Patient centered healthcare monitoring in an outpatient scenario

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Abstract—Aging demographic, intermittent treatment and increasing cost of care characterize the current situation that the Healthcare sector is facing. Further, increased access to more sophisticated and cheaper technology, and growing usage of wearable technology sets the opportunity for the development of Healthcare related solutions based on wearable technology that can bring about a positive transformative change in the Healthcare landscape. This study presents the development of an alarm algorithm and the respective monitoring strategy for an outpatient scenario employing wearable technology. This can be achieved through the proposed methods and research fundamentals, which identified the Vital Body Signs (VBSs) and their respective thresholds; and also, through validation tests, specifically a survey conducted among Healthcare experts and the analysis of Health Data sets. These signals by being continuously monitored and analyzed, enable the prediction of Health risk situations prematurely. The VBSs and their respective thresholds were validated, with agreement rates over 71%, enabling the detection of both life-threatening and increased Health risk situations.

Index Terms—Continuous monitoring; Wearable technology; Preventive Healthcare; Alarm algorithm; Vital Body Signs.

1 INTRODUCTION

LIFE expectancy in most countries has been increasing continually thanks to significant improvements in the healthcare and technological sectors. Aging demographic, as a result of decreased birth rates and increasing life expectancy, economic pressures to curb the escalating costs of care and changes in the standard of care demanded by patients imposes severe concerns on the healthcare sector.

The structure of the current medical sector offers only intermittent treatment, where a patient is analyzed sporadically by a doctor and only in case of presence of any clinical condition the patient is treated. Employment of preventive healthcare strategies are beginning to be used, but due to their inherent cost structure, it is difficult for a healthcare provider to set up a cost-effective system (Habetha, 2006). These strategies require continuous healthcare delivery processes, and in the current technological scenario, novel methods are needed to provide continuous healthcare strategies in a cost-effective way. The average European gives their health system a score of six out of ten (Arak and Wójcik, 2017), which demonstrates that the slow progress of the sector makes the average population to be displeased with the health system of their countries.

Unlike the healthcare sector, the technological sector has suffered remarkable advancements. The emerging wireless technology in conjugation with sensor technology allow for continuous sensing, which then can be processed and transmitted to a higher level. These technological innovations in a healthcare scenario can be used for real-time monitoring of VBSs, allowing to remotely assess the health condition of a patient. In the World Economic Forum, futurists were asked about the tipping point that is expected to occur by 2025 and more than a tenth of them had something to do with healthcare (Ornish, 2015).

There are two emerging concepts associated with technology in healthcare: eHealth and mHealth: eHealth is "the application of

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information and communications technologies across the whole range of functions that affect the health sector" (Ornish, 2015). This definition comprehends a variety of digital applications, processes and platforms including Electronic Health Record (EHR) systems, TeleHealth (remote medical consultation), smartphone apps, remote monitoring devices and biosensors, computer algorithms and analytical tools to aid decision making, providing solutions across all levels of the healthcare system; mHealth (mobile health) is considered as a subsegment of eHealth and is the use of mobile technology to support health information and medical practices. This includes health call centers, emergency number services, smartphone apps and wearable medical devices and biosensors. Both concepts are described by Peterson et al. (2016).

Healthcare providers face growing number of major health challenges, which are putting unprecedented pressure on public and private healthcare systems. Digital tools, such as one able to monitor and assess patient's health status outside the hospital/clinical environment, are able to cope with the pressure and to improve the quality of the care provided, enabling more people to have access to healthcare while reducing the costs, overall improving the efficiency of the healthcare services.

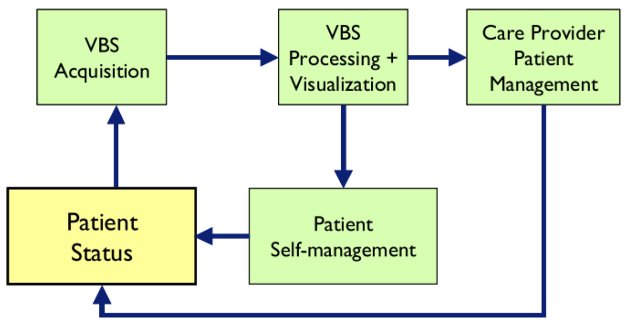

Figure 1. Preventive strategy scheme for continuous healthcare. Source: (Habetha, 2006)

