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Design of a Telemedicine System to Monitor Sleep Disorders in the Diani Context

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Resumo

Este trabalho teve como objetivo o desenvolvimento de um sistema de telemonitorização do sono, que pudesse vir a ser integrado num sistema de telemedicina já existente, o Diani. O sistema Diani foi desenvolvido pelo o instituto de pesquisa Albertov. É utilizado para finalidades educacionais e de investigação. A sua equipa pretende ser capaz de o usar com pessoas que possam sofrer de distúrbios do sono.

A inclusão de novas variáveis no sistema Diani requer a adoção dos sensores apropriados para a extração dos dados fisiológicos respetivos. A primeira fase do trabalho consistiu em encontrar um dispositivo de uso doméstico que pudesse extrair sinais relevantes para a avaliação do sono, tais como frequência cardíaca, estágios do sono, e eventos respiratórios. O Withings Sleep Sensor foi escolhido porque é fácil de adquirir, não é caro, não é invasivo e fornece uma API pública. Além disso, a tecnologia por trás deste sensor, a balistocardiografia, tem mostrado resultados promissores quando combinada com a actigrafia, algo já em uso no Diani. O desenvolvimento de um programa C# que utiliza a API Withings possibilita a extração das informações de cada noite de sono coletadas com o sensor. Esses dados são armazenados em duas tabelas diferentes do banco de dados do SQL Server, cujo conteúdo é exportado para arquivos .csv. Esses arquivos são analisados com a ajuda de dois scripts Python, que processam os dados e os traçam em vários gráficos, um hipnograma, um gráfico da variação da frequência cardíaca durante a noite, e um gráfico de barras com estatísticas, como o tempo do sono total e cada fase do sono. Foram projetados *mockups* para planear a aparência do sistema para os utilizadores quando este for totalmente integrado no Diani. O sistema proposto pode ser útil na criação de um histórico de sono mais preciso, mostra a qualidade da noite de sono e serve como um guia para o utilizador adquirir melhores hábitos de sono. Tem potencial para ajudar na detecção de distúrbios, como insónia. Como possíveis melhorias futuras podem-se mencionar, a medição da temperatura corporal central e os níveis de saturação de oxigénio no sangue que podem ajudar a detectar outros distúrbios do sono.

Abstract

The aim of this work was to develop a sleep telemonitoring system that could be integrated into an already existing telemedicine system, the Diani. The Diani system has been developed by the Albertov Research Center for research and educational purposes. Their team wants to be able to use it with people that may suffer from sleep disorders. The inclusion of new variables in the Diani system requires the adoption of the adequate sensors to capture the respective physiological data. The first phase of this work was dedicated to find a home sleep-monitoring device that could collect relevant signs for sleep assessment, such as heart rate, sleep stages, and respiratory events. The Withings Sleep Sensor was chosen due to being easily acquirable, not expensive, unobtrusive, and comes with a public API. Plus, the technology behind this tracker, ballistocardiography, has shown promising results for sleep monitoring when combined with actigraphy, something already in use on Diani. The development of a C# program that uses Withings API makes it possible to extract information of each night of sleep collected with the sensor. This data is stored into two different SQL Server Database tables, whose content is exported to .csv files. Those files are analyzed with the help of two Python scripts, that process the data and plot it into several graphics, a hypnogram, a graph of the heart rate variation during the night, and a bar plot with statistics, such as the time of the total sleep and each sleep phase. Some mockups were designed to plan how the system should look to the users when fully integrated into Diani. The proposed system can be helpful in creating a more accurate sleep history, shows how good was the sleep, and can be used as a guide for the user to achieve better sleeping habits. It has the potential to help the detection of sleep disorders, like insomnia. As future improvements on can mention the addition of the monitoring of body core temperature and blood oxygen saturation levels, that could help to detect other sleep disorders.

