

Information System for Monitoring and Assessing Stress among Medical Students

Silva, E¹., Aguiar, J¹., Reis, L. P²., Sá, J. O¹., Gonçalves, J³., & Carvalho, V³.

¹University of Minho, Guimarães, Portugal

²University of Porto, Porto, Portugal

³Optimizer Lda, Porto, Portugal



Introduction

Modern lifestyle exerts an enormous burden on individuals by pushing towards increasing productivity and longer working hours.



Introduction

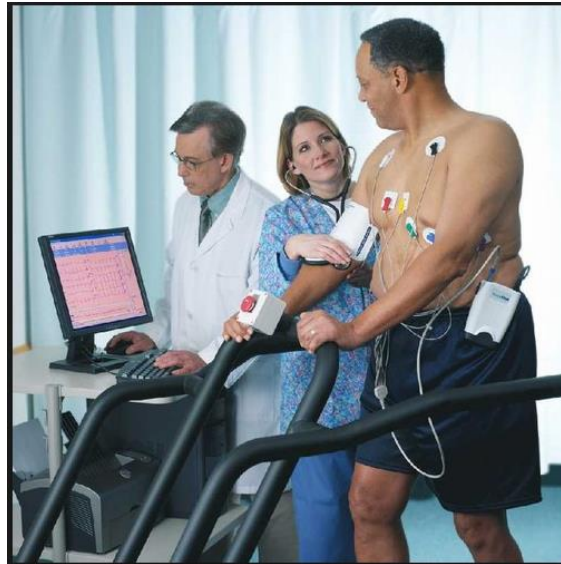
Stressful environments can be seen everywhere in our daily life, although for some occupations there is an increase in risk factors.



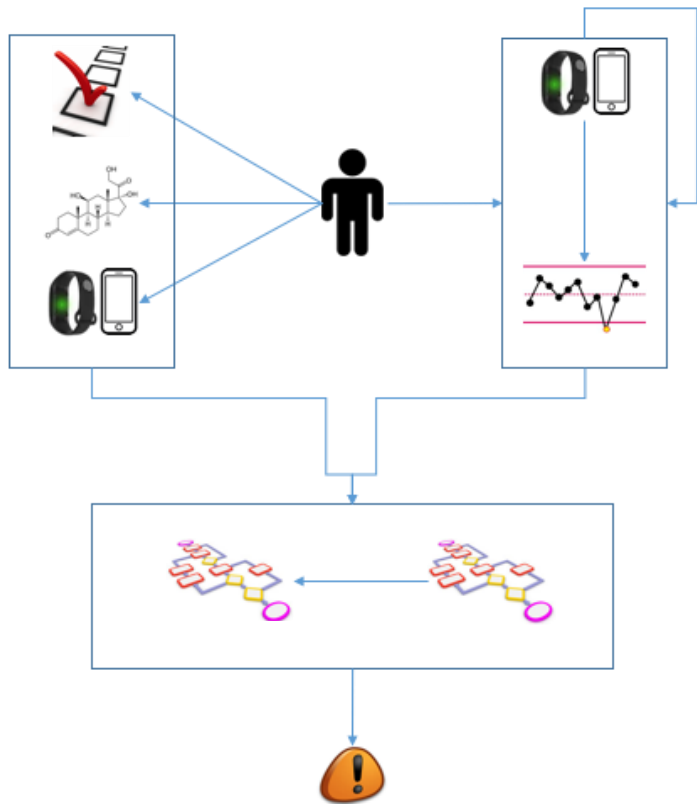
To monitor the stress levels, in order to anticipate chronic stress

Introduction

Usual stress-assessment methods: cannot be applied continuously; invasive ways for evaluation; non real life situations, may skewing the results.



EUSTRESS Project



Information System:

adapted to the individual stress profile;
monitor stress levels, continuously and in real time;
predict chronic stress

Mobile/wearable devices (to collect without his/her explicit interaction)

Machine learning techniques to process stress-related data

Stress-control mechanism: alerts in case of excessive levels or cumulative effects (chronic stress)

Stress among medical students

Higher education → transition before students reach the labor market

Students → progressive focus on autonomy and continuous assessment.

Stressful workload

Perception that their cognitive performance is belowered their expected standards.