Continuous monitoring systems, illustrated in Figure 1, can be used for helping people lead a healthier life as well as improving the management of medical conditions (from detection to follow-up). Such a system has the potential to modernize the healthcare system and to enable it to cope with future demographic challenges (Habetha, 2006). The capacity for the system to remotely monitor patients makes healthcare more accessible for people who do not have access to healthcare providers in their community or have to travel great distances. It also enables to increase bed availability in hospitals once it is possible to foresee certain medical conditions and act accordingly, reducing the need for hospitalization. As a consequence, it also allows medical staff to have more time to be attentive to the patient's needs, improving the care provided. In critical situation, these systems prevent delays in the arrival of patients' medical information to healthcare providers and reduce the amount of data that has to be manually inputted. Professor Sir Bruce Keogh, Medical Director of National Health Service of England said "...continuous monitoring devices hold enormous promise, and will be an important part of the medical landscape in the very near future. Monitoring of vital signs ... will play a significant role in patient care as uninterrupted monitoring can give insight into a patient's condition in real time".

The amount of data that will be generated/recorded hold the promise of supporting a wide range of medical and healthcare functions, including decision support, disease surveillance and population health management (Raghupathi and Raghupathi, 2014). The adherence of the population to wearable devices capable of measuring VBSs is expected to be around 10% in the US by 2025, which in health terms mean real-time monitoring (Ornish, 2015).

Further, data can be analyzed in order to disclosure hidden patterns and trends, that otherwise would not be discovered or discovered not so promptly, granting healthcare providers more information to diagnose and treat accordingly for a higher quality care at lower costs and with better outcomes overall. The patient's data in a physical examination will be readily available which aided by decision-support systems that also have access to a large corpus of observation data for other individuals, allow the healthcare provider to make a better prognosis for the patient's health and recommend treatment, early intervention, and life-style choices that are particularly effective in improving the health's quality. Further, the data available from patients may be used in conjugation with the costs and outcomes of different procedures to identify the most clinically and cost effective treatment, reducing costs and improving the outcomes. Such a disruptive technology could have a transformative impact on global healthcare systems and drastically reduce healthcare costs and improve speed and accuracy for diagnoses (Hassanalieragh et al., 2015). The employment of mHealth and eHealth technologies have the potential to increase the efficiency of a healthcare system while decreasing costs. By exploiting these technologies it is possible to:

- improve patient diagnosis efficiency (reduce medical errors, reduce repetitive exams;
- improve speed of care delivered (with preemptive measures);
- improve quality of care;
- improve productivity;
- better planning and resource allocation;
- cost efficiency - more efficient health landscape.

The economic effect of the implementation of eHealth and mHealth was studied by Arak and Wójcik (2017). The public health expenditure of most European countries would reduce on average 0.31% Gross Domestic Product (GDP) or 5% less spent on health by the tax payer, while the efficiency increased on average by 5%. Health expenditure and health efficiency were studied in Portugal in 2014, Table 1 and Table 2, and there is a decrease in expenditure with an increased efficiency, proving the positive impact such technologies can have on a healthcare system.

According to the resources available, the depth of applicability of these system varies based on the profile of the healthcare provider:

From the private healthcare sector perspective, these systems will allow to monitor important physiological signs of their patients in real time, assess health conditions and provide feedback, improving the quality of the care provided. They also allow the application of advanced analytics to patient profiles (e.g., segmentation and predictive modeling) to proactively identify individuals who would benefit from preventive care or life-style changes. The value proposition of private healthcare providers through the employment of these system will change considerably, as it will allow to increase the number of patient without increasing the costs per patient, once this technology will operate remotely, and without decreasing the quality of the care provided (one-to-one care maintained). Patients' information will enable creating new revenue streams by aggregating and synthesizing patient clinical records and claim data sets to provide data and services to third parties, for example, licensing data to assist pharmaceutical companies in identifying patients for inclusion in clinical trials (Raghupathi and Raghupathi, 2014).

From the public healthcare sector perspective, these systems will allow to manage the populations' health status from a cost containment mindset, that is, broad scale disease profiling to identify predictive events and support prevention initiatives (Raghupathi and Raghupathi, 2014), reducing overall costs, once it is less expensive to monitor than to treat, and treatment occurs at an early stage which is

Table 1
Portuguese Public Health Expend. & Savings in 2014 due to eHealth and mHealth (% of GDP). Source: (Arak and Wójcik, 2017)

$\star$	$\bullet$	$\circ$
5.90	5.79	5.63

Legend: $\star$ public health spending
$\bullet$ Spending after savings after eHealth implementation
$\circ$ Spending after savings after eHealth and mHealth implementation

Table 2
Efficiency gains per capita in Portugal (2014) due to ePrescriptions and online consultations. Source: (Arak and Wójcik, 2017)

$\star$	$\bullet$	$\circ$
4.10	4.32	4.47

Legend: $\star$ consultation per capita
$\bullet$ consultation per capita with ePrescriptions
$\circ$ consultations per capita with ePrescriptions and online visits.

more effective. Further, big data can be analyzed and trends can be identified, in order to outline more targeted and efficient strategies for containment and treatment.