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Inês Soares Silva

"Life begins at the end of your comfort zone"

Neale Donald Walsch

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Abbreviations

AASM	American Academy of Sleep Medicine
AHI	Apnea Hypopnea Index
ANS	Autonomic Nervous System
ASDA	American Sleep Disorders Association
BCG	Ballistocardiography
CPAP	Continuous Positive Airway Pressure
CPC	Cardiopulmonary Coupling
DM	Diabetes Mellitus
DSWPD	Delayed Sleep-Wake Phase Disorder
e-LFC	Elevated Low-Frequency Coupling
ECG	Electrocardiogram
EEG	Electroencephalogram
EMG	Electromyography
EOG	Electrooculography
ESS	Epworth Sleepiness Scale
HFC	High-Frequency Coupling
HR	Heart Rate
HRV	Heart Rate Variability
ICSD	International Classification of Sleep Disorders
ICT	Information and Communication Technologies
LFC	Low-Frequency Coupling
NREM	Non-Rapid Eye Movement
OSA	Obstructive Sleep Apnea
PACs	Premature Atrial Contractions
PNS	Parasympathetic Nervous System
PSG	Polysomnography
PSQI	Pittsburgh Sleep Quality Index
PVCs	Premature Ventricular Contractions
PVDF	Polyvinylidene Fluoride
REM	Rapid Eye Movement
RR	Respiratory Rate
SE	Sleep Efficiency
SNS	Sympathetic Nerve System
SOL	Sleep Onset Latency
SOT	Sleep Onset Latency
SpO_2	Peripheral Oxygen Saturation
SWS	Slow Wave Sleep
TIB	Total Time In Bed
TST	Total Sleep Time
WASO	Wake After Sleep Onsets
WHO	World Health Organization
WK	Wake Time

Chapter 1

Introduction

1.1 Objectives

The goal of this dissertation was to design a sleep telemonitoring system that could be used to detect sleep disorders that can be related to different clinical conditions. In the future, this system is meant to be fully integrated into the Diani telemedicine application. Diani is a telemedicine application developed by the Research Center Albertov in Prague. It resorts to multiple mobile devices to collect physiological data, that can be analyzed for research and educational purposes. The data is displayed in a Web Dashboard that is built with C#. It stores the information in a web platform displaying it in graphs and tables that can be visualized by both physicians and researchers. So far, the main focus has been patients with diabetes and hypertension. Some examples of studies conducted with Diani were finding the combination of wearable devices that best suits the control of this chronic condition, taking into account the lifestyle, education level, personality type, and other factors; control of patients with hypertension for periods of 3 months, and compare measurements made both in the lab and at home to understand if it is feasible to do a long-term home monitoring.

Sleep disorders appear as a new field of interest to apply Diani. The aim of this research is to understand if it is possible to monitor sleep with the health trackers available in the market, and if sleep disorders can be correctly diagnosed. The development of this system requires, in first place, a study on sleep, its disorders and consequences on health, as well as of the standard methodology being used to diagnose sleep disorders, Polysomnography (PSG). Then, to understand which PSG parameters can be obtained by using only portable devices, and how they can be made relevant for sleep tracking and in what clinical situations this monitoring is most useful. Therefore, it is relevant to start by analyzing what is available in the market having the cost and low obtrusiveness as the main factors to consider in the final device(s) choice. After these studies, the development of the proposed system to integrate the Diani system must start. This includes the processing of the device(s)'s data, which format is going to be used and how it is going to be transmitted and stored in Diani's server. Then, data should be refined. It is necessary to filter the recorded signals and discuss with the main users (researchers and doctors) the best way to present the information. This part of the work should lead to the design of mockups that can serve as a guide for the front-end implementation. The data that is being extracted and processed should be verified with the one shown by the manufacturer of the device. These tasks will lead to the goal of the dissertation, a propose of a sleep telemonitoring system that can be fully implemented by Diani's team into the system that is already developed. This dissertation can add some relevance to the telemedicine field, by supporting that is already possible to have continuous insights into a person's health through the use of portable devices. This is a very promising field that grows at each moment, it can have a tremendous impact on people's life, therefore, is very important to keep developing projects around this topic.

1.2 Motivation

The field of health has always sparked an interest on me. Being one of the primary factors of humans' well-being, it is a great pleasure to be able to have a positive impact on it. Following my university academic path that started with a bachelor degree on Informatics Engineering, it was always of my interest to make an alliance with the knowledge that I was going to acquire in the biomedical field. That is when telemedicine caught my attention. To have the possibility of bringing healthcare closer to the people, making it more available for everyone, was the personal motivation to engage within this work.

