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Using wearables and user behavior on smartphones to help cope stress

A Degree Thesis

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by

Anna Paré Rico

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Advisors:

Ajantha Dahanayake

Josep Ramon Casas

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Abstract

Stress per se is not a negative fact, actually it is a survival mechanism in response to danger; we need it. Stress can show our ability to handle pressure without breaking, it provides us challenges and tests our adaptability to face them. However, prolonged and high stress levels might cause serious illnesses. In modern life, negative stress has become an extremely common problem.

In this Bachelor thesis we propose the design of a stress detection and monitoring app, Shama, which uses data collected from the smartphone to infer the user's daily stress state. If the user wears a wristband, Shama also extracts Heart Rate Variability (HRV) features to enhance the stress detection. The app proposal is partially validated by building a stress classification model with a Sequential Minimal Optimization (SMO) classifier, which provides an accuracy of almost 73%. We also present the user interface of Shama, with all its functionalities for stress coping and management, as well as for encouraging the user to incorporate daily healthy habits to reduce unnecessary and unhealthy stress levels.

Resum

L'estrès, en si mateix, no és absolutament negatiu, sinó que és un mecanisme de resposta davant del perill i, de fet, el necessitem. També demostra la nostra capacitat de suportar certa pressió, ens aporta reptes i posa a prova la nostra flexibilitat a l'hora d'enfrontar-los. Tanmateix, alts nivells d'estrès en períodes prolongats poden tenir conseqüències altament prejudicials per a la nostra salut, tant mental com física. I, malauradament, avui dia l'estrès és un problema excessivament comú.

En aquest treball de fi de grau proposem el disseny teòric de Shama, una aplicació mòbil capaç de detectar l'estrès diari de l'usuari mitjançant informació extreta del seu mòbil, així com d'una polsera intel·ligent en cas que l'usuari en disposi. Aquesta proposta d'app és parcialment validada amb la construcció d'un model de *machine learning* mitjançant *Sequential Minimal Optimization* (SMO), que té una precisió del 73% en un problema de classificació binària. Shama també monitora l'usuari per ajudar-lo a lidiar amb l'estrès un cop detectat i li proporciona eines per incorporar en el seu dia a dia hàbits per millorar el seu benestar general.

Resumen

El estrés, de por sí, no es algo totalmente negativo, sino más bien un mecanismo de supervivencia que nos permite reaccionar delante del peligro. Así que de hecho, lo necesitamos. Además, puede ser constructivo y mostrarnos lo capaces que somos de soportar cierta presión, retándonos y poniendo a prueba nuestra flexibilidad frente a desafíos. Sin embargo, altos niveles de estrés o períodos prolongados bajo sus efectos, pueden tener consecuencias muy perjudiciales para nuestra salud, tanto la mental como la física. Y, desafortunadamente, hoy en día el estrés en un problema excesivamente extendido.

En este trabajo de fin de grado proponemos el diseño teórico de Shama, una aplicación móvil capaz de detectar diariamente el estrés del usuario mediante información extraída a través de su móvil o de su pulsera inteligente, en caso que se disponga de una. Esta propuesta teórica es parcialmente validada construyendo un modelo de *machine learning* mediante *Sequential Minimal Optimization* (SMO) capaz de alcanzar una precisión de aproximadamente el 73% enfrente a un problema de clasificación binaria. Asimismo, Shama también proporciona monitorización al usuario para ayudarlo a lidiar con el estrés cuando se encuentra bajo sus efectos, y le motiva a incorporar hábitos diarios para mejorar su bienestar general.

I would like to dedicate my final Bachelor's thesis to my family and friends, especially to my mother, father, brother and Marc, for their unconditional and crucial support along this journey, and for always giving me hope and motivation to achieve my ambitions.

To enjoy good health, to bring true happiness to one's family, to bring peace on all, one must first discipline and control one's own mind. If a man can control his mind he can find the way to Enlightenment, and all wisdom and virtue will naturally come to him.

- Buddha

Nothing is at last sacred, but the integrity of your own mind.

- Ralph Waldo Emerson

No problem can be solved from the same level of consciousness that created it.

- Albert Einstein

Acknowledgements

I would also like to thank Professors Ajantha Dahanayake and Josep Ramon Casas for their expert advice, help and motivation throughout the realization of this thesis.

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9	11/04/2018	Document edition
10	23/04/2018	Document edition
11	27/04/2018	Document edition
12	28/04/2018	Document edition
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Name	E-mail
Student:	
Anna Paré Rico	annaparerico@hotmail.com
Supervisors:	
Josep Ramon Casas Pla	josep.ramon.casas@upc.edu
Ajantha Dahanayake	Ajantha.Dahanayake@lut.fi

Written by:		Reviewed and approved by:	
Date	03/05/2018	Date	07/05/2018
Name	Anna Paré Rico	Name	Ajantha Dahanayake
Position	Project Author	Position	Project Supervisor

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1. Introduction

1.1. Project purpose

The objective of this project is to show how stress, a major and increasing problem in today's society, can be detected and monitored by means of two currently available and accessible technology devices: wearables and smartphones.

In order to do so, we present the design of a functional smartphone application, **Shama**, which integrates both stress detection and monitoring tasks. Using input from the user's data collected from a wearable and a smartphone, fed into machine learning classification algorithms and obtaining an output: the daily stress state of the user identifies as "stressed" or "not stressed". If stress is detected, the application notifies the user and offers him support and coaching to manage and cope stress, allowing the user to incorporate healthy daily habits for his overall wellness, both physiological and psychological.

The name of the app, Shama, is not a fortuitous choice, but an eloquent Sanskrit term that means tranquillity, absence of passion but more usually translated as mental discipline or self-control [31], which is the state that we expect for the user to acquire through the use of our application.

One of the limitations of this work is the unfeasibility of collecting real data from real participants. The work of this thesis is based not on an own practical experience but on a theoretical background, substantiated by an exploratory study from existing researchers' work.

1.2. Project requirements

Project requirements include a theoretical design of the global application, containing a high-level flowchart, indicating its main blocks and justifying each decision made, from the data collection process at the beginning to the monitoring stage at the end, passing through an appropriate classifier choice for stress detection.

As the project is based on a theoretical background, the classification app building block is chosen to partially validate the app proposal, offering a detailed explanation of its functioning and testing some of its machine learning algorithms by means of an existing free software suite, Weka[1], and a freely available dataset from a related project work [11].

Although this work is based on the exploration of related works made by a number of different research groups, this particular project starts from scratch. It is not the continuation of a previous one, but an independent project, not performed in the framework of a specific research department or company. The research work is carried out by the student herself with the support of their supervisors.

[1] Waikato Environment for Knowledge Analysis (Weka): https://www.cs.waikato.ac.nz/ml/weka/

1.3. Project work plan

During the project realization no significant incidents occurred, just some of the initial work packages underwent a few internal modifications, which are all detailed in the updated work packages below.

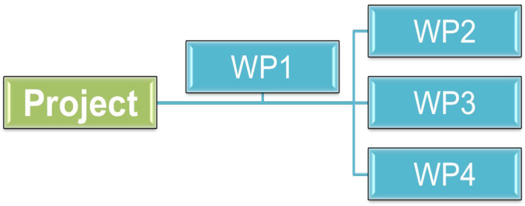


Figure 1: Work breakdown structure

Updated work packages:

Title: **Theoretical exploration**	**WP1**	
Major constituent: information	Sheet 1 of 4	
Short description: This is the principal work package: its goal is to collect the essential information for the project.	Start date: 09/01/2018 End date: 25/02/2018	
	Start event: T1 End event: T11	
• Internal task **T1**: 1st meeting with destination supervisor. • Internal task **T2**: Make a work plan for the whole semester. • Internal task **T3**: Define clearly the project's objectives. • Internal task **T4**: Start looking for general information on the Internet. • Internal task **T5**: Info: how to detect stress from a person (physiological and behaviour indicators). • Internal task **T6**: Info: how to detect stress with wearables. • Internal task **T7**: Info: how to detect stress with smartphones. • Internal task **T8**: Info: interaction between smartphones and wearables. • Internal task **T9**: Online Weka Course (Future Learn portal). • Internal task **T10**: Finish reading all the papers and information previously collected. • Internal task **T11**: Look for a freely available useful dataset.	Deliverables: T2	Dates: 16/01/2018

<table>
<tr><th colspan="2">Title: Internal settings</th><th colspan="2">WP2</th></tr>
<tr><td colspan="2">Major constituent: SW</td><td colspan="2">Sheet 2 of 4</td></tr>
<tr><td colspan="2" rowspan="2">Short description:

Using all the information collected in WP1, and using the free dataset, decide the internal configuration of the app.</td><td colspan="2">Start date:
26/02/2018
End date:
20/03/2018</td></tr>
<tr><td colspan="2">Start event: T1
End event: T6</td></tr>
<tr><td colspan="2">Internal task T1: Project Proposal and Work Plan delivery.
Internal task T2: decide which features to use for stress classification.
Internal task T3: decide which kind of wearable will be used.
Internal task T4: decide which kind of classifier will be used.
Internal task T5: Test the classifier with the (partial) dataset.
Internal task T6: define app inputs and outputs.</td><td>Deliverables:

T1</td><td>Dates:

05/03/2018</td></tr>
</table>

<table>
<tr><th colspan="2">Title: App Design</th><th colspan="2">WP3</th></tr>
<tr><td colspan="2">Major constituent: SW</td><td colspan="2">Sheet 3 of 4</td></tr>
<tr><td colspan="2" rowspan="2">Short description:

Design of the final smartphone application: a functional combination of the collected data from the wearable and the smartphone and the user monitoring to palliate the stress and help incorporate healthy daily habits.</td><td colspan="2">Start date:
21/03/2018
End date:
07/05/2018</td></tr>
<tr><td colspan="2">Start event: T1
End event: T7</td></tr>
<tr><td colspan="2">Internal task T1: app blocks design.
Internal task T2: detail the stress classification block.
Internal task T3: app design for user monitoring/coaching when stress detected.
Internal task T4: start writing the Final degree thesis Document.
Internal task T5: Final screenshots of the app interface, using Marvel app online tool for its design.
Internal task T6: More dataset testing with Weka using some features from the StudentLife dataset.
Internal task T7: Critical Review delivery.</td><td>Deliverables:

T5
T7</td><td>Dates:

24/04/2018
07/05/2018</td></tr>
</table>

<table>
<tr><th>Title: Final tasks</th><th colspan="2">WP4</th></tr>
<tr><td>Major constituent: documentation</td><td colspan="2">Sheet 4 of 4</td></tr>
<tr><td rowspan="2">Short description:

Finals tasks to be done to finish the project.</td><td colspan="2">Start date:
07/05/2018
End date:
31/05/2018</td></tr>
<tr><td colspan="2">Start event: T1
End event: T3</td></tr>
<tr><td>• Internal task T1: adjustments to the final document.
• Internal task T2: Final Review document delivery.
• Internal task T3: oral presentation.</td><td>Deliverables:

T2
T3</td><td>Dates:

07/05/2018
24/05/2018</td></tr>
</table>

Milestones:

