square differences of consecutive RR intervals (RMSSD), and percentage of consecutive RR intervals that differ by more than 50 ms (pNN50).

4 Results

Data were collected from 83 medical students who volunteered to enroll both in baseline and stress conditions. Sixty-three (76.8%) were female and 19 (23.2%) were male aged 17 to 38 years ($M = 22.13$; $SD = 5.55$). For approximately 63% of the participants, the attendance of the course did not imply the change of the residence.

Participants’ academic year ranged from 1st to the 5th, with 19.5% of the participants from the 3rd year alternative program for graduate individuals. About 85% of the

sample defined as the reason for the application to higher education the vocational interest.

We performed an Independent Samples *t* -Test in order to compare the HR and HRV variables at baseline and at exam condition. Table 1 presents the mean and standard deviation for each one. It was found significant differences between baseline and exam condition, except Diff Mean, Diff p mean and pNN50. The Mean, Min, Median, and Diff Min were significantly higher in baseline condition than in the exam condition. In contrast, SDDN, Max, Diff SDDSD, and diff Max were significantly higher in the exam than in baseline condition.

Table 1. Comparing HR and HRV across two different conditions (baseline and exam)

	Baseline	Exam
Mean	.48 (.06)	.45(.04)***
SDNN	.12(.02)	.14(.02)***
Min	.48(.06)	.45(.04)***
Max	1.22(.17)	1.25(.19)***
Median	.82(.12)	.72(.09)***
Diff Mean	.11(.02)	.11(.02)
SDDSD	.11(.02)	.11(.01)***
Diff Min	.48(.06)	.45(.04)***
Diff Max	.57(.10)	.69(.09)***
Diff Median	.07(.03)	.07(.02)***
Diff p mean	.02(.01)	.02(.01)
RMSSD	.15(.03)	.16(.02)*
pNN50	.54 (.12)	.54(.10)

* $p < .05$; *** $p < .001$

Following these results, we performed different statistical tests: logistic regression, neural network, naïve Bayes, support vector machines, random forest, and k-nearest neighbor in order to predict stress based on HR and HRV variables. For each test, two models were established. In the model 1, we include all variables listed; in the model 2, we only include the significant variables. Table 2 presents the comparison between Model 1 and Model 2 for each test calculated. The neural network revealed the better results for both models. In specific, the sensitivity value was 77.8% for Model 1 and 77.21% for Model 2. The specificity values were 77.9% and 78.1%, respectively for Model 1 and Model 2.

Table 2. Comparing statistical tests to predict stress from the HR and HRV variable

8		Model 1 (All variables)				Model 2 (Significant variables from the Independent Samples <i>t</i> -Test)			
		Predicted			Σ	Predicted			Σ
Logistic regression	Actual	0	0	1	Σ	0	0	1	Σ
		1	72.9%	27.1%	480	1	73.1%	26.9%	480
		Σ	27.7%	72.3%	480	Σ	27.7%	72.3%	480
		Σ	483	477	960	Σ	484	476	960
Neural network	Actual	0	0	1	Σ	0	0	1	Σ
		1	77.9%	22.1%	480	1	78.1%	21.9%	480
		Σ	24.8%	75.2%	480	Σ	25.8%	74.2%	480
		Σ	493	467	960	Σ	499	461	960
Naive Bayes	Actual	0	0	1	Σ	0	0	1	Σ
		1	65.0%	35.0%	480	1	62.7%	37.3%	480
		Σ	30.6%	69.4%	480	Σ	25.8%	74.2%	480
		Σ	459	501	960	Σ	425	535	960
Support Vector Machines	Actual	0	0	1	Σ	0	0	1	Σ
		1	43.1%	56.9%	480	1	47.5%	52.5%	480
		Σ	14.2%	85.8%	480	Σ	17.9%	82.1%	480
		Σ	275	685	960	Σ	314	646	960
Random Forests	Actual	0	0	1	Σ	0	0	1	Σ
		1	75.2%	24.8%	480	1	74.8%	25.2%	480
		Σ	26.5%	73.5%	480	Σ	28.8%	71.2%	480
		Σ	488	472	960	Σ	497	463	960
k-nearest neighbors	Actual	1	0	1	Σ	1	0	1	Σ
		Σ	70.8%	29.2%	480	Σ	69.0%	31.0%	480
		0	19.8%	80.2%	480	Σ	24.4%	75.6%	480
		Σ	435	525	960	Σ	448	512	960

5 Conclusions and Future Work

In this paper, we discussed our ongoing research EUSTRESS and presented its main goals. Therefore, we focused on describe the architecture and the framework related with the development of this project.

Our results represent the firsts steps in order to develop the machine learning algorithms. For this, we performed different statistical tests and compare them. The neural network had the better model fit. In fact, this technique is robust enough to deal with

the possibility of some possible badly classified data. Despite of we had classified the moments as without stress (baseline) and with stress (during exam), it is possible that some individuals had experienced stress in the first condition. As well, the exam situation could be not stressful for some of them. Therefore, it is possible that some of our data could not correspond to the real condition. For overpass this limitation, as next steps we will validate these results with the salivary cortisol samples and self-report questionnaires.

Future steps intend to design an intervention program where failing students are identified based on the real-time collection from exams (reactivity to stress/anxiety, biological markers, cognitive performance, and decision-making behavior) and recovered by customized coaching programs. Although the Information System is being validated in a sample of medical students, it will be applied to any individual in any occupational setting.

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