Plus, developing this on 2020, when the world stopped due to a pandemic, and we saw ourselves confined to our houses for unlimited period, gave me an understanding that this year is going to mark a major switch to remote health care. Several obstacles can still be found in this shifting of the medical approach, like the technology acceptance being a barrier for some patients. This is also why it is becoming more and more relevant the development of this field, helping to bring telemedicine in the most easier format possible. I'm glad to develop a work that can add relevance into telemedicine field, by showing that is already possible to have relevant information about person's sleep health and alert it of possible disorders without consulting a clinic. For this, I want to focus that this is even possible by using a complete non-invasive system. Is important to note that a system like this does not replace a laboratory but it avoid some clinic appointments and it gives the user a long-term monitoring system. Going back to my personal decisions that made me take this path, I need to return to 2019 when, during a small summer course about Biomedical Engineering held in Prague, I discovered the Albertov Research Center, that focus mainly on telemetrics and biosignals analysis. An opportunity to join their team by developing a telemedicine system for sleep sound very exciting to me. The choice for my dissertation was done, the theme matched my fields of interest, biomedical and informatics, also, the idea of being able to do an Erasmus exchange program added value to me. Besides being able to extend my experience in two academic fields, I learned how to work in a international environment, face all the challenges that moving to a foreigner country comes with and allowing myself to grow as a person.

1.3 Structure of the Dissertation

This dissertation is organized in six chapters that refer the two major components of the work. Firstly, the theoretical foundation and then the development part, followed by the conclusions and future work. This introduction constitutes the first chapter. Chapter 2, 'The Human Sleep', describes how our sleep is characterized in REM (Rapid Eye Movement) and NREM ...

stages, how does these stages progress during a night of sleep, how it is possible to observe and evaluate sleep, and finally what are the influences of this biological function over a person's health, as well as the main existing sleeping disorders. Following to chapter 3, 'Home Sleep-Monitoring Devices', it is exposed the market study over trackers that can be use in a home environment, what each type of device measures and what are their key features, as well as their drawbacks. Chapter 4 regards the developments carried out in this work. It is presented the choice the sensor, the reasons behind them and how the device works. The Diani telemedicine system functionaly and its architecture are described. Lastly, the proposed sleep telemedicine system is explained, the steps for the C# development and the proposed front-end implementation. The final chapter (5) includes the conclusion, where the developed work is highlighted, and what was achieved and the limitations of the work are discussed. Finally, a set of future tasks is proposed to improve further what has been done.

Chapter 2

The Human Sleep

Sleep is a complex and reversible physiologic state accompanied by unresponsiveness to the environment and perceptual disengagement. It is characterized by sequences of stages with related autonomic nervous system functions that are responsible for controlling the unconscious activity of the human body, like regulating heart rate (HR), blood pressure, body temperature, respiratory rate (RR), and digestion, so, sleep has effects over the entire organism [10][11].

Sleep occupies nearly one-third of the life span of each individual. There are two separate systems that regulate our sleep and wake system, to make sure that they keep as distinct episodes: the twenty-four-hour circadian rhythm of the suprachiasmatic nucleus and the sleep-pressure signal of adenosine. Although they are independent, they normally stay aligned according to figure 2.1 [2].

Sleep-pressure builds up during the day, reaches its high peak just before bedtime and decreases during the night [7].

The circadian rhythm functions as our internal clock, organizing our body functions into near-24-hour oscillations making it coordinated with the environmental light-dark cycles. It promotes wakefulness and alertness, that count-reacts with adenosine during the day. When the bedtime approaches, the circadian wake-promoting system begins to decrease, this is when the sleep pressure is higher, these two moments lead to sleep onset[12].