WP#	Task#	Short title	Milestone / deliverable	Due Date
1	T10	Finish reading all the collected information	-	25/02/2018
1	T11	Find freely available dataset	-	25/02/2018
2	T2	Final features for stress classification	-	20/03/2018
2	T4	Final Weka's classifier	-	20/03/2018
3	T5	Shama design	Marvel app design	24/04/2018
4	T2	Final Review document	Final Thesis Document	07/05/2018
4	T3	Oral presentation	Presentation material	24/05/2018

Updated Gantt diagram:

	Nombre	Duración	Inicio	Terminado
1	⊟WP1	34 days?	**9/01/18 8:00**	**23/02/18 17:00**
2	T1: 1st meeting	1 day?	9/01/18 8:00	9/01/18 17:00
3	T2: semester workplan	4 days?	10/01/18 8:00	15/01/18 17:00
4	T3: clear project objectives	1 day?	16/01/18 8:00	16/01/18 17:00
5	T4: search general info	6 days?	9/01/18 8:00	16/01/18 17:00
6	T5: stress indicators	5 days?	16/01/18 8:00	22/01/18 17:00
7	T6: stress w/wearables	5 days?	23/01/18 8:00	29/01/18 17:00
8	T7: stress w/smartphones	5 days?	30/01/18 8:00	5/02/18 17:00
9	T8: interaction w-s	5 days?	6/02/18 8:00	12/02/18 17:00
10	T9: online Weka Course	8 days?	31/01/18 8:00	9/02/18 17:00
11	T10: finish reading all info	10 days?	12/02/18 8:00	23/02/18 17:00
12	T11: free dataset	5 days?	13/02/18 8:00	19/02/18 17:00
13	⊟WP2	17 days?	**26/02/18 8:00**	**20/03/18 17:00**
14	T1: Project Proposal delivery	6 days?	26/02/18 8:00	5/03/18 17:00
15	T2: decide features	17 days?	26/02/18 8:00	20/03/18 17:00
16	T3: decide wearable	17 days?	26/02/18 8:00	20/03/18 17:00
17	T4: decide classifier	3 days?	1/03/18 8:00	5/03/18 17:00
18	T5: partially test with dataset	4 days?	6/03/18 8:00	9/03/18 17:00
19	T6: define app inputs/outputs	12 days?	5/03/18 8:00	20/03/18 17:00
20	⊟WP3	34 days?	**21/03/18 8:00**	**7/05/18 17:00**
21	T1: app blocks design	10 days?	21/03/18 8:00	3/04/18 17:00
22	T2: detail classifier block	10 days?	3/04/18 8:00	16/04/18 17:00
23	T3: user monitoring design	14 days?	17/04/18 8:00	4/05/18 17:00
24	T4: start Final Review doc.	25 days?	3/04/18 8:00	7/05/18 17:00
25	T5: final design app interface	9 days?	12/04/18 8:00	24/04/18 17:00
26	T6: more testing with dataset	6 days?	22/04/18 8:00	30/04/18 17:00
27	T7: Critical Review delivery	11 days?	23/04/18 8:00	7/05/18 17:00
28	⊟WP4	14 days?	**7/05/18 8:00**	**24/05/18 17:00**
29	T1: Final Document 1st delivery	0 days?	7/05/18 8:00	7/05/18 8:00
30	T2: Final Review	9 days?	14/05/18 8:00	24/05/18 17:00
31	T3: oral presentation	12 days?	9/05/18 8:00	24/05/18 17:00

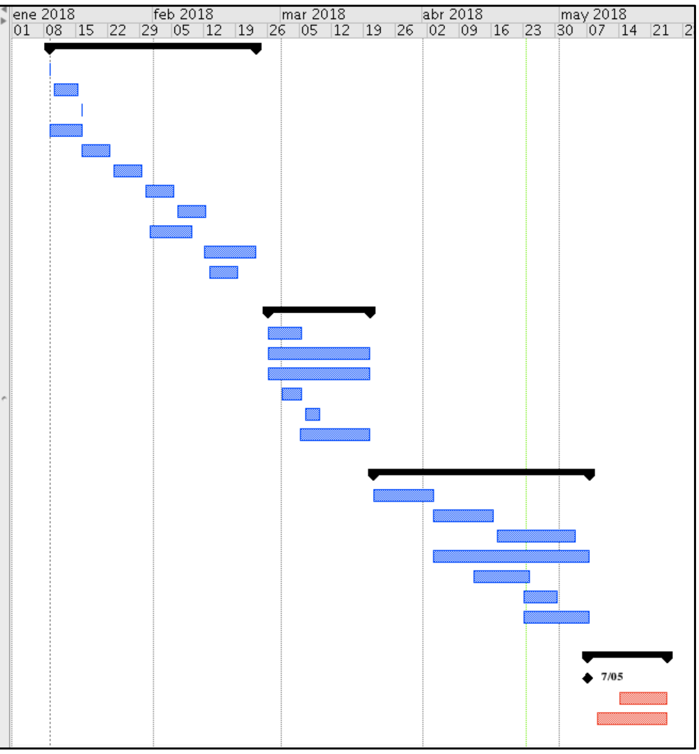


Figure 2: Gantt diagram

1.4. Document structure

This document is organized as follows. In section 2 we provide background information about stress, its detection and related published studies, as well as the technology involved.

In section 3 we describe our research methodology. This section is divided into four main parts: In 3.1 we present our Shama application, offering an overview of its functionality. The following section, 3.2, describes the study carried out to collect the necessary information for stress detection in the app. This section provides the design approach based on the literature study, and leads to the construction of our own dataset, which is not formed by our own real data, but designed using some of the features and information from a publicly available dataset [22][11]. Section 3.3 describes our stress detection design, from the data logging process using the information described in 3.2, to the machine learning model training and the final stress inference acquisition. The last section of the Methodology part is 3.4 and presents the final design of the Shama application interface.

In section 4 we show the results obtained by the classification process using the StudentLife dataset information and Weka, a machine learning platform.

In sections 5 and 6 we provide, respectively, the budget and the environmental impact of the project development. Ultimately, we finish the document allocating a section to the conclusions and the future development of the project.

2. State of the art

2.1. What is Stress?

Stress is our body's way of responding to any kind of demand, being it essential for survival, as it is the reaction of the organism to a change of its equilibrium. In fact, the term *stress* itself is not really useful from a scientific point of view, as it is a very subjective experience, difficult to define accurately [32].

However, what is evident is that for the majority of us the quotidian stress is related to the tension we experiment in response to a threat or challenge, when we are feeling overloaded and struggling to cope with demands, which can be related to work, relationships, finances or other situations. And even though stress can be a motivator [34], depending on the severity of the stressor and the person's ability to cope it, stress can become really harmful for a person's mental and physical health.

In our constantly demanding society, with hurried and busy lifestyles, excessive stress is the second most frequent problem in the European Union [35]. Stress consequences include heart disease, high blood pressure, low immunity, sleeping difficulties, anger, anxiety, concentration issues, depression, forgetfulness, sadness, food cravings and eating to much or too little, drug and alcohol abuse, sudden angry outbursts, frequent crying or relationship problems.

With stress being such a significant and increasing problem, numerous studies have been carried out, trying to understand better its causes and consequences, as well as exploring new detection and management tools. In the following section we provide a summary of the current background.

2.2. Stress detection with smartphones and wearables

Stress assessment is commonly performed by means of questionnaires or physical measurements. In the current global context, where technology plays an essential role, surrounding us and being present in our quotidian activities, both directly and indirectly, its use in scientific studies is more important than ever.

Stress recognition is one of the main research topics in the area of affective computing [1]. Technical devices like smartphones, and biosensors incorporated in wearable devices have become the main tools for collecting data and analysis.

As part of our everyday life, smartphones are a consistent data source to collect environmental and behavioural information associated with stress. Along these lines, a number of published studies base stress detection on data gathered by means of smartphones. In [2] data from the smartphone's built-in accelerometer is used as the only source to detect behaviour correlated with subjects' stress levels, reaching a detection accuracy of 71% with user-specific models. Many studies rely on features extracted from smartphone usage and its sensors for stress detection. App usage information is used in [19] as a predictor of perceived stress levels at workplace on 28 employees monitored over a 6-weeks period. Besides, [3] [20] and [7] add to this information data from call logs, SMS, Wi-Fi, and smartphone sensors (microphone, light sensor, accelerometer or GPS). [20] and [7] also use weather information as a stress correlated feature.

In [16] the mood sensor MoodScope is built from smartphone usage patterns of 32 participants over two months of data collection, acquiring an accuracy of 93% after a two-month personalized training period.

Other studies use smartphones to collect information about mobile-user's direct interaction that can be closely related to stress. In [12] the user's emotional state is identified by analysing the finger stroke pattern under different emotional categories in a laboratory-controlled environment. In a similar way, [13] assesses the stress level from the analysis of the duration and intensity of touches on the smartphone tactile screen, training a detection classifier with decision trees and support vector machines algorithms. ISenseStress [18] uses the tap, scroll, swipe and also text input patterns of the user for the stress recognition.

Several projects choose to support smartphone stress assessment with additional devices for users' physiological measurement analysis, being the most commonly used the wrist and chest wearables. In the literature reviewed the most used physiological signals for stress detection are the heart rate variability (HRV) and the galvanic skin response (GSR).

The galvanic skin response, also known as skin conductance (SC) or electro-dermal activity (EDA) is one of the most sensitive markers of emotional arousal. It modulates the amount of sweat secretion, which is controlled by the sympathetic nervous system and increased when an individual is under mental stress. In [9] smartphone usage is combined with a wrist sensor to collect information from accelerometer data and GSR. In [14] only GSR patterns from a wristband sensor data are used for stress detection, besides they explain the major problems of dealing with GSR data, which is a complex task, and propose simple approaches to deal with them.

Other studies like [4] [8] and [5] combine features from GSR with HRV features extracted by means of wristbands or chest belts. HRV is also controlled by the sympathetic nervous system and altered under acute stress. Analysing HRV temporal, frequency, and non-linear features leads to consistent stress detection, being it also employed to investigate mental disorders. In [1] both smartphone usage and HRV features are used to identify stress in a real work environment within 35 workers. They report how the stress detection is enhanced when adding HRV features to the smartphones features, reaching a 61% of accuracy with the combination of all features for a three-stress level classification problem (low, moderate and high perceived stress).

The consulted literature proves how stress detection is possible using information from physiological signals, sleep, social interaction, location, physical activity, ambient information and behavioural patterns.

2.3. Stress Apps and Machine Learning

All the mentioned studies make use of machine learning techniques to infer the stress state of the users. But, what does it exactly mean?

Machine learning is a branch of artificial intelligence that has its basis on the idea that systems alone can automatically learn from data and, with minimal human interaction, identify patterns on these data and make decisions through building a model from sample inputs [36].

In Shama, our designed application, daily data from the smartphone and the wearable is collected, and further, the selected features extracted from it are analysed by machine learning techniques in order to provide the user feedback about his/her daily stress state, and finally to offer resources to deal with stress if detected, as well as to promote awareness.

Nowadays, we can find quite a lot of stress related apps in the market. As [1] states, they can be categorized into four different classes, according to their functionalities:

- Diaries: to collect subjective ratings.
- Guides: offer tips and tricks to deal with stress.
- Relaxations: techniques to calm down.
- Sensor measures: tracking of behaviour related to stress.