2 Objectives & Methodology

The objective of this research is to propose a personal continuous monitoring solution for patients outside a clinical scenario. This solution comprises an alarm algorithm and the respective monitoring strategy.

The collected information required for the the alarm algorithm will be defined based on two questions:

- what is the importance of the signal/information for the overall health status assessment of the patient, and is it predictive of an underlying medical condition?
- how is it measured?

The first objective will be to define the minimal set of information based on an extensive research of health signals' nature and associated medical conditions in case of deregulation, considering the preventive purpose of the project.

The following objective is understanding and defining how each VBS is measured and do a market research on the current available solutions for measuring the signals. It is important to analyze the currently available technology and its accuracy, because there may be insightful information in monitoring a specific signal but if the process is not wearable ready or not accurate, it does not meet the requirements for a continuous monitoring device. Consequently, it is important to note that there are signals which are discarded, regardless of their importance, due to the complexity associated with measuring and processing of the data.

Outlining the conditions that cover the two objectives mentioned above, the signals must meet the agreement criteria: The sign must have predictive power, and there must be wearable technology commercially available that can monitor the signal

As any scientific study, the research made must be validated. Consequently, the following objective is to validate the research made in the previous objectives. Once this project is being made in collaboration with a private health provider, it is possible to interview medical experts to understand the opinion regarding this type of innovative health services and the defined minimal set of information for a continuous monitoring solution. Thus, a survey is performed to experts in several medical areas regarding the VBSs, that are going to be continuously measured.

A data set is a collection of data that can be manipulated as a unit. Open Health data sets are freely available data sets that contain anonymous health information about patients' health status in several scenarios. To further validate the defined minimal set of information, Health data sets will be analyzed where the VBSs are characteristics under study.

3 Contributions

With this study, and in line with the motivation and established objectives, an alarm algorithm and monitoring strategy were developed for an outpatient scenario. By employing this strategy and running the acquired data through the algorithm it is possible to:

- Detect life-threatening situations: the detection of life-threatening situations such as hypoxia or extremely low Body temperature, and notification of healthcare experts so that to employ immediate action to prevent major patient harm or even death;
- Detect of increased risk situations: the early detection of increased risk situations, for instance the gradual change of a monitored signal over time, may indicate an underlying condition. This may lead the Healthcare expert to advise the patient to preventive treatment or change an habit that is harmful, and avoid more complex situations.

The ultimate goal is for the algorithm to be able to detect changes prematurely and suggest appropriate therapy, constituting a decision support tool that goes far beyond the scope of physiologic monitoring, that ultimately helps both the care receivers and care providers.

The development of the alarm algorithm and monitoring strategy lays the foundation for the implementation of a platform (Web app and Mobile app) that receives the data automatically from wearable devices, analyzing it in real-time and notifying the patient and the care provider in case there is an Health risk situations. Such implementation is being developed, by the student Miguel Soeiro, and is part of the study of developing a cyber-physical system supporting the research made in this study. This system will encompass the following processes:

- Data Acquisition & Data Transmission: Acquisition of signals through wearable devices and definition of Data Transmission protocols, that are scalable;
- Scalability of the System: The definition of a Database model to store the data acquired needs to be scalable, to be able to adapt to new technology;
- Data processing: Design of the Data Processing components for employment of the alarm algorithm, such as Data analyzing tools;
- Security of the system: Ensure the confidentiality, integrity, privacy, authentication and non-repudiation;
- Compliance with regulations: namely the General Data Protection Regulation (GDPR), to ensure the desired protection level, and to minimize the risk of exposing sensitive data;
- Integration: Development of Integration Protocols to integrate this model with established Healthcare platforms.

4 Methodological procedures

In order to design the result analysis and, ultimately, validate the research made, the methodological procedures were defined. The first methodological procedure is a survey to healthcare providers/experts. The second methodological procedure is the analysis of Health Data set.