2.1 Sleep Stages

Kleitman is considered the father of sleep, he discovered with one of his students, Aserinsky, rapid eye movements during sleep, in this period the eyes dashed from side to side underneath the lids [13]. Their research was the start for further studies that lead to the conclusion that sleep is divided into two major states: the Rapid Eye Movement (REM), where brain activity is almost identical to the awake phase, and the Non-Rapid Eye Movement (NREM) which subdivides into 4 phases, stages 1 and 2 are known as light sleep and stages 3 and 4 as deep sleep or Slow Wave Sleep (SWS) [2].

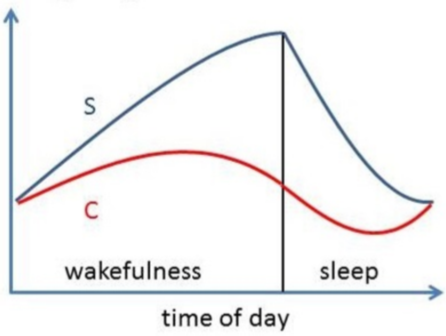

Figure 2.1: Sleep-wake regulation diagram. S represents the sleep-pressure signal conducted by the chemical, adenosine. Its levels increase in the brain through out the day, inhibiting arousal and promoting sleepiness. C represents the circadian system that count-reacts with human's drive for sleep during the day. Sleep occurs when S reaches is high peak and C reaches a low level, then the need for sleep starts to dissipate. (taken from [1])

Nowadays, the most common terminology used for sleep scoring is the one used by the American Academy of Sleep Medicine (AASM), where sleep is divided into 5 stages - awake stage (W), REM stage (R), and the NREM stage that subdivides into N1, N2, N3.

N1 and N2 are considered light sleep and N3 corresponds to SWS or deep sleep. This is the classification that is going to be used in this document [14].

When comparing to the awake state, sleep stages are characterized by several physiological differences that are listed in the following table, 2.1.

Bellow is going to be presented the major differences that characterize REM and NREM, some of their functions, and their time weight in total sleep duration.

Overall, in NREM phase, all of the physiological parameters decrease, which includes HR, RR, body temperature, blood flow, brain activity, and sympathetic nerve system (SNS), to help the body rest. SNS is part of the autonomic nervous system (ANS), that is responsible for sending impulses from the brain and spinal cord to specific organs, controlling them without the person's consciousness. ANS is composed of SNS and parasympathetic nervous system (PNS). The first one is related to physical activity, so it influences physiological parameters that can improve body activity, like increasing the heart rate and expanding the airways for a higher entrance of oxygen. PNS enhances recovery by decreasing HR and RR, therefore, it is associated with rest periods, being predominant in the NREM phase. SNS is activated when the REM phase occurs, this might be related to two things - higher brain activity thus the brain blood circulation is high, and changes of muscle tone where some twitches normally occur resulting in surges of the blood pressure[15][16].

2.1.1 NREM

NREM is composed by different depths, N1, N2, N3, that are distinguish by electroencephalogram (EEG). EEG is slow with high voltage, and muscle tone is present but low [17] The deep sleep is also related to sleep pressure, more hours awake induces more time spent in NREM phase [18]. N1 is the transition state from awake to sleep. It accounts approximately 5% of total sleep time [19].

Table 2.1: Physiological parameters that change during the sleep in NREM and REM phases. Adapted from [7].

Physiological Parameters	Wakefulness	NREM	REM
Airway Resistance	Baseline	Increases	Varies
Respiration Rate	Baseline	Decreases	Varies and it can show some stoppages
Body Temperature	Baseline	Decreases	Varies and it's not regulated, changing based on the environment temperature.
Blood flow to brain	Baseline	Decreases	increases
Blood pressure	Baseline	Decreases	Varies
Brain Activity	Baseline	Decreases	Increases
Heart Rate	Baseline	Decreases	Varies
Sympathetic Nerve Activity	Baseline	Decreases	Increases
Muscle Tone	Baseline	Decreases	Absent, some twitches might occur

If a person doesn't suffer from disorders like narcolepsy, this is first phase of sleep. There is still some awareness of the surroundings, so it's easy to wake up in this state, but there is an increase sensation of relaxation. Some physiological differences are experienced like drop of the body core temperature, slow eye movements and lack of sleep spindles in the electroencephalogram.