Shama offers a combination of all these functionalities in a unique smartphone application, and additionally, using machine learning it offers a stress detection based on the data extracted from the sensors and the smartphone usage patterns, as will be detailed later in this document.

3. Methodology

In this chapter we detail the methodology followed to acquire the whole design of **Shama**, our smartphone application for stress detection and monitoring, with the aim to help the user dealing with stress and incorporating daily routines for a better wellness, both physical and psychological. The app is intended to be available for both Android and iOS platforms.

Shama is an unobtrusive smartphone application that runs in the background, gathering environmental and behavioural data associated with stress, being this task unperceived by the user. We want to avoid constant questionnaires for user self-reporting during the day, as most of the existing related applications demand, since we could consider them even more stressful and perturbing for the user. Hence, Shama just requires the user to fill one daily survey, every evening, in order to use his daily self-reported stress level as the ground truth data for the stress classification.

After a profound analysis of literature on both stress indicators, smartphone, and wearable based sensing of physiological, behavioural, and environmental features, we started building a theoretical foundation that led us to our own design methodology, described in the following sections.

3.1. Shama Outline

Nowadays smartphones are equipped with a variety of sensors that can continuously track the user and use the gathered information to deduce much about user's behaviour. The majority of the emerging apps for smartphone based stress detection make use of the common sensors in nowadays phones: accelerometer, microphone and GPS; and so does Shama, besides collecting many other phone usage features.

Although several studies have proved that stress detection is feasible by just using mobile phone data, in our project we enhance the application by letting the user wear an optional wrist wearable device, which provides additional data for a more accurate stress inference. Hence, if the wrist device is worn, it provides extra information to be used for stress detection.

Using all the smartphone and/or wearable data collected during the day, Shama provides a daily stress tracking, classifying every day with a "stressed" or "not stressed" label, allowing the user to observe the outcomes in a calendar view through the app interface. In addition, Shama also tracks the user's daily physical activity, as it should be tackled together with mental health, since they are closely related and they impact simultaneously the overall health condition.

All the tasks carried out by the Shama application can be represented by means of the following flowchart diagram, which is detailed in the following sections.

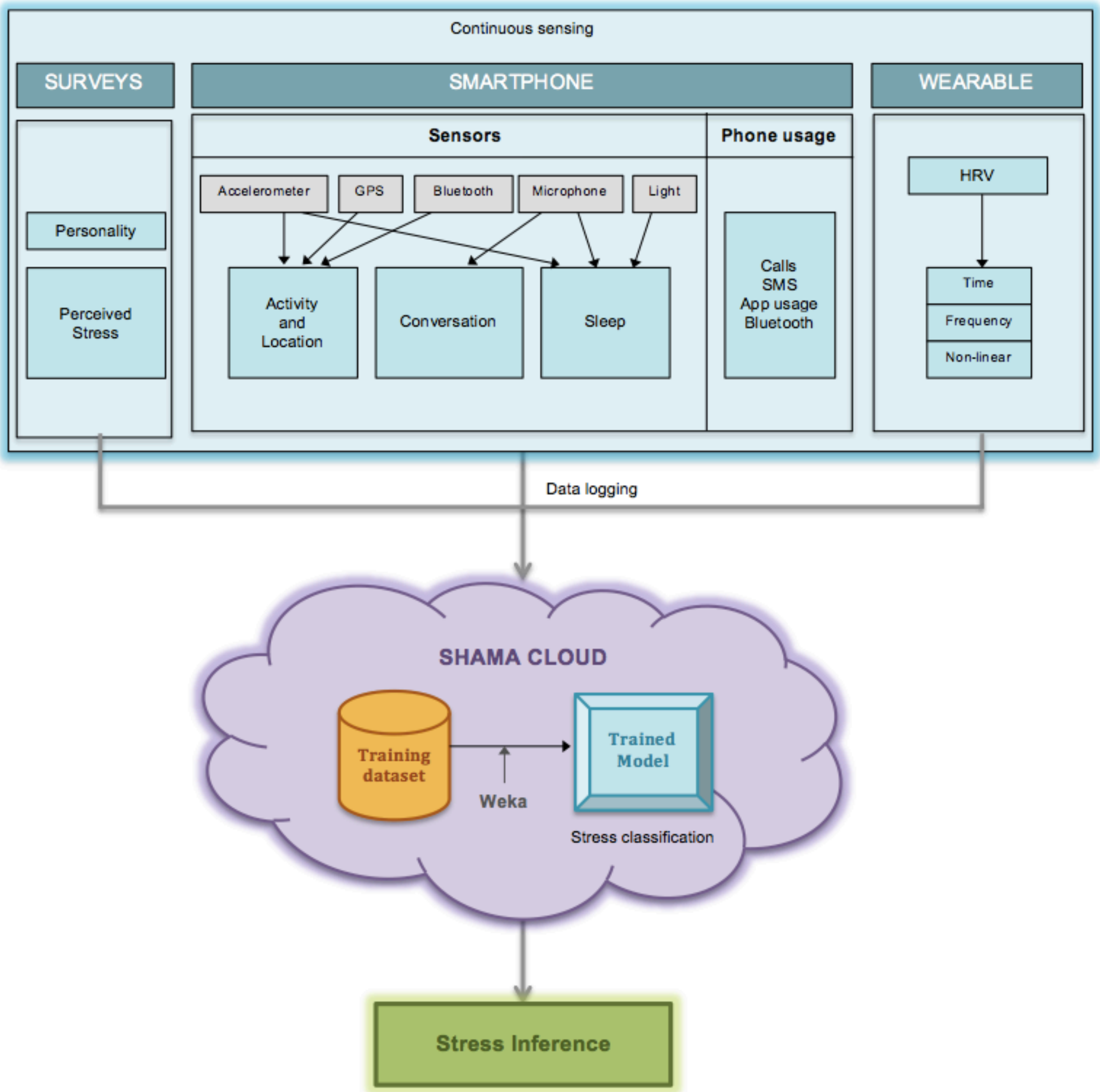


Figure 3: Shama flowchart diagram

3.2. Approach

In order to implement the design of the final smartphone application, a prior substantial amount of work has to be done, taking into account a number of factors and leading to a lengthy study with two clearly defined stages: user's data collection and feature extraction from these data, which will be used for the next stage, the stress detection.

3.2.1. Data Collection

The first and primordial stage is to obtain a dataset for the study development, which will allow the training of the model for stress detection and, essentially, the implementation of the whole app.

In our project, this part is presented in a hypothetical way, due to the previously mentioned material and temporal impossibility of recruiting a proper number of project participants for a real data collection.

To face this issue, we have partially used the information contained on the real and publicly available dataset from the StudentLife study [11], which is a large dataset from 48 students at Dartmouth College over a 10 week term, with the objective to assess their mental health (depression, loneliness and stress), academic performance and behavioural trends (stress, sleep, physical activity, etc.) in response to their college workload. This dataset contains automatic sensor data, educational data and EMA data (self-reported student states through daily questionnaires), as well as pre and post surveys about several aspects of mental and physical health.

In addition to some of the StudentLife dataset information, we add to our own theoretical dataset features from Heart Rate Variability (HRV), measured through the wrist wearable device when it is worn by the user, as will be explained later.

Therefore, our own data collection can be divided into three main groups, considering their source:

- Surveys

  Following many other research criterion [9][11], we decide to use the information provided by surveys administrated to the participants before and after the data collection process of the study. For this purpose, we choose two of the StudentLife dataset surveys information: the Big Five Test and the Perceived Stress Scale (PSS).

  We use the **Big Five Test** as a pre data collection survey. It is a personality model that owes its name to the five personality traits it uses to determine people's personality: Openness, Consciousness, Extraversion, Agreeableness and Neuroticism. Being used in several stress related studies [9][20], it has shown significant links between stress and neuroticism, extraversion and consciousness. People with more adaptive personalities, i.e. with high levels of extraversion and consciousness are more sociable and positive, and consequently less affected by stress. However, people with high scores in neuroticism tent to be more overwhelmed by stressful events. This correlation with stress, already demonstrated in [9] and [20], has been the main reason for incorporating its information in our dataset.

  Perceived stress scale (PSS) has been taken as a pre and post survey, and used as the ground truth for the future stress classification analysis.

  Through 10 questions, this test measures the degree to which situations in a person's life are stressful. It is scored between 0 (least stressed) and 40 (most stressed). Scores between 0-13 correspond to a low stress level, scores between 14-26 to a moderate stress, and scores between 27-40 to a high stress. Taking into account our two-class classification (stressed/not) problem and the bibliography consulted, we will consider that scores below or equal 20 correspond to non-stress and scores greater than 20 reveal a stressed state.

  Besides these two kinds of surveys, every evening Shama asks the user to report his daily self-perceived stress level by the question "*How stressed have you felt today?*" (See Figure 17), and this is daily asked from the study participants during the data collection process.

The user answers choosing from a 7-level scale by a scrolling bar, meaning each level: 1= not stressed; 2= minimally stressed; 3= mildly stressed; 4= neutral; 5= quite stressed; 6= very stressed; 7= extremely stressed.

- <u>Wearable sensing</u>

As explained before, wearable use is not mandatory, however, if it is used, classification inference is improved.

Even though wearables may not be as common as smartphones in our daily lives yet, their use is quite widespread, especially for sport and health applications. Several studies support the use of wearable devices to track physiological features for stress detection. One example is [1], which presents a solution for assessing the stress levels of 35 employees over 4 months, using smartphones during the workday to collect information from audio, physical activity and communication data, and using a chest belt wearable to collect heart rate variability (HRV) data at night, during sleep. In the study they clearly prove that the combination of smartphone and HRV data outperforms the accuracy for stress classification compared to the accuracy obtained by just using one of the two methods. It is also remarkable that using only HRV features they get an accuracy of 59%, while using only smartphone features they get a 55% accuracy.

Considering the work and the results from many other papers that use HRV as a stress related measure, we decide to incorporate HRV features as an extra contribution if the wristband is worn.

For our design we choose the Microsoft Band[2] as the wearable provided to the participants for the data collection, as it is used in several real studies for HRV feature extraction and we found various smartphone applications that use it to extract the same features in which we are interested and for similar purposes, such as HRV Band[3] and Kubios[4]. The features extracted will be detailed later in the document.

Figure 4: Microsoft Band

[2] Microsoft Band: https://www.microsoft.com/en-us/band/techspecs

[3] http://hrvband.de/about.html

[4] http://www.kubios.com/

➢ Smartphone sensing

Apart from wearable sensing, the smartphone automatic and continuous sensing takes the most important part in the user's tracking role. The largest number of features comes from the mobile phone, as it could be expected, since we carry it with us almost the whole day, being it able to tell a lot about our behaviour patterns and daily habits, reason why it is currently used in many study areas as a source of reliable information [37][38][39].

Most of the stress related studies analyse three indicators that are closely associated with stress: physical activity, social interaction, and sleep. Accordingly, in our study we design to collect, through user's smartphone automatic sensing, information about: activity and location (using accelerometer and GPS data), conversation (in real time and space, through the phone's microphone), sleep duration (through light sensor, among others), and also other phone data related to sociability (calls, SMS, Bluetooth scan or application usage information).