The construction of the survey to be answered by healthcare providers/experts has the objective of guiding the research's minimal set of information and validate the model. In order for the data collected via a survey research to be valid, several rules in its design and development must be followed. Kelley et al. (2003) describes the good practices in the conduction and reporting of survey research. The methodological procedure of survey research consists of five broad stages, Figure 2.

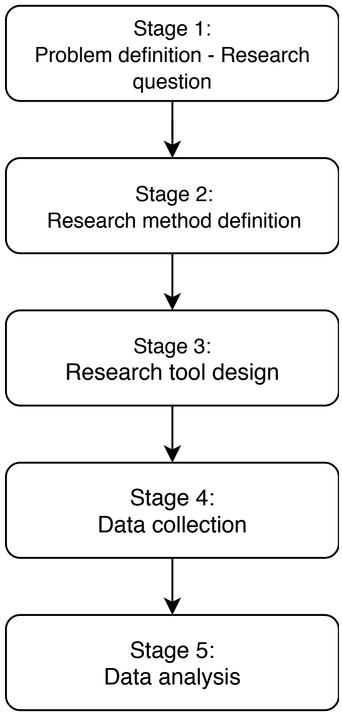

Figure 2. Description of survey research procedure

The analysis will be made under the parameters defined, that is, the patients' characteristics in the data sets will be analyzed under the thresholds defined in order to undercover if there is a relation between the patient health status and a specific characteristic. A Health data set is defined as a set of information which is associated with an end status. For example, a cardiac disease data set records several cardiac parameters and the end status is the presence or absence of cardiac disease. The procedure of analysis will be to isolate each data set characteristics under the thresholds defined and relate it with the end status, undercovering if there is a pattern associated with that specific characteristic and threshold. There are also Health data sets which are made exclusively of subjects with a specific medical condition. By analyzing these data sets, it is possible to understand if the defined thresholds are valid to these specific conditions, or, in case the thresholds are not valid, understand the difference between a healthy subject and one with that specific condition and adapt the thresholds.

5 Results

Based on relevant literature these signs could be determined – Sleep duration, Body temperature, Body Mass Index (BMI), Resting heart rate, Normal heart rate, Blood pressure and Oxygen saturation. For each signal, it was determined how the data is acquired and what the thresholds are from which there is an increased Health risk. The Health risk factors were determined – Gender, Age, Smoking habits, Alcohol consumption habits, Pre-existing medical conditions and Family medical record/history. Regarding the Survey performed, 21 Health experts from different backgrounds/expertise answered the survey, providing useful insights regarding the validity of measuring each signal and if the defined thresholds are appropriate. The minimum agreement rate regarding the validity of measuring a signal was 76%, and the minimum agreement rate regarding the validity of threshold was 71%. Table 3 summarizes the analysis performed.

Table 3
Summary of the analysis of the survey performed to medical experts

Vital body signal	Monitoring	Upper threshold	Lower threshold
Sleep	76%	81%	81%
Body temperature	81%	76%	96%
BMI	76%	88%	100%
Resting heart rate	86%	71%	-
Normal heart rate	95%	89%	-
Blood pressure	89%	76%	-
Oxygen saturation	95%	-	89%

Regarding the Data set analysis method, more than two thousand patients/subjects were analyzed across eight Health Data sets, allowing to validate the minimal set of information and to understand the limitations of the model designed. Table 4 summarizes the most important information and conclusions drawn form the Data sets' analysis.

By validating the minimal set of information and the thresholds, it was possible to develop the alarm algorithm, Table 5 and the monitoring strategy, Figure 3, meeting the objectives defined. By designing a complete and thorough, the alarm algorithm detects life-threatening and increased risk situations, promoting preventive treatment with all of its benefits.