N2 marks the real sleep onset is still easy to wake up and it constitutes the majority of total sleep, between 45% to 55% of the time. The muscle tone continues to decrease, as well as the heart rate and blood pressure. The brain activity in this state is marked by K-complexes and sleep spindles, it's hypothesized that the latter is associated with memory consolidation [19].

N3 is known as deep sleep or SWS, and it happens mostly in the first third of the night. The muscle tension is very low in this phase. The heart rate and respiration slow dramatically. Brain activity decreases the frequency of delta waves. No eye movements are reported, and it's difficult to wake up in this state and if it happens the person may feel disorientated [20]. It has an important restorative function in the human body. The immunity system gets stronger, cells are repaired, bone and muscle are developed [21]. Glucose homeostasis is also related to this phase, because there is a reduction of cortisol and sympathetic activity, two factors that when are highly present in the body induce the inhibition of insulin secretion [22]

Neurotoxins are removed from the brain, and long-term memory is improved. Age affects this state, when an individual gets older, less time it is going to be spent here and more time in N2 state [21].

2.1.2 REM

REM is characterized by fast EEG, muscle atonia, and accompanied by dreaming. However, the muscles of the eyes and respiratory system remain active. If the skeletal muscle atonia does not occur, there must be a sign of a REM sleep disorder, where individuals act-out their dreams.

Both the breathing rate and respiration rate increase but with irregular patterns. This phase happens normally after 90 minutes of sleep onset, with the first period taking just 10 minutes, and the final one can reach 60 minutes[21]. REM sleep is considered to be important for memory consolidation, learning ability, stimulation of human creativity, and emotion regulation. It accounts for 20% to 25% part of the total sleep[19].

2.2 Sleep Cycles

For a normal adult, the recommended sleep amount is 7 to 9 hours [23]. During the sleep period, REM and NREM alternate cyclically every 90 minutes, approximately. This fairly predictable progression of NREM to REM phase is called sleep cycle.

During a normal sleep night, 4 to 6 cycles happen, according to the figure 2.2.

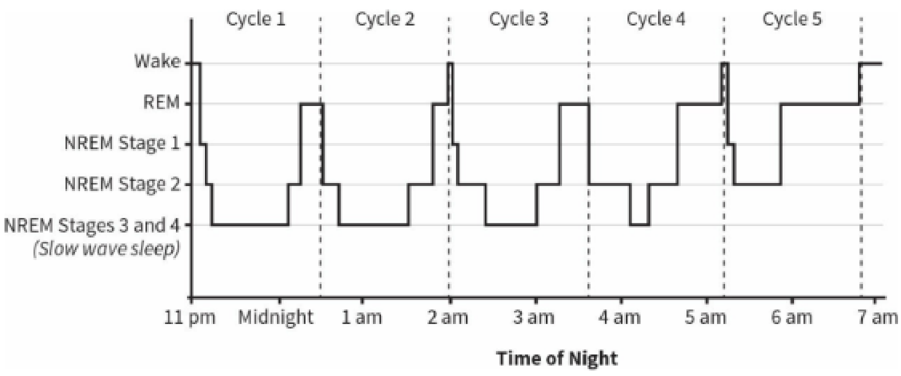

Figure 2.2: Hypnogram that illustrates the sleep cycles through a night of sleep and the sleep stages within each cycle. (taken from [2])

Sleep begins in NREM phase and progresses into is deeper stages. It is considered real sleep onset, the moment when N2 is detected. The awake period normally accounts of 5 % to 10 % of the total bed time, which represents 30 to 60 minutes of an 8h sleep. REM phase represents 20% to 25% of total sleep time, which in an 8h sleep duration, translates to 1.5 to 2 hours. Normally, the REM phase only appears after 90 minutes of sleep onset, reoccurring 90 to 120 minutes later [10][2].

NREM period represents 75 % to 80% of total sleep time, therefore an individual spends most of their time in this phase. N2 takes the biggest part of NREM total spent time, it occupies normally 50%, in an 8h sleep this represents 3h. N3 occupies 12.5% to 20%, which is the equivalent of 45 minutes to 72 minutes, and N1, 30% to 37.5% of time [10].