3.2.2. Feature Extraction

As explained previously, we derive features from the smartphone, the collected data from the wearable and the surveys are used as predictors to build the stress classification model and discriminate among stressed and non-stressed user states.

In this part we expound the extracted features, as well as their origin and particular estimation. We present the extracted features divided into three main categories, according to their source.

➢ Surveys:

In total eight features are extracted, five from the Big Five survey, and three from the Perceived Stress surveys:

Personality – Big Five Test

- Openness score
- Consciousness score
- Extraversion score
- Agreeableness score
- Neuroticism score

Through the 44-question questionnaire developed by John et al. [29], by means of 5-point Likert scale, the scores on the five traits are computed as the average over the raw scores (inverted when needed) of the items pertaining to each trait. These measures are only taken once, the day prior to study beginning.

Perceived Stress

- Pre-PSS score
- Post-PSS score
- Daily self-reported score

PSS is measured by means of the mentioned perceived stress scale [30], and it is done twice during the study (pre and post data collection), the day prior and the day after the study data collection process.

Besides, the user's self-reported stress is also collected as a daily measure through the app. In this case stress levels are scored from 1=not stressed, to 7=extremely stressed. Scores <= 4 are labelled as "not stressed", and scores >4 as "stressed".

These three stress scores are not used as features themselves for stress classification, but used as the ground truth for the classification problem, as will be explained later in section 4.

- Wearable sensing:

HRV relation with stress has a reasonable explanation. The autonomic nervous system (ANS) regulates the body's principal physiological activities, including the heart's electrical activity. The ANS has two parts: the sympathetic nervous system (SNS) and the parasympathetic nervous system (PNS).

Under acute stress, the SNS increases heart rate, respiration activity, sweating activity, etc. After the stress state, the PNS reverses the stress response and relaxes the body. Since the ANS controls the heart, analysing cardiac activity is an ideal tool for evaluating the state of the ANS, and hence, the stressfulness of an individual. The HRV refers to the beat-to-beat variation in the R-R interval.

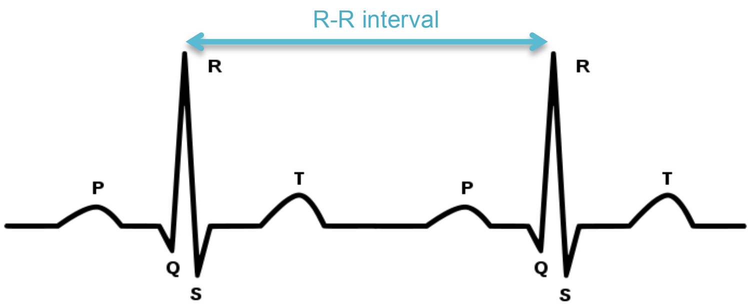


Figure 5: Electrocardiogram (ECG) sample

Literature review [1][5] and [4] revealed that for HRV analysis, a group of specific features are always selected, being commonly present in most of the studies. By means of our selected wearable device, Microsoft Band, all these features can be extracted and analysed, either when it comes to time domain, frequency domain or non-linear features.

Considering that, we choose to extract a total number of 13 features from the HRV collected data:

Time domain

- Mean RR: mean value of heartbeat intervals (ms).
- Mean HR: mean heart rate (beats per minute).
- SDNN: standard deviation of RR intervals.
- RMSSD: root-mean-square successive difference of RR intervals
- pNN50: the percentage of RR intervals with a difference in successive RR intervals greater than 50ms.
- HRV index: total number of RR intervals divided by the height of the histogram of all RR intervals measured on a scale with bins of 1/128s.
- TiNN: triangular interpolation of RR interval histogram.

Frequency domain

- LF: normalized value of low frequency component (0.04-0.15Hz).
- HF: normalized value of high frequency component (0.15-0.4Hz).
- LF/HF ratio: used as an index of automatic balance.

Non-linear features

- SD1: represents the fast RR variability in the HRV data.
- SD2: describes long-term variability in the HRV data.
- SD1/SD2: ratio of short interval variation to the long interval variation.

➢ Smartphone sensing:

As said before, we use the StudentLife dataset [22] as the smartphone data for our dataset.

For feature extraction the StudentLife study makes use of its prior work on the BeWell [15] app and Jigsaw [10]. Jigsaw is a continuous sensing engine for mobile phone applications that require continuous monitoring of human activities and context in order to recognize user's activities, as is the case of Shama.

Jigsaw uses the three most common sensors found on mobile phones nowadays: accelerometer, microphone and GPS, and develops sensing, processing and classification pipelines for all of these sensors. This includes building three classifiers that are then used in the StudentLife study: a physical activity classifier, a sleep classifier and a conversation classifier. These classifiers are, in fact, the ones on which the automatic inference of our app is based, as they let us obtain all the necessary features.

For our smartphone feature selection we took example of a previously published study that uses StudentLife dataset for loneliness detection [17]. We chose the smartphone features selected by them through Principal Component Analysis (PCA) on the original set of features for a feature dimension reduction, considering the high dimension of the initial features resulting from the sensing data.

A total of 21 features are extracted, and we divide them into four main categories:

Activity and location

- Indoor mobility during the day
- Daily activity duration
- Activity duration during the day
- Activity duration during the evening

In order to obtain these features, the physical activity classifier from Jigsaw is used. This classifier extracts features from the pre-processed accelerometer data stream, and then applies a decision tree of depth 7, in particular a J48 classifier using the software Weka, to infer the user's activity as follows:

Inference ID	Description
0	Stationary
1	Walking
2	Running
3	Unknown

Table 1: Jigsaw activity inference IDs [22]

Specifically, Jigsaw extracts 24 accelerometer features from time and frequency domain, and it divides the activity classes (stationary, walking, running…) into subclasses depending on the body location of the phone (lower body, upper body, hand, pocket, bag…) and builds different specific classification models for each subclass, so that the inference robustness is improved. After the classification, a lightweight sliding window smoothing is applied to the output to filter outliers. It must be said that this activity classifier reaches an accuracy of 94%.

Once the activity inference is done by means of the classifier, some extra work has to be done, as what we want to know is the activity duration. The activity classifier generates an activity label ('0','1','2' or '3') every 2 seconds. In order to know the activity duration, we just need to know whether the user is moving or not. Hence, following the StudentLife [11] approach, every 10 minutes period the ratio of non-stationary inferences is computed. If the ratio overtakes a threshold, then that period is considered an active one. So, the daily activity duration is the sum of the 10-minute active periods. And from here, the activity duration throughout the day or the evening can also be extracted.

Regarding the indoor mobility during the day, it is computed as the distance a user (student from StudentLife) travels inside the buildings during the day, by means of Wi-Fi scan logs, as detailed in [11].

Conversation

- Conversation duration
- Conversation duration during the day
- Conversation frequency
- Conversation frequency during the day
- Conversation frequency during the evening

The conversation features are also extracted by the use of Jigsaw's previous work. This time the conversation classifier is used. The phone's microphone captures the audio on the fly as an input, from which acoustic features are extracted. After, an audio classifier is applied to detect human voice, inferring speech segments by means of a Hidden Markov Model (HMM). Then, the output of the audio classifier is used as the input of the conversation classifier, which functioning is detailed in [10] and offers as outputs the number of independent conversations and their duration, by means of which our conversation duration and frequency features can be obtained.

Sleep

- Sleep duration

In a similar way, Jigsaw's sleep classifier is applied to determine the daily sleep duration of the user.

Sleep duration is inferred without any interaction of the user, just by using a sleep model that assumes it as a linear combination of four kinds of features: light features, phone usage features (including phone lock state), activity features (coming from the physical activity classifier) and sound features from the mobile phone's microphone. They [10] state that "*any of these features separately is a week classifier for sleep duration, due to the wide variety of phone usage patterns*". Finally, besides bedtime and wakeup time, the classifier offers as an output the sleep duration.

Phone data

Mobile phone data from calls, SMS, Bluetooth and app usage is also automatically collected daily, gathering a total number of 10 features.

- Calls:
  - Call frequency
  - Call frequency during evening
  - Call duration
  - Call duration during evening
- SMS:
  - SMS frequency
  - SMS frequency during evening
- Bluetooth:
  - Bluetooth frequency
- App usage:
  - App frequency
  - App frequency during the day
  - App frequency during the night

Survey features	
Personality	• Openness score • Consciousness score • Extraversion score • Agreeableness score • Neuroticism score
Perceived stress	• Pre-PSS score • Post-PSS score • Daily self-reported score
Wearable features	
HRV	• Mean RR • Mean HR • SDNN • RMSSD • pNN50 • HRV index • TiNN • LF • HF • LF/HF • SD1 • SD2 • SD1/SD2
Smartphone features	
Activity and location	• Indoor mobility during the day • Daily activity duration • Activity duration during the day • Activity duration during the evening
Conversation	• Conversation duration • Conversation duration during the day • Conversation frequency • Conversation frequency during the day • Conversation frequency during the evening
Sleep	• Sleep duration
Phone data	• Call frequency • Call frequency during evening • Call duration • Call duration during evening • SMS frequency • SMS frequency during evening • Bluetooth frequency • App frequency • App frequency during the day • App frequency during the night

Table 2: Extracted features

3.3. Stress Detection

After data collection and feature extraction, the succeeding step is to build the model that will lead to the automatic stress detection of the user.

Our goal is to estimate the user's stress as an underlying affect, considering its progress along the days, rather than focusing on detecting short period events, but trying to identify a stressful tendency of the user's behaviour patterns in his quotidian life. That is, a robust estimation of daily stress state that serves to indicate when the user's state is shifting from normal.

To do so, we design a stress detection mechanism, which has as input the feature table presented in the previous section (Table 2), coming from the data collected by Shama through the smartphone sensing and the wearable (if worn, otherwise HRV features are omitted).

Shama's stress detection mechanism is composed of two basic software parts, one residing on the phone and the other in the cloud. The one on the phone is responsible for data collection and user stress labelling. The cloud part stores the collected data and the stress model built.

The methodology for the final stress inference acquisition consists of the three stages detailed below.

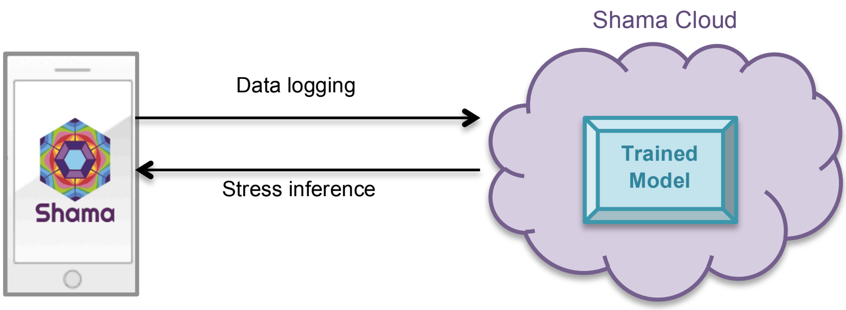


Figure 6: Shama Stress Inference

3.3.1. Data logging

Once Shama application is installed on the smartphone, in order to maintain data privacy, the user has to manually activate the data collection, and it can also be paused at any time. Then, operating in the background, with no user interaction, it periodically captures the sensing information from the smartphone and the wearable. Daily collected data is temporarily stored in the phone, and uploaded to a server (Shama cloud) at night, and only if the phone is being charged and under an existing Wi-Fi connection, to ensure the logging process. Following this methodology, all the study participants' data is daily collected to build our own dataset.