Stress among medical students

Potentially stressful moments experienced by medical students:

- Student's first contact with the patient;
- He/she often lives alone and away from home;
- Long hours of study;
- Concerns about professional performance at the end of the course

Stress among medical students

Academic exams are potential sources of stress

Although it is a fundamental phase, it is also one of the strongest stress factors due to the high-stake implications (academic progress and self-perceived image)



EUSTRESS Solution



App implemented in Android (Samsung Galaxy 3/5 phone)

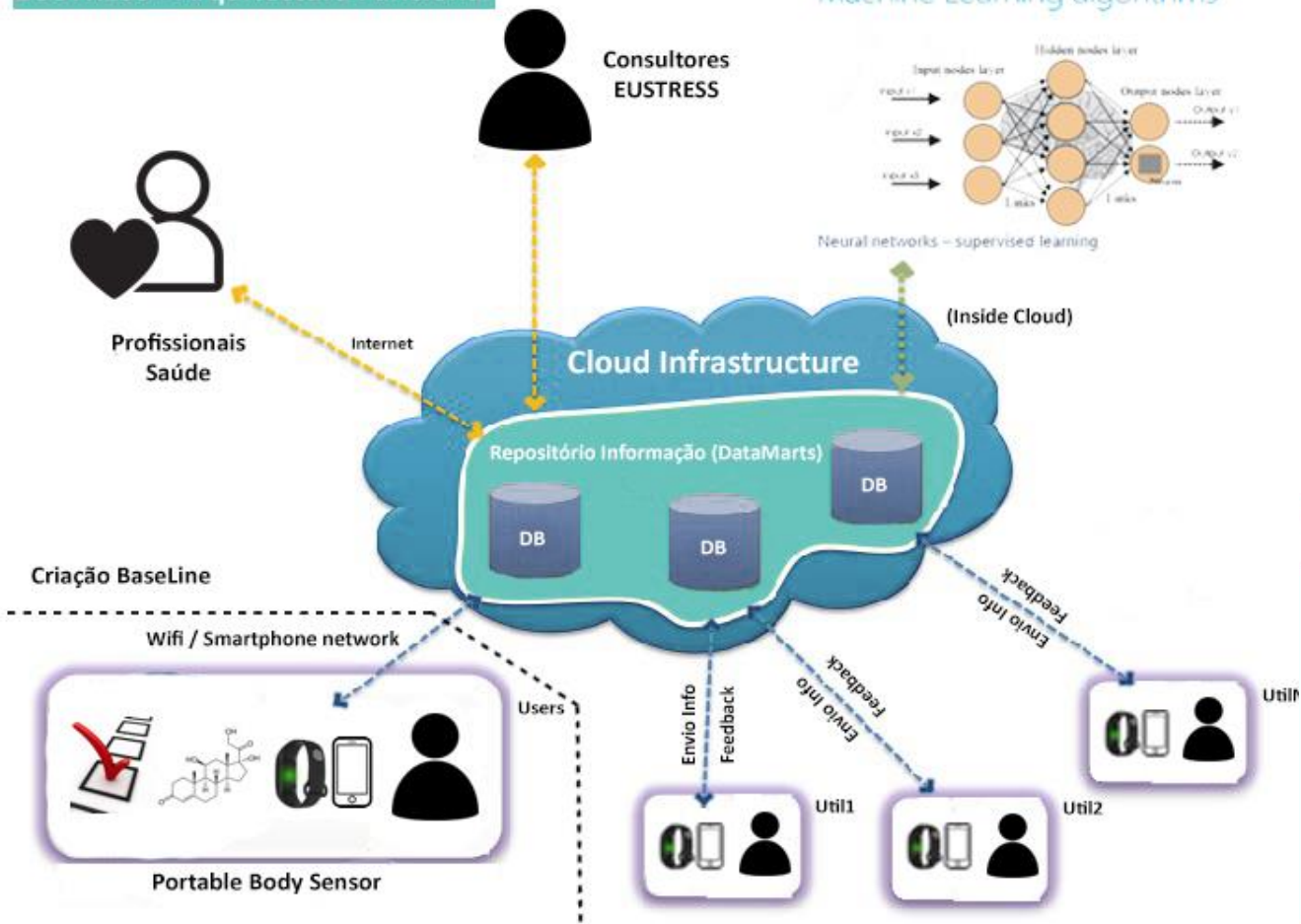
Microsoft Smartband: skin conductance, body temperature, heart rate variability, calories intake and expenditure, and sleep patterns.