Brief episodes of wakefulness occur, usually near REM sleep transitions, they don't last enough for people to remember it. REM sleep episodes increase during sleep and are longer in the last one-third of the night. Also with sleep progression in the NREM phase, N2 becomes more predominant and the SWS stage may disappear [7].

Sleep scoring suffers the influence of other biological parameters that faces an inter-individual variance, like age. Changes in the sleep pattern occur after the fifth decade of age - longer sleep-onset latency, advanced sleep times (i.e., earlier bedtimes and rise times), shorter overall sleep duration, higher sleep fragmentation (i.e., more arousals, awakenings, and transitions from deep to light sleep), higher probability of awakening due to external sensory stimuli, reduced amount of deeper NREM sleep, increased time spent in N1 and N2 phases, shorter and fewer NREM-REM sleep cycles, increased duration of the awake periods [24].

EEG complexity increases until 60 years old, especially in SWS, it is recorded faster beta waves and fewer delta waves, after that limit age it tends to become stagnant or to slightly decrease [25].

2.3 Sleep Observation

In this section, it's going to be presented the existing methods used to track sleep. For a better sleep assessment in order to measure its quality or to detect possible disorders, both subjective and objective measurements should be taken into account. The parameters used for screening sleep disorders are further discussed in the following section. There is not an exact definition widely accepted about what sleep quality means. However, the sleep variables that can be involved in the evaluation of the sleep quality normally include [3]:

- Time in bed (TIB): total time spent in bed during a sleep session in minutes;
- Total Sleep Time (TST): defined as the total time spent asleep during the time in bed in minutes;
- Sleep onset: the date-time when the person falls asleep;
- Sleep offset: the date-time when the person wakes up and is not able to fall asleep again;
- Awake time (WK): TIB minus TST;
- Wake after sleep onset (WASO): total time spent in stage W after sleep onset in minutes;
- Number of awakenings: number of events when the person is awake during the night, normally is considered awake events if the person is awake for more than 5 minutes;
- Sleep onset latency (SOL): defined as the time taken till the person falls asleep;
- Sleep efficiency (SE): defined as TST/TIB in percentage;
- REM sleep: percentage of time spent in REM phase compared to TST;
- N1 sleep: percentage of time spent in the N1 phase compared to TST;
- N2 sleep: percentage of time spent in the N2 phase compared to TST;
- N3 sleep: percentage of time spent in the N3 phase compared to TST.

Among all of this, the number of awakenings after sleep onset seems to be the one that has more influence on the sleep quality [3]. To obtain these parameters, and other ones that allow detecting sleep disorders is necessary to use sensors that can track physiological parameters that help to characterize the sleep architecture, as well as subjective methods. Firstly, the objective methods are going to be covered, and then the existing subjective strategies for the sleep assessment. The subjective parameters like self-reports help to create a correlation with the objective parameters. However, it is important to understand that self-reports have less relevance since during sleep the individual can not have a good perception of its behavior due to the lack of consciousness[26].

2.3.1 Objective Measurements

In this section, the objective parameters used to measure sleep are going to be explained. Firstly, it is going to be analyzed the gold standard scientific verification of sleep, polysomnography, including its drawbacks.

Secondly, is going to be discussed the second strategy for sleep monitoring, sleep telemonitoring. In this field, ambulatory commercial devices are used, most of them are not validated as clinical devices but they allow to visualize sleep patterns and habits which may trigger an alert for sleep disorders.

And finally, the main parameters that can be involved in sleep assessment are covered. The parameters typically recorded in PSG are going to be discussed, such as oximetry, airflow, respiration rate through thoracic and abdominal events, and the bioelectrical signals, EEG, EOG, EMG, and ECG. Parameters that gained more interest has the field of sleep telemonitoring grown are also going to be reviewed, like audio, actigraphy, video, body temperature, heart rate, respiratory rate, and ballistocardiography.

2.3.1.1 Polysomnography

The clinical test to evaluate sleep is called polysomnography (PSG). This word means read-out,"graph", of sleep, “somno”, that is made out of multiple parameters, “poly”[2].