3.3.2. Training Process

Using the feature set extracted from the collected data, our stress classification model is trained with all the participants' data collected in the dataset.

We build a generalized model, in order to reduce the amount of training required and choosing a feasible approach for our study.

Our design generates the stress classification model using the data mining software Weka, choosing as a classifier the Sequential Minimal Optimization (SMO) algorithm with a 10-fold cross-validation, which proceeds as follows: Weka divides the dataset into 10 pieces (folds) and uses 9 of them for training (90% of the data) and 1 for testing (10% of the data), and repeats it 10 times, using each time a different fold for testing. Finally, it runs the SMO algorithm one more time on the whole dataset (100% of the data) to get the final model, a classifier trained on the entire data, which will be the one deployed in practice for real stress detection.

SMO is one of the Weka's implementations of Support Vector Machines (SVM), a machine learning technique which consists on driving a straight line between the two classes (in our case, "stressed" or "not stressed"), taking the perpendicular bisector of the line joining the two support vectors, which are the two critical members for the classification, one from each class. If the classes cannot be separated by a straight line, a device called "Kernel trick" enables SVMs to make boundaries of different shapes by using different formulas for the "kernel". The boundary just depends on a very small number of points in the dataset (the support vectors) and therefore it is not going to cause overfitting, i.e. the classifier will not fit too tightly the training data.

After the training process, the final model obtained is uploaded to the Shama cloud, in order to be used by the phone for later inferring of user's stress.

3.3.3. Stress inference

When Shama application is installed in the user's phone, data from the smartphone and wearable (if worn) will be gathered along the day, temporarily stored on the phone and lately uploaded to the Shama cloud every night, as stated in 3.3.1. At the same time, every evening Shama will ask the user to enter his self-reported stress level, in order to use it as the ground truth, where scores <= 4 are labelled as "not stressed", and scores >4 as "stressed".

Then, using all the daily features extracted from the user as the input, Shama will access the model stored in the cloud to locally infer the user's stress, obtained as a daily output of the stress state of the user, classifying each day into "stressed" or "not-stressed". This result will be presented to the user through the application interface.

Hence, even though the model is stored in the cloud, the stress classification is performed entirely and locally on the smartphone, which prevents data privacy concerns.

3.4. Shama App Interface

Shama is designed to be a user-friendly stress journaling tool, to effectively collect user stress data and provide useful functionalities to users to review their stress history and encourage them to acquire beneficial daily habits for stress coping and minimization.

In this section we present the application interface, illustrating its appearance and explaining the functioning.

Figure 7: Start screen

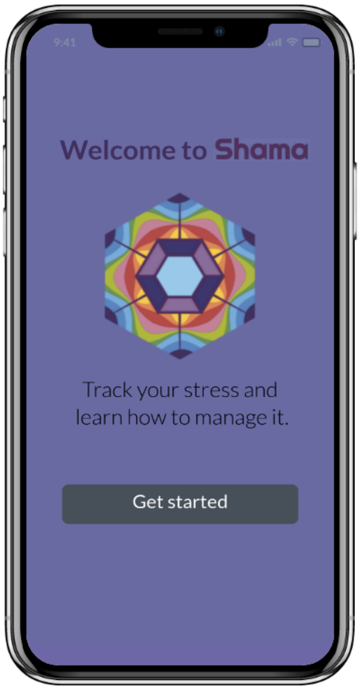


Figure 8: Splash screen

These are the Splash and Start screens, the first views after installing the application.

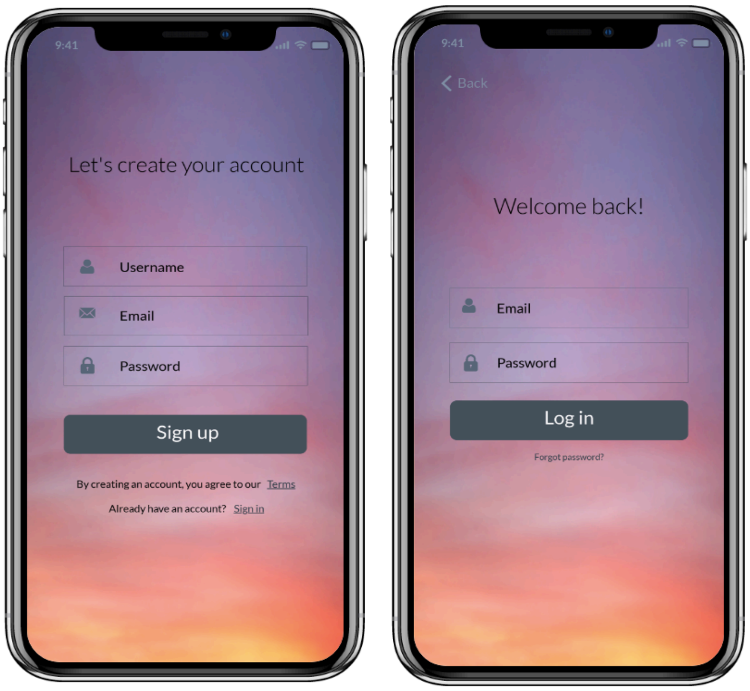


Figure 9: Sign up and Login Screens

Second step after installing the Shama app is to create a user account, introducing a username, an email address and a password by means of the Sign up screen presented on the left. On the right, the Log in screen lets the user enter again his session after logging out.

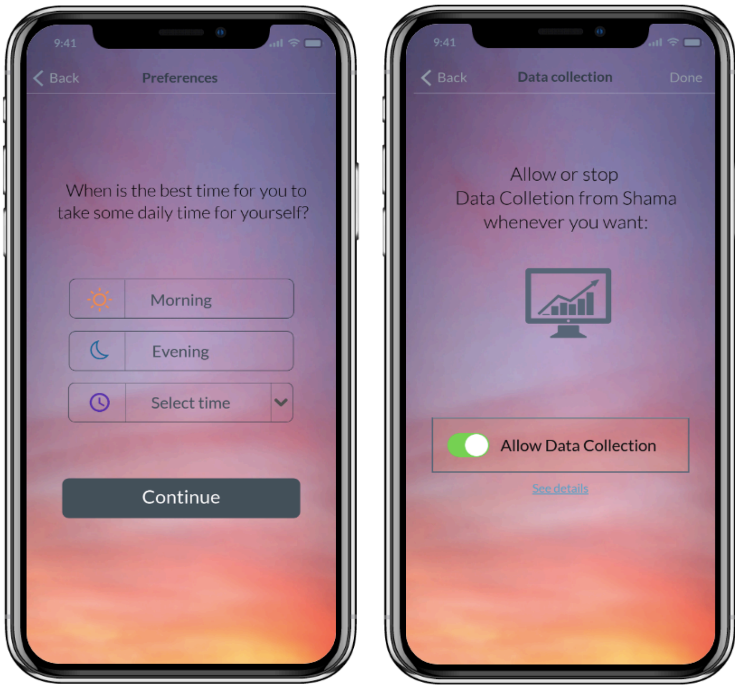


Figure 10: Initial settings

After installing the app and creating an account, the user is asked for the time he prefers to dedicate a daily time to himself and thus receive proposed activities and notifications from Shama. The user can choose between morning time, at the beginning of the day, evening, or rather selecting a specific time using the drop-down tab.

The following step is to allow the data collection from Shama, in order to let it get the information for stress detection from the smartphone. Even presented during the first time the application is used, this screen can be reached in the Settings section of the main menu of the app, so that the data collection can be allowed or stopped by the user at any time.

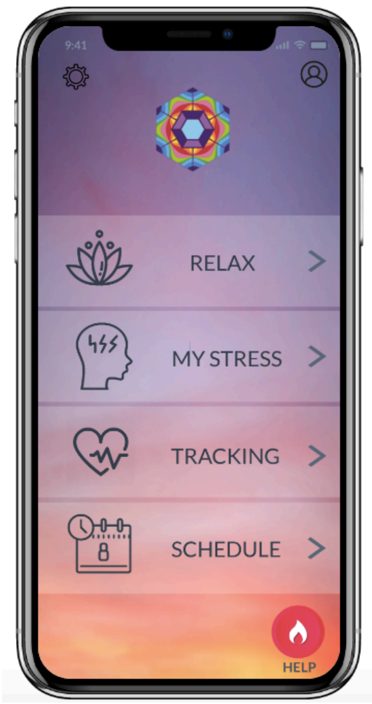


Figure 11: Shama main menu

This is the main menu of the Shama application. On the upper-left corner, the Settings section can be accessed by means of its illustrative button. The same happens for the user's profile in the upper-right part, where account settings and information can be consulted and edited.

The rest of the screen is taken by a four-option menu that leads to the app's main functionalities:

RELAX, MY STRESS, TRACKING and SCHEDULE.

On the bottom-right corner a Help button offers instant help resources for the user in case he wants immediate assistance.

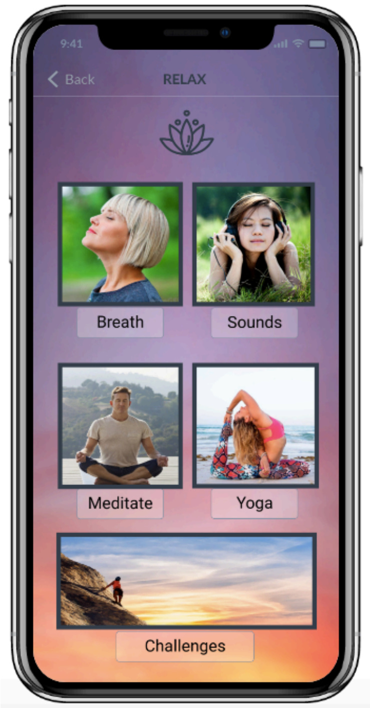


Figure 12: Relax

RELAX is the first option in the main menu. It is intended to be the space for the user to find calm by means of multiple relaxation tools.

Its organized distribution aims the user to clearly visualize the five main resources he can access for stress palliation. These resources, accessed simply clicking on the images or their pertinent labels, are detailed in the following pages of this document.

Figure 13: Relax - Breath and Sounds screens

<u>Breath</u>

In this section Shama provides several breathing techniques, illustrated by videos from professionals in the subject. These videos are designed so that in a short period of time the user can enter in a deep state of relaxation and learn how to listen to and calm the stress symptoms. Each breathing technique is completely guided by the monitor and can be listened with headphones or the mobile speaker with the screen locked if necessary, considering the location and the circumstances surrounding the user.

<u>Sounds</u>

Different kinds of sounds are provided to immerse the user in a calmness environment for a proper relaxation, having at disposal a wide variety of sounds, from natural to instrumental sources.

Meditation

A broad number of guided meditations are available in Shama, all of them presented in a video format to direct the user through the appropriate body position and breathing. The length and the main purpose of each meditation vary, and they are both indicated to the user in the video presentation image to let him choose the most suitable one in every moment.