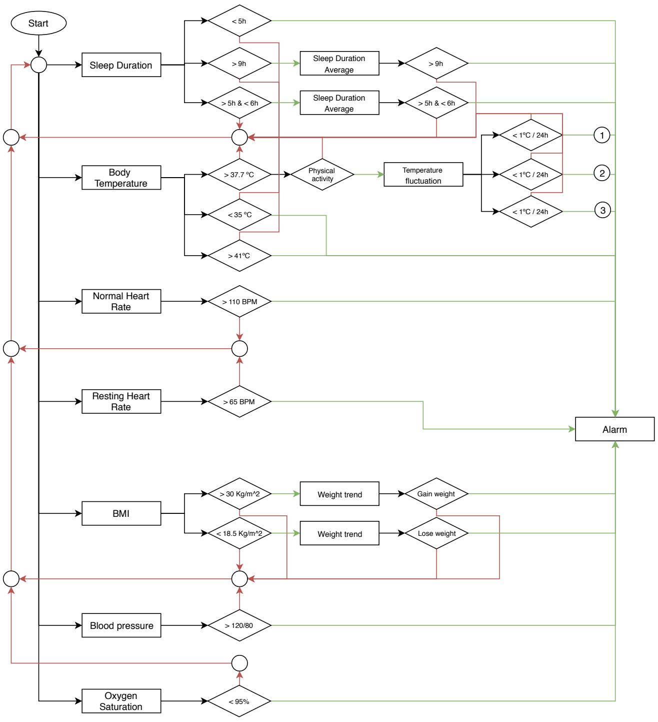

Figure 3. Monitoring strategy for the defined Minimal set of information, for an outpatient scenario. 1 - Continuous Fever; 2 - Remittent fever; 3 - Heat stroke

6 Conclusion

The development of an alarm algorithm and a monitoring strategy was motivated by the increasing pressures the Healthcare sector is facing, the shift in the value proposition of the Healthcare providers and the changing needs the patients are requiring. As such, this model emerged as a patient centered healthcare monitoring solution in an outpatient scenario that addresses all these problems.

Table 4
Summary of the analysis of Health Data sets.
Legend: BP (Blood Pressure); BT (Body Temperature); TSP (Total Sleep Duration); HR (Heart Rate); BMI (Body Mass Index)

Data set	Title	Population size	Charact. analyzed	Signals analyzed	Conclusions
1	Post-operative Patient Data set	90	-	BP BP stability BT BT stability O_2 saturation	BT ↑ ↔ Discharge % ↓ BP ↑ ↔ Discharge % ↓ BP stability ↓ ↔ Discharge % ↓
2	Sleep Stage Data set	12	Age	Sleep stage duration	Age ↑ ↔ TSP ↓ Sleep quality required for accurate analysis
3	Paranoia Sleep Data set	439	Age; Gender	Total sleep duration	Female ↔ Inc. of rel. conditions ↑ Age ↑ ↔ TSP ↓ TSP ↑ ↔ Inc. of rel. conditions ↑ Sleep quality required for a accurate analysis
4	Physical activity monitoring Data set	9	-	Resting HR Normal HR	Physical intensity ↑ ↔ HR ↑ Overly sensitive resting HR threshold
5	University of Queensland Vital Signs Data set	32	-	Normal HR O_2 saturation	Overly sensitive normal HR threshold
6	Statlog Heart Data set	270	Age; Gender	BP; HR	Age ↑ ↔ Heart disease incidence ↑
7	Heart Disease Data set	721	Age; Gender	BP, HR	Age ↑ ↔ Heart disease incidence ↑ Age ↑ ↔ Heart disease severity ↑ Male ↔ Heart disease incidence ↑ Male ↔ Heart disease severity ↑ BP ↑ ↔ Heart disease incidence ↑ BP ↑ ↔ Heart disease severity ↑
8	Arrhythmia Data set	452	Age; Gender	BMI	Age ↑ ↔ Heart disease incidence ↑ Male ↔ Heart disease incidence ↑ BMI ↑ ↔ Heart disease incidence

Sources: (Dheeru and Karra Taniskidou, 2000), (Dheeru and Karra Taniskidou, 2017b), (Attila and Stricker, 2012), (Scott et al., 2017), (Lui et al., 2012), (Dheeru and Karra Taniskidou, 2017b), (Dheeru and Karra Taniskidou, 2017a), (Acar et al., 1997)

The validation of the defined minimal set of information enabled the design of the alarm algorithm and the respective monitoring strategy, meeting the objectives set.

The following objective for future research is to apply the solution and study a real population. In this study, this was not possible as the resources required for the testing of a population were not available. With the development of the platform, a step forward is being taken, that will allow the testing of real patients, ultimately validating the concept and the model defined.

By analyzing the data from the survey and Health Data sets, and from the design of the alarm algorithm and monitoring strategies, the limitations of the model were identified. 27% of the respondents of the survey suggested signs that are not contemplated in this model and are significant considering the monitoring scenario. These signs were identified – Respiratory rate, Electrocardiogram (ECG), Blood glucose level and Sleep quality. All of these VBSs were considered in the preliminary research. However, the Respiratory rate, the Blood glucose level and ECG were excluded once they did not meet the criteria defined, explicitly the criteria that there must be wearable technology commercially available.