Starting with the parameters analyzed in this exam that require the utilization of electrodes that are placed in three different regions: in the brain, to collect the brainwave activity through electroencephalography (EEG); in the eyes, to collect the eye movement activity through electrooculography (EOG), and in the chin or/and legs to capture the muscle activity through electromyography (EMG) [27].

Besides the electrical exams, PSG can also record airflow with nasal prongs, thoracic and abdominal events with respiratory belts, and oximetry [18].

Additional devices can be used, for example, placing another electrode in the chest to measure heart rate through electrocardiography (ECG). The parameters normally recorded in a PSG test are summarized in the table 2.2.

Table 2.2: The physiological parameters that are normally tracked by PSG, with their corresponded method and what they help to identify during the sleep. Adapted from [1]

Method	Physiological Parameter	Identifies
EEG	Brain activity	Sleep stages
EOG	Eye muscle activity	REM/wakefulness
EMG (chin)	Chin muscle activity	REM/wakefulness
EMG (leg)	Leg muscle activity	Movement and posture
Nasal prongs	Breathing pattern	Apnea and hypoapnea
Respiratory Belts	Breathing effort	Apnea type
Oximetry	Arterial oxygen saturation	Level of blood oxygen
ECG	Heart rate	Arrhythmias

Video recording may also be used to track body movement [28]. The clinical assessment requires a minimum of 6 hours of monitoring, different devices attached to the patient, and it is performed overnight. The figure 2.3, illustrates what a typical PSG setup looks like [21].

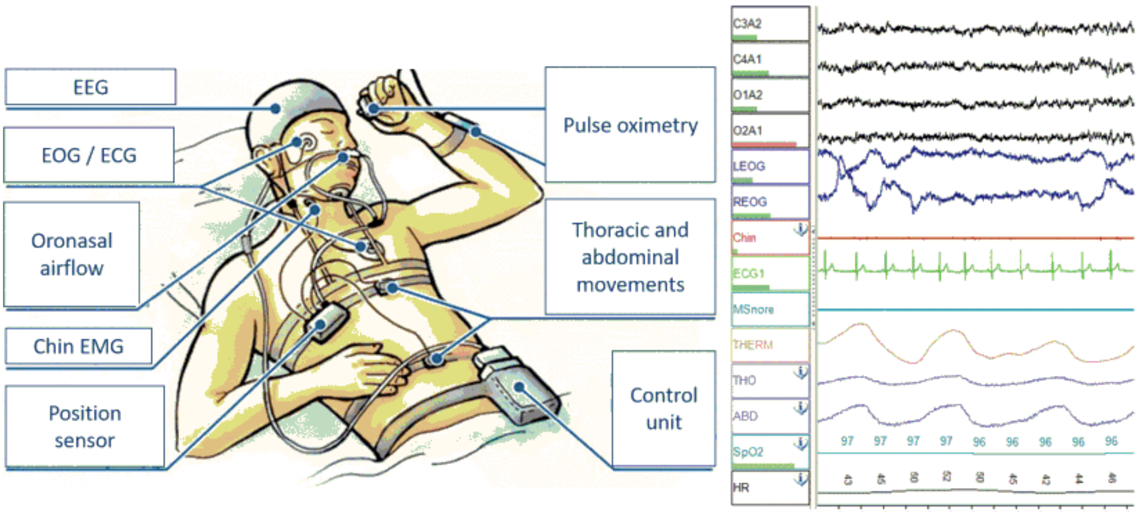

Figure 2.3: The typical setup of a PSG test, as well as the signals that are extracted and analysed by the sleep technicians (taken from [3]).

This assessment is time-consuming, and it is done visually by sleep technicians, though they are skilled professionals it can still introduce subjectiveness. The results can vary between technicians, and there are some limitations on the sleep scoring rules, especially when analysing patients with disorders [29].

There is also another disadvantage commonly associated with this test, called the "the first-night effect". This phenomenon is explained by the cause of the adaptation of the patient to the unrealistic sleep environment of PSG. This reflects alterations in scoring values of the test of the first night, such as less total sleep time and worst sleep efficiency [30].