Figure 14: Relax – Meditate and Yoga screens

Yoga

In a similar format guided yoga practices are offered. It is well known that yoga is a great tool for mind-body connection, providing a number of physical and psychological benefits, such as stress and anxiety reduction, sense of well-being, lower heart rate and sound sleep… which make it indispensable to be integrated in our smartphone application.

Challenges

Challenges are the remaining option of relaxing resources. They are planned to be a journey for a better self-knowledge and reinforcement. This journey can take from 3 days to 1 month, depending on the user's choice or the option proposed by Shama. That is Shama may recommend a specific challenge regarding the user's background of stress detected during a specific period of time.

Figure 15: Relax – Challenges screens

On the right screen we illustrate the internal appearance of a challenge, in particular, the Reduce Stress 7-day challenge. In each challenge daily knowledge information about the challenge related topics is provided to the user in order to increase his awareness, as well as healthy habits like meditations and yoga practices intended to the daily topic goal.

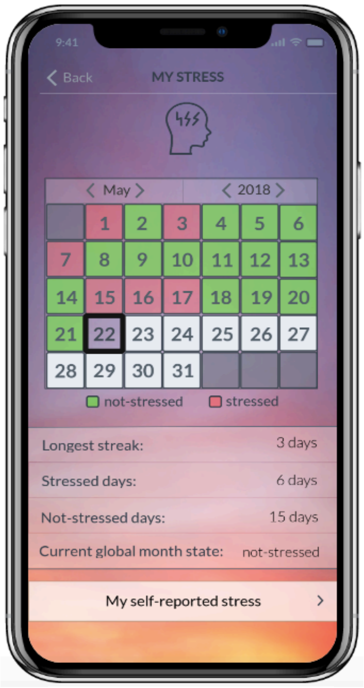


Figure 16: My Stress

MY STRESS is the second option in the main menu. It offers a calendar view of the stressed days throughout the month. Days predicted as “stressed” by Shama are indicated with a red colour, while “not-stressed” days remain in green. The upper month and year selectors allow the access to past stress predictions.

Shama indicates, among other measures, the longest streak, which is the largest number of consecutive stressed days. The lower tab drives to the user’s self-reported stress register, presented in the following page.

Figure 17: Daily Self-Report

The user is asked every evening to enter his self-reported stress level of the day, for both user’s self-awareness and app’s prediction evaluation purposes.

The left image shows the screen that lets the user enter his daily self-report by scrolling the thermometer pointer, from 1 (not stressed at all) to 7 (extremely stressed), being scores greater than 4 considered as stressed.

The right image shows the self-reported stress levels throughout the week, with the possibility of consulting previous entries. The table below indicates the matches between the daily stress prediction from Shama and the self-report from the user. The bottom button leads directly to the Daily Self-Report screen on the left.

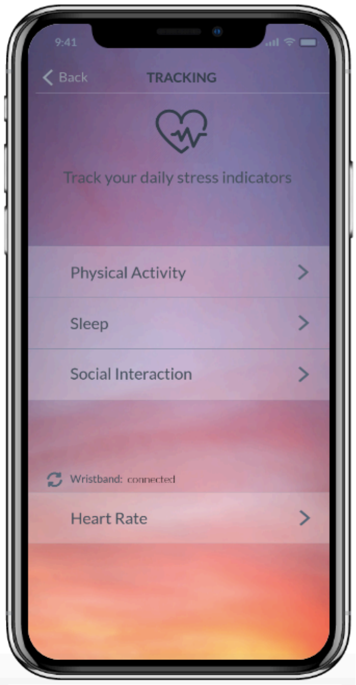


Figure 18: Tracking

TRACKING is the third option in the main menu. As its title suggests, this Shama functionality aims to daily track the user's main indicators on which the stress detection mechanism us based: the physical activity, the hours of sleep, the social interaction and the heart rate.

The three first indicators are always tracked on the background, as long as the user allows data collection from Shama (Figure 10). The heart rate measurements, however, can only be tracked if the user wears a wristband. In that case, HRV features are added in the feature table for stress classification, and the user's heart rate is displayed on the screen. Otherwise, HRV features are not used for the stress classification problem nor visualized in the app.

Figure 19: Tracking – Physical Activity and Sleep

<u>Physical activity</u>

On the upper part the active minutes per day are shown in a weekly view, making the user aware of his weekly amount of physical activity. This amount presented in the chart is the total activity per day, which can be seen at the bottom of the screen, being it the sum of the "walking/running/unknown" activities movement. These three options, plus the "stationary" state are the four inferences in which the StudentLife [11] activity classifier labels the user's activity along the day, and therefore the information available in their dataset.

<u>Sleep</u>

In a similar way, the outputs from the StudentLife sleep classifier are shown daily, indicating the total sleep of the previous night, and presenting the week's results on the chart, suggesting in green the appropriate range of daily sleeping hours.

Figure 20: Tracking - Social Interaction and Heart Rate

<u>Social interaction</u>

Social interaction is also a powerful indicator of stress levels. Shama internally uses user's conversation, calls, SMS and Bluetooth features for stress classification. However, in this section of the app we choose to daily show the user only three of them, but to assign each day a social interaction level (low/mid/high) considering all the internally used features.

<u>Heart rate</u>

When a wristband is worn, user's heart rate (beats per minute, bpm) during the day can be seen at the bottom, together with the review of the minimum, maximum and the average bpm of the day. The later measurement is presented on a weekly chart at the top.

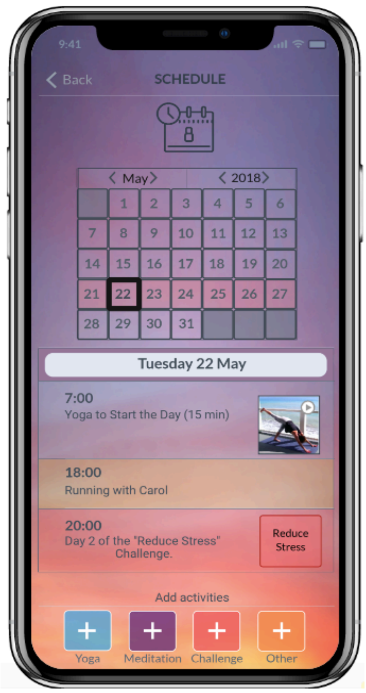


Figure 21: Schedule

SCHEDULE is the last functionality in the main menu of the app. Its aim is to be a very functional tool for the user to organize his everyday life and reserve a daily time to take care of his overall health, making him conscious of the importance of having this time to disconnect from the daily responsibilities and cumulative situations that may be the stress causes.

The user can directly add to the calendar, at the desired time, yoga, meditations and challenges included in the app by means of the bottom buttons, as well as personalized activities or entries using the button "Other".

When a challenge is added, the corresponding days are marked with a red shadow on the calendar, as shown in the screenshot. Besides, the day number of the challenge is shown on the current day schedule, which can be accessed just by clicking the challenge icon, and the same applies for the yoga and meditation booked activities. For all the programmed activities Shama sends a previous notification to remind them to the user.

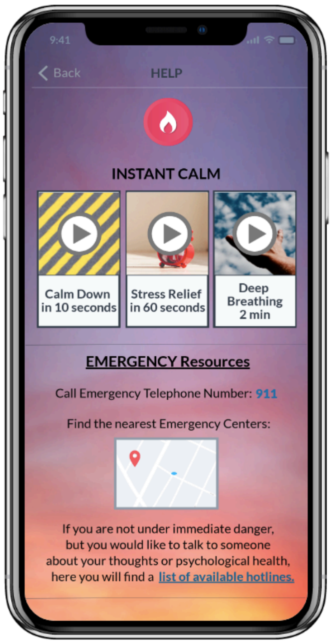


Figure 22: Help

The HELP section is also accessed through the main menu of the app, by clicking the bottom-right red button.

Although Shama already offers a wide amount of relaxing techniques through breathing, meditations and yoga practices, this resource is designed to be an emergency supply for users when feeling dominated by high stress levels and needing immediate help. In the upper part, Instant Calm techniques for rapid stress palliation are given, all intended to calm down the user in the shortest time possible, from 10 seconds to 2 minutes.

While Shama is designed to offer the user a stress detection and monitoring for coping its effects at short and long term, we want to emphasize the importance of being aware of one's self mental health and contacting healthcare professionals when feeling permanently coexisting with stress or anxiety. Therefore, we provide an Emergency Resources section to find professional help, containing a list of available hotlines to speak with qualified professionals, as well as a browser to find nearby emergency centres and the direct link to call the Emergency Telephone Number 911.

Figure 23: Daily Self-Report notifications

On the screenshots above we present the daily notifications sent every evening to the user in order to make sure he enters the self-reported stress level of the day.

The left image shows the notification received when the smartphone screen is locked. The middle one shows how the notification persists when the phone is unlocked, and by clicking "Enter" lets the access the Shama application to directly introduce the Self-Report through the thermometer screen (Figure 17). In case the user selects "Cancel", the notification disappears, but when opening Shama in a future time before midnight, it will re-appear on the main menu to remind the user again, as shown on the right image.

Figure 24: Stress detected and consequent advice notifications

When a stressed day is detected, the following morning Shama sends the user a notification, proposing activities to deal with it (left image). When entering Shama (right image), the user can see the recommended activity and access it by clicking "Go!" If the user refuses the notification, another one will be sent to him at the desired time selected by means of the initial settings (Figure 10) (which can be edited in the Settings section), in order to encourage him to take daily actions for stress management.

Figure 25: Advice notifications

If Shama detects that the user has been stressed for 3 consecutive days, it sends a notification proposing to join some of the Challenges, in order to help the user create consistent daily habits for the betterment of wellness.

If the stress is detected during a whole week, Shama throws the notification shown on the right image; advising the user to follow the daily proposed activities and recommending him to consider asking for psychological support from a professional if needed.

Note: all the Shama notifications can be disabled from the Settings section.

4. Results

In order to partially validate our application proposal and its internal mechanism for stress detection, we made use of the StudentLife dataset [11][22] to gather some of its information and build our own dataset for the classification problem.

For this purpose we used Weka. Weka is open source software that contains machine learning algorithms for data mining tasks, including tools for data classification that can be directly applied to a dataset or called from a Java code.

Considering the magnitude of the StudentLife dataset and the fact that in most of the cases the information provided is separated into different .csv files per each user, and the information provided is data from sensors and complex to interpret, we selected just some features from our feature table (Table 2) to validate the stress classifier design using Weka.

The StudentLife study, among other published studies, identified a strong correlation between automatic sensing data from the smartphone and the perceived stress scale (PSS) measured with the pre and post surveys that we also decided to incorporate in our study. In [11] the authors report a number of significant correlations between sensor data and PSS, using Pearson Correlation, where r ($-1 \le r \le 1$) indicates the strength and direction of the correlation, and p the significance of the finding.