Data was sent to the mobile application via Bluetooth[®]

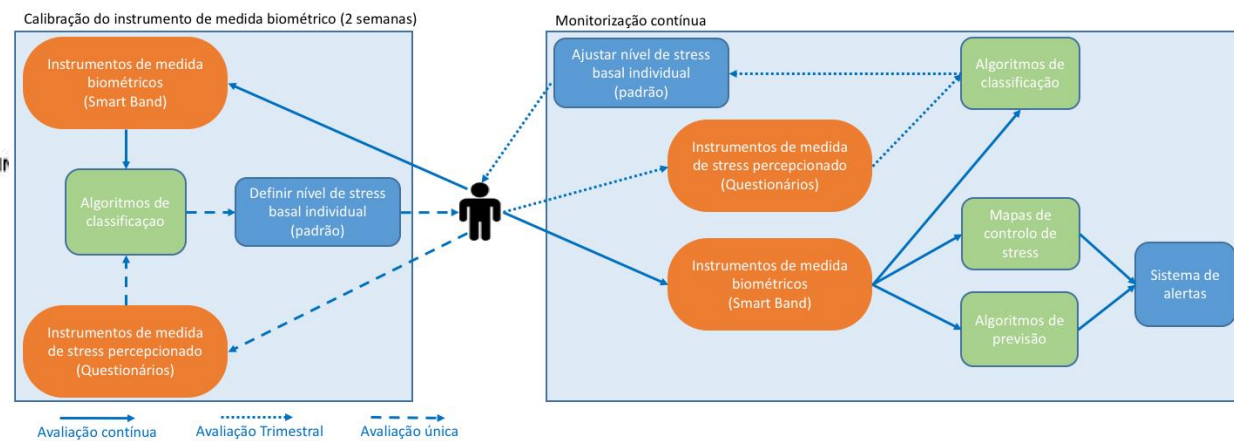


Context

EUSTRESS - Arquitetura Funcional



EUSTRESS



Method

Participants

N= 83 medical students (baseline and stress conditions)



63



19

17 to 38 years ($M = 22.13$; $SD = 5.55$)

1st to the 5th (19.5% from the 3rd year)

85% vocational interest

Method

Procedures

Without the stress induced from academic tests (baseline condition)

During academic tests (stress condition)

Ethical Committee of the University of Minho (Portugal)

National Data Protection Commission

All participants were informed about the objectives of the study and provided written informed consent

Method

Measures

13 Heart Rate (HR) and Heart Rate Variability (HRV) time domain indices

Mean RR	Mean heartbeat intervals
Min RR	Minimum heartbeat interval
Max RR	Maximum heartbeat interval
SDNN	Standard Deviation of the RR intervals
RMSSD	Root mean square differences of consecutive RR intervals

Method

Mean RR
Min RR
Max RR
Median RR
SDNN
pNN50
RMSSD
SDSD
Diff Median
Diff ρ mean
Diff Min
Diff SDSD
Diff Max

Results

	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)
SDSD	.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)

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

Results

Different statistical tests: logistic regression, neural network, naïve Bayes, support vector machines, random forest, and k-nearest neighbor

Model 1: all variables listed;

Model 2: only significant variables

Results

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

Discussion

EUSTRESS Project and its initial results

APP

Data collection ongoing

Neural network had the better model fit (robust technique)



Discussion

Limitations:

For some participants, exam situation could be not stressful (data could not correspond to the real condition)

Next steps → validate these results with salivary cortisol samples and self-report questionnaires (PSS)

Discussion

Future directions:

Intervention program → students 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

After validation in this sample, apply the IS in other occupational settings

Information System for Monitoring and Assessing Stress among Medical Students

Silva, E¹., Aguiar, J¹., Reis, L. P²., Sá, J. O¹., Gonçalves, J³., & Carvalho, V³.

¹University of Minho, Guimarães, Portugal

²University of Porto, Porto, Portugal

³Optimizer Lda, Porto, Portugal