Technology is always evolving, and it is expected for new sensors to be develop that enables the continuous monitoring, and consequently, the integration in the alarm algorithm defined. Thus, future upgrades should consider

Table 5
Description of each alarm consisting the alarm algorithm proposed in this model

	Alarm	Value	Description	Alarm type
1	Sleep duration	< 5 hours	The sleep duration is insufficient and impacts negatively the user's health status	🟠
2	Sleep duration	> 5 hours < 6 hours	The sleep duration is insufficient and may impact negatively the user's health status	🟡
3	Sleep duration	> 9 hours	The sleep duration is excessive and may impact negatively the user's health status	🟠
4	Body temperature	$> 37.7\ ^\circ$C	The temperature exceeds the normal physiological state and may be associated with an underlying condition	🟡
5	Body temperature	$> 38.5\ ^\circ$C	The temperature exceeds the normal physiological state and the user may be in critical Health risk	🟠
6	Body temperature	$> 41\ ^\circ$C	The temperature exceeds the normal physiological state and the user is in critical Health risk	🔴
7	Body temperature	$< 35\ ^\circ$C	The temperature is below the normal physiological state and the user is in critical Health risk	🔴
8	BMI	> 30 Kg/m^2	The BMI exceeds the normal physiological state and may impact negatively the user's health status	🟡
9	BMI	> 35 Kg/m^2	The BMI exceeds the normal physiological state and impacts negatively the user's health status	🟠
10	BMI	< 18.5 Kg/m^2	The BMI is below the normal physiological state and may impact negatively the user's health status	🟡
11	Resting heart rate	> 65 BPM	The heart rate exceeds the normal physiological state and may be associated with an underlying condition	🟡
12	Resting heart rate	> 80 BPM	The heart rate exceeds the normal physiological state and may be associated with an underlying condition	🟠
13	Normal heart rate	> 110 BPM	The heart rate exceeds the normal physiological state and may be associated with an underlying condition	🟡
14	Normal heart rate	> 130 BPM	The normal heart rate has an irregular pattern and may be associated with an underlying condition	🟠
15	Blood pressure	$> 120/80$ mmHg	The blood pressure exceeds the normal physiological state and may be associated with an underlying condition	🟡
16	Blood pressure	$> 140/90$ mmHg	The blood pressure exceeds the normal physiological state and may be associated with an underlying condition	🟠
17	Oxygen saturation	$< 95\%$	The oxygen saturation is below the normal physiological state and may be associated with an underlying condition	🟡
18	Oxygen saturation	$< 90\%$	The oxygen saturation is below the normal physiological state and may be associated with an underlying condition	🟠

the technological breakthroughs, applying the research strategy employed in this study, where the predictive power, how the signal is monitored and the threshold values are evaluated. Regarding the Health risk factors, the model designed does not contemplate these factors due to the associated complexity of integration. In order to integrate these signals, each threshold of each VBS would need to be adjusted according to risk levels. Also, the model should consider other factors that are not Health risk factors but influence the threshold values, such as the activity intensity or the menstrual cycle. The monitoring strategy considers if the user is performing physical activity, however the intensity of such activity is not contemplated. It was proven that the Heart rate varies considerably based on the intensity of the activity, and relevant evidence can be extracted from this variability. Other VBSs, such as Oxygen saturation, Body temperature or Blood pressure also vary according to the intensity of the activity being performed, requiring adjustment. The menstrual cycle influences several VBSs, specifically the Body temperature, which fluctuates considerably in this situation, falsely triggering the alarm, once the deviation is not caused by an underlying condition. By introducing a menstrual calendar, the algorithm would be able to adjust the threshold values considering this situation. By correctly adjusting the thresholds for each scenario, the algorithm assesses the behavior of the sings and operates correctly, reducing the occurrence of false alarms. By reducing the occurrence of false alarms, less resources are employed in the monitoring and analysis of alarms, reducing the costs for the Healthcare providers that employ this system.

Ultimately, the stability of the signal over time proved to be a signal itself, that should be considered. In order to introduce the stability factor analysis for each VBS, further research and validation would be required in order to adjust the new algorithm's parameters.

As an added feature, a fall detection mechanism would be relevant to implement in future upgrades. Considering the scope of the proposed system, this signal is outside the ambit (as it is not a preventive monitoring system), but considering that the device will be able to detect physical activity, it is also possible to detect a fall. By detecting falls, a rapid intervention is enabled, reducing the physical and mental damage caused not only by the fall but time after the fall before discovery.

All of the research and analysis performed were used in the development of an alarm algorithm and monitoring strategy that enables the user to continuously monitoring its VBSs, and prevent critical medical situations.

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