Table 6. Correlations between automatic sensor data and perceived stress scale (PSS).

automatic sensing data	r	p-value
conversation duration (post)	-0.357	0.026
conversation frequency (post)	-0.394	0.013
conversation duration during day (post)	-0.401	0.011
conversation frequency during day (pre)	-0.524	0.001
conversation frequency during evening (pre)	-0.386	0.015
sleep duration (pre)	-0.355	0.024

Figure 26: StudentLife correlation analysis

The table above, extracted from the study paper [11], shows the most significant features in terms of correlation with PSS scores from pre and post surveys. From it we can see that:

- Conversation duration and frequency are negatively correlated with **post**-perceived stress.
- Conversation frequency during the day has a strong negative correlation with **pre**-perceived stress. Besides, conversation duration during the day has a strong negative correlation with **post**-perceived stress.
  This means that users with more frequent and longer conversations during the day are less stressed.
- Conversation frequency during the evening is also negatively correlated with stress. Meaning that users with more conversation during evening also feel less stressed.
- And finally, sleep duration is also negatively correlated with stress: sleeping more hours contributes to lower stress levels.

Taking into account this information we decided to choose these features for our app partial validation with Weka. Therefore, we built our dataset for Weka, extracting the mentioned features from the StudentLife dataset files.

Conversation information in StudentLife dataset is presented as an individual .csv file for each participant, with the timestamps corresponding to the start and the end of the conversations in which the user was involved during the whole 10-week term of data collection in the real study. The study was conducted in the Easter Time Zone (UTC-4h), so we assumed this time difference to select among every file, the total number of timestamps corresponding to a whole 24h day cycle. And from them, we computed the 5 conversation features for each user.

- Conversation duration: duration in minutes along 24 hours.
- Conversation duration during day: in minutes, from 9am to 6pm.
- Conversation frequency: number of conversations along 24 hours.
- Conversation frequency during day: from 9am to 6pm.
- Conversation frequency during evening: from 6pm to 12am.
- Sleep duration: in hours (night corresponding to the conversation collection day).

For the remaining feature, the sleep duration, we did not have at our disposal the results from the sleep classifier in [10], so we extracted it from the Sleep EMA questionnaires that users are asked during the StudentLife study.

Hence, for each user we gathered these 6 features corresponding to a 24h period, as would be done in our Shama app for the daily stress classification.

In total we were able to built our own dataset with 37 users, taking into account that some users' data was missing. The dataset, adjusted to Weka's format requirements, is a .csv file with 37 instances (users) as rows, and 7 attributes (features) as columns. For the classification model building in Weka, the classifier needs to see in the dataset the ground truth class of each instance as the last attribute (last column).

We designed that for Shama the value of the class, i.e. whether the user's day is stressed ("yes") or not ("no") would be determined by our own statement:

"yes" ←→ average(Pre-PSS score,Post-PSS score)>20 && Daily self-reported score>4

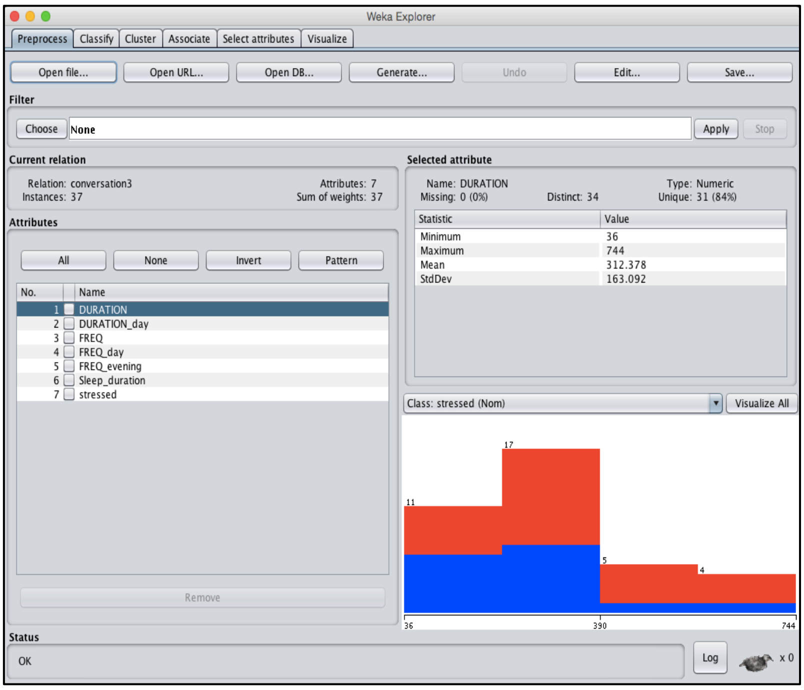
"no" ←→ average(Pre-PSS score,Post-PSS score)>=20 && Daily self-reported score<=4

However, under the impossibility of disposing of the real Daily self-reported scores from the users, for our model training with Weka we just considered the following:

"yes" ←→ average(Pre-PSS score, Post-PSS score) > 20

"no" ←→ average(Pre-PSS score, Post-PSS score) <= 20

Finally, our dataset entered in Weka had the following appearance:



Attributes →

Instances →

No.	1: DURATION (Numeric)	2: DURATION_day (Numeric)	3: FREQ (Numeric)	4: FREQ_day (Numeric)	5: FREQ_evening (Numeric)	6: Sleep_duration (Numeric)	7: stressed (Nominal)
1	570.0	184.0	18.0	13.0	5.0	9.0	yes
2	744.0	347.0	38.0	21.0	12.0	8.0	no
3	403.0	301.0	27.0	9.0	18.0	7.0	yes
4	161.0	113.0	22.0	17.0	3.0	6.0	yes
5	385.0	155.0	39.0	16.0	17.0	6.0	no
6	596.0	327.0	30.0	16.0	14.0	5.0	no
7	476.0	309.0	43.0	15.0	21.0	5.0	no
8	317.0	202.0	28.0	13.0	14.0	8.0	no
9	172.0	124.0	21.0	6.0	14.0	6.0	no
...	425.0	140.0	42.0	21.0	13.0	5.0	no
...	153.0	18.0	22.0	4.0	18.0	8.0	no
...	275.0	133.0	32.0	16.0	16.0	10.0	yes
...	202.0	198.0	28.0	25.0	2.0	1.0	yes
...	235.0	57.0	24.0	9.0	15.0	9.0	yes
...	231.0	147.0	19.0	10.0	8.0	5.0	yes
...	247.0	173.0	24.0	5.0	14.0	3.0	no
...	178.0	89.0	25.0	13.0	5.0	8.0	yes
...	702.0	398.0	39.0	10.0	23.0	9.0	no
...	101.0	6.0	14.0	1.0	11.0	3.0	yes
...	501.0	225.0	30.0	15.0	11.0	8.0	no
...	328.0	226.0	32.0	22.0	10.0	15.0	no
...	271.0	72.0	14.0	5.0	8.0	9.0	yes
...	314.0	180.0	32.0	12.0	20.0	7.0	no
...	36.0	14.0	11.0	7.0	0.0	6.0	no
...	315.0	129.0	52.0	22.0	14.0	8.0	no
...	231.0	161.0	17.0	9.0	7.0	5.0	no
...	315.0	155.0	41.0	22.0	18.0	8.0	no
...	159.0	96.0	28.0	17.0	10.0	8.0	no
...	345.0	102.0	30.0	12.0	9.0	3.0	yes
...	125.0	70.0	21.0	9.0	9.0	7.0	yes
...	236.0	36.0	26.0	11.0	12.0	3.0	no
...	206.0	0.0	22.0	0.0	22.0	8.0	no
...	186.0	60.0	17.0	8.0	9.0	8.0	yes
...	341.0	108.0	26.0	6.0	18.0	5.0	yes
...	314.0	175.0	17.0	10.0	4.0	6.0	yes
...	249.0	171.0	27.0	16.0	8.0	11.0	no
...	513.0	205.0	40.0	25.0	9.0	5.0	no

Figure 27: Built dataset views in Weka

We tried out several Weka classifiers, being the following ones the most precise, in ascending accuracy order, and using 10-fold cross validation: SMO, Logistic and Random Forest. In the table below we summarize their classification results.

	SMO	Logistic	RandomForest
Accuracy (%)	72.94	62.16	59.46
Kappa statistic	0.4272	0.1981	0.1315
Mean absolute error	0.2703	0.4161	0.4262

Table 3: Classification results with Weka

The considerably high accuracies acquired by all of them prove how stress can be successfully predicted by means of the selected features. This gives our designed application a reliably stress classification, considering that adding all the features contained in the complete feature table (Table 2) would enhance even more the performance of the classifier.

However, we can see SMO outperforms the other two classifiers, showing a significantly superior accuracy, with the minimum classification error, as well as the highest kappa statistic measure, which indicates that SMO is the classifier with the maximum agreement of prediction with the true class (being kappa=1.0 the complete agreement).

Regarding the results, we decided to choose SMO as the classifier for our 2-class classification problem, and thus the one used to create the classification model of the Shama application. However, as we could just partially validate the whole real feature set, we cannot ensure that SMO would be the most favourable classifier when adding the rest of the features designed to be used for stress classification.

Nonetheless, what we can affirm is that Weka's classifier SMO (Sequential Minimal Optimization) implements Support Vector Machines, an advanced machine learning technique very resilient to overfitting, even with large numbers of attributes, which is the case of our design.

5. Budget

The object of this thesis is neither a real prototype nor real components have been used for its realization, but being it based on a whole design of a smartphone application and all of its associated tasks.

Even though the budget does not contain any material component, we provide the cost of the Microsoft band, which is the wearable device planned to be used for the HRV features in the data collection process for the study dataset formation.

Component	Cost
Microsoft Band 2	120€

The software used for the classification model creation is Weka, which is freely available. Therefore, the only computable cost is the hours dedicated to the thesis, evaluated at an estimated cost of junior engineer (8€/hour).

Task	Total Hours Cost
Degree Thesis Realization	660h x 8p= 5.280€

Table 4: Budget

6. Environment Impact

The tasks that have led to the realization of this thesis may not have a clearly identifiable environmental impact. However, considering environment preservation an extremely important subject, we would like to seize the opportunity of being this thesis based on a design to state some contemplations that should be taken into account for a real implementation of the project.

Nowadays smartphones are not only data consumers, but also data producers, and they are every day more integrated with the Internet, implying that the need of cloud services and the corresponding energy to handle them. IT services now represent 2% of the global carbon emissions, which is approximately the same as the aviation sector. If efficient measures are not applied, those emissions will increase dramatically.

Shama as an app is designed to make use of cloud service, which has a lower environmental cost than traditional IT hardware and software, as by sharing computing resources carbon and energy consumptions are reduced. However, being it an emerging technology, it raises significant questions regarding its environmental sustainability.

Therefore, we aim Shama's app software to be designed and implemented in an optimal way, avoiding long running with high memory and processing requirements in order to reduce energy consumption. In the same way, we focalize the cloud service used to be powered 100% by renewable energies and to be settled on a Green Cloud framework.

7. Conclusions and future development

We present the design of Shama, a smartphone app that combines data logging from smartphones and wearables for user's stress detection and further monitoring.

To partially validate this design we use the freely available dataset from StudentLife, a study using smartphones that collects data from students during a 10-week academic term with the purpose to relate the sensor data gathered to the students' mental health and academic performance. In the study they discuss the strong correlations between objective sensor data and perceived stress, among other measurements.

In our study we select some of these data to create a 37-user dataset and build our own stress classification model with the software Weka, envisioned for the presented Shama design.

After testing several Weka classifiers, we find out that SMO, a support vector machine algorithm, turns out to be the most suitable in terms of classification parameters, reaching an accuracy of almost 73%, which is on average with the results achieved in related published studies. Even the accuracy obtained with the Random Forest classifier, which is around 60%, can be considered a proper one, taking into account that we used a real-life dataset, outside of a laboratory environment and without artificial stressors in constrained scenarios. Besides, it also has to be considered that we built a generalized model, whilst most of the presented studies use personalized or hybrid models.

Concerning the Shama app interface designed, we intended it to be the most functional possible, letting the user know his daily stress state and offering him powerful tools for its coping, and what is more important, helping him build consistent healthy habits to enhance the overall wellness, both psychological and physiological.

Further future work in our project remains open when thinking about ways to improve the results obtained and acquiring a final real implementation of the Shama application.

As mentioned, the classification model built in this project is a generalized one, meaning that aggregated data from all the users in the training dataset is intended to fit any other new user's stress patterns, which despite providing a considerable accurate inference, is not the greatest approach.

Consequently, a future upgrade would be to train personalized models for the users, using feature sets specifically selected for each user. In this context, when a new user would install the Shama app, the generalized model would be used for the stress classification until enough data from the user is collected. At that point, the user's personalized model would be built and used for stress classification, based on the specific user patterns. Just as in the presented Shama design, daily stress inferences would be done, and the daily self-report would also be asked from the user in order to constantly update the models and detect fluctuations in the users' states and obtain higher classification accuracies.

With a view to improve the design in that way, real users' data would have to be collected, both from smartphones and wearable devices, taking the time to experiment with all the features, specially the HRV features coming from the wristband, a fact that has not been possible for this project.

Finally, the farthest future purpose is to make a real implementation of Shama, for both Android and iOS platforms, being able to put into practice all the design work done in this final thesis. Because, although smartphones itself can be considered potential stressors, nowadays they are undeniably present in our daily lives, and exploring their advanced and constantly improved technologies for users' tracking and health enhancement support can be absolutely worthwhile.

Bibliography

[1] A. Muaremi, B.Arnrich, G.Tröster. "Towards Measuring Stress with Smartphones and Wearable Devices During Workday and Sleep". In *BioNanoScience*, 8 May 2013. DOI 10.1007/s12668-013-0089-2.

[2] E. Garica-Ceja, V. Osmani, O.Mayora. "Automatic Stress Detection in Working Environments from Smartphones Accelerometer Data: A First Step". *IEEE Journal of Biomedical and Health Informatics.* DOI:10.1109/JBHI.2015.2446195, 2015.

[3] T. Stütz, T. Kowar, M. Kager, M. Tiefengrabner, M. Stuppner, J. Blechert, F.H.Wilhem, S.Ginzinger. "Smartphone Based Stress Prediction". *Springer International Publishing Switzerland* 2015. F. Ricci et al. (Eds.): UMAP 2015, LNCS 9146, pp. 240–251, 2015. DOI: 10.1007/978-3-319-20267-9 20.

[4] A.Zenonos, A.Khan, G. Kalogridis, S.Vatsikas, T.Lewis, M.Sooriyabandara. "HealthyOffice: Mood Recognition At Work Using Smartphones and Wearable Sensors". *The Second IEEE International Workshop on Sensing Systems and Applications Using Wrist Worn Smart Devices*, March 2016. DOI: 10.1109/PERCOMW.2016.7457166.

[5] F-T. Sun, C.Kuo, H-T. Cheng , S. Buthpitiya, P. Collins, M. Griss. "Activity-aware Mental Stress Detection Using Physiological Sensors". Carnegie Mellon University. Nokia rsearch Center.

[6] H. Lu, M. Rabbi, G.T. Chittaranjan, D. Frauendorfer, M.S. Mast, A.T. Campbell, D.Gaticia-Perez, T. Choudhury. "StressSence: Detecting Stress in Unconstrained Acoustic Environments using Smartphones". *UbiComp '12*, Sep 5-Sep 8, 2012, Pittsburgh, USA.

[7] H. Gimpel, C. Regal, M. Schmidt. "MyStress: Unobtrusive Smartphone-based Stress Detection". *Twenty-Third European Conference on Information Systems (ECIS),* Münster, Germany, 2015.

[8] M. Gjoreski, V.Janko, H. Gjoreski, B. Cvetkovc, M. Lustrek, M. Gams. "Activity and stress monitoring using smartphone and wrist device". Department of Intelligent Systems, Jozef Stefan International Postgraduate School, Ljubljana, Slovenia.

[9] A. Sano, R. W. Picard. "Stress Recognition using Wearable Sensors and Mobile Phones". *2013 Humaine Association Conference on Affective Computing and Intelligent Interaction*, 2013.. DOI 10.1109/ACII.2013.117.

[10] H.Lu, J.Yang, Z. Liu, N.D. Lane, T.Choudhury, A.T. Campbell. "The Jigsaw Continuous Sensing Engine for Mobile Phone Applications". Dartmouth College. *SenSys'10*, November 3–5, 2010, Zurich, Switzerland.

[11] R. Wang, F. Chen, Z. Chen, T. Li, G. harari, S. Tignor, X. Zhou, D.Ben-Zeev, A.T. Campbell. "StudentLife: Assessing Mental Health, Academic Performance and behavioural Trends of College Students using Smartphones". Dartmouth College, The University of Texas at Austin, Northeastern University. *Ubicomp '14*, September 13-17 2014, Seattle, WA, USA. http://dx.doi.org/10.1145/2632048.2632054.

[12] D. Dai, Q. Liu, H. Meng. "Can Your Smartphone Detect Your Emotion?".[Online] Available:https://www.researchgate.net/publication/309437752_Can_your_smartphone_d etect_your_emotion

[13] D. Carneiro, P.Novais, M. Gomes, P.M. Oliveira, J. Neves. "A Statistical Classifier for assessing the Level of Stress from the analysis of Interaction Patterns in a Touch Screen". University of Minho, Braga, Portugal.

[14] J. Bakker, M. Pechenizkiy, N. Sidorova. "What's your current stress level? Detection of stress patterns from GSR sensor data". Department of Computer Science, Eindhoven University of Technology, Eindhoven, P.O. Box 513, 5600MB,The Netherlands.

[15] N.D. Lane, M. Lin, M. Mohammod, X. Yang, H. Lu, G. Cardone, S. Ali, A. Doryab, E. Berke, A.T. Campbell, T. Choudhury. "BeWell: Sensing Sleep, Physical Activities and Social Interactions to Promote Wellbeing". *Springer Science+Business Media,* New York, 2014. DOI 10.1007/s11036-013-0484-5.

[16] R. LiKamWa, Y. Liu, N.D. Lane, L. Zhong. "MoodScope: Building a Mood Sensor from Smartphone Usage Patterns". *MobiSys'13*, Taipei, Taiwan, June 25–28, 2013.

[17] Z. Li, D. Shi, F. Wang, F. Liu. "Loneliness Recognition Based on Mobile Phone Data". *2016 International Symposium on Advances in Electrical, Electronics and Computer Engineering* (ISAEECE 2016).

[18] M. Ciman, K. Wac, O. Gaggi. "iSenseStress: Assessing stress through human-smartphone interaction analysis".

[19] R. Ferdous, V. Osmani, O. Mayora. "Smartphone app usage as a predictor of perceived stress levels at workplace". *CREATE-NET*, Trento, Italy.

[20] A. Bogomolov, B. Lepri, M. Ferron, F. Pianesi, A. Pentland. "Daily Stress Recognition from Mobile Phone Data, Weather Conditions and Individual Traits". MM'14, November 3–7, 2014, Orlando, Florida, USA. http://dx.doi.org/10.1145/2647868.2654933.

[21] StudentLife Study. [Online] Available: http://studentlife.cs.dartmouth.edu/dataset.html

[22] StudentLife dataset. [Online] Available: http://studentlife.cs.dartmouth.edu/

[23] Microsoft Band. [Online] Available: https://www.microsoft.com/en-us/band/techspecs

[24] Kubios. [Online] Available: http://www.kubios.com/

[25] FreeLogoServices. [Online] Available: https://www.freelogoservices.com/

[26] Data Mining with Weka. FutureLearn Course. [Online] Available: https://www.futurelearn.com/

[27] Epoch Unix Time Stamp Converter. [Online] Available: https://www.unixtimestamp.com/index.php

[28] Galvanic Skin Response (GSR): The Complete Pocket Guide. March 15th, 2016. [Online] Available: https://imotions.com/blog/galvanic-skin-response/

[29] John, O. P., Naumann, L. P., & Soto, C. J. (2008). Paradigm Shift to the Integrative Big-Five Trait Taxonomy: History, Measurement, and Conceptual Issues. In O. P. John, R. W. Robins, & L. A. Pervin (Eds.), Handbook of personality: Theory and research(pp. 114-158). New York, NY: Guilford Press.

[30] Perceived Stress Scale. [Online] Available:
https://das.nh.gov/wellness/Docs/Percieved%20Stress%20Scale.pdf

[31] Shama meaning. Dictionary of common Sanskrit spiritual words. [Online] Available: http://www.advaita.org.uk/sanskrit/terms_s3.htm

[32] “Why stress happens and how to manage it”. In *MedicalNewsToday*. Last updated 28 November 2017. [Online] Available: https://www.medicalnewstoday.com/articles/145855.php

[33] “Coping with and Managing Stress”. In *Boundless Psychology*. [Online] Available:

https://courses.lumenlearning.com/boundless-psychology/chapter/coping-with-and-managing-stress/

[34] “11 Ways Stress Affects Survival”. In *Seeker*, by DNEWS. Published 19 July 2011. [Online] Available: https://www.seeker.com/11-ways-stress-affects-survival-1765306912.html

[35] “Facts and figures about stress and psychological risks”. [Online] Available: https://hw2014.osha.europa.eu/en/stress-and-psychosocial-risks/facts-and-figures

[36] “Machine Learning”. From *Wikipedia free encyclopaedia*. [Online] Available: https://en.wikipedia.org/wiki/Machine_learning

[37] V. Berisha, J. Liss. “What if your cellphone data can reveal whether you have almzheimer’s?”. In *Slate*. June 5 2017. [Online] Available: http://www.slate.com/articles/technology/future_tense/2017/06/using_smartphone_data_to_diagnose_health_problems_like_alzheimer_s.html

[38] M. Trucano. “Using mobile phones in data collection: Opportunities, issues and challenges” in EduTech. April 18, 2014. [Online] Available: https://blogs.worldbank.org/edutech/using-mobile-phones-data-collection-opportunities-issues-and-challenges

[39] “Ten Ways to Use Mobiles and Smartphones in Market Research” in Insightrix, posted in Research by Sharday, Agust 14, 2018. [Online] Available: https://insightrix.com/ten-ways-use-mobiles-smartphones-market-research/

Glossary

ANS: Autonomic nervous system

EMA: Ecological momentary assessment

GSR: Galvanic skin response

HRV: Heart rate variability

PNS: Parasympathetic nervous system

PSS: Perceived stress scale

SMO: Sequential minimal optimization

SNS: Sympathetic nervous system

SVM: Support vector machine

WEKA: Waikato Environment for Knowledge Analysis