However, due to the high demands that this exam requires, it is normally limited to a one-night evaluation. So, if the patient feels difficulties in the adaptation to the laboratory environment, despite the high accuracy of the results, there is a high chance that they can be far from the results of normal night sleep [29].

The disadvantages in this exam can be compiled in the following list:

- High costs involved;
- Time consuming, and has often long waiting lists for the sleep labs;
- High complexity, requiring the presence of sleep specialists;
- Record analysis is done visually by the specialists, making room for subjective interpretations between different technicians;
- Obtrusive exam, not fitting in a long-term assessment of sleep;
- Unfamiliar environment that can lead to alterations in scoring values.

Therefore, there is a drive for investing in the sleep telemonitoring field, a topic that is going to be covered next.

2.3.1.2 Sleep Telemonitoring

The term telemedicine (TM) remotes to the 1970s, since then there is not an unified definition, which highlights the fact that is a science still evolving and in continue adaptation to new advancements in technology and to the demands of the societies in health care.

One of the most used definitions is provided by the World Health Organization (WHO), that defines telemedicine as the use of information and communication technologies (ICT) to provide medical care at a distance in order to improve health outcomes. Nowadays, the increasing availability and utilization of ICTs helped TM to grow worldwide bringing significant advantages to the world of medicine [31].

TM can potentially help extend access to healthcare, reduce waiting times for medical visits or investigations, and increase adherence to treatments. The goal in sleep TM is to provide good quality sleep recordings outside the sleep lab. The motivation for this appeared for two main reasons: to provide quick reports resulted in unattended PSG, i.e., performed at home, with reduced costs, and to ensure the quality of those tests by allowing a continuous remote supervising of the records [32].

Therefore, sleep telemonitoring can appear as a solution for addressing the previous enumerated issues of PSG and provide a way for long-term evaluation, the advantages of adopting this type of assessment can be summarized [33]:

- More comfort;
- Cost-saving;
- Possibility of earlier diagnosis;

- Avoid unnecessary medical visits;
- Provide long-term sleep data;
- Can improve adherence to treatments and provide a follow-up.

This strategy of monitor sleep can be done with the integration of sleep trackers and a software to process the data recorded by them.

However, it is still not possible to achieve the same reliability of sleep assessment using wearable devices or home trackers. The pay-off of having cheaper and less invasive solutions is having fewer tracked physiological parameters, which result in less accurate evaluations.

The brain is still the most powerful information source about sleep regulation, yet brainwaves signals are in the range of microvolts, making it more prone to noise and hard to extract in an unobtrusive way.

Hence, most of the trackers approach is to obtain autonomic physiological parameters, such as breathing, body movements, and heart activity. The changes in these parameters are still correlated with the brain and they can be obtained without causing discomfort to the subject, plus the ECG signal is displayed in a higher frequency, milivolts range, making easier its analysis [34].

The most common physiological features extracted using sleep trackers are summarized in the table 2.1.

Table 2.3: The most common types of sleep trackers and the parameters monitored by them.

Type of Sleep Tracker	Physiological Parameter
Fitness wearable or watch	Movement, heart rate and blood oxygen levels (less common)
Smartphone app	Body movement and noise
Mattress sleep tracker	Body movement, heart rate and respiration rate
Rings	Movement, heart rate and blood oxygen levels (less common)
Night stand	Noise, temperature and motion
Sleep Tracking headgear	Body movement, heart rate, EEG

2.3.1.3 Bioelectrical Signals

PSG always includes bioelectrical signal such as EMG, that is used to detect muscle activity where sensors are placed at the chin and legs, it records the level of muscle tone allowing the detection of sleep-onset latency (SOL), atonia in the REM stage or the lack of it when in presence of REM related disorders.

EOG allows the detection of eye movement, two electrodes are placed to record horizontal and vertical movements. This test helps to identify the sleep onset when slow eye movements happen and the REM phase [35][36].

The EEG determines brain activity, being the most important electrodiagnostic for sleep stage scoring. It is categorized by frequency in distinct groups: Δ, θ, α and β, like in the following table, 2.4

Table 2.4: Frequency categories of EEG.

Δ	0 - 4 Hz
θ	4 - 8 Hz
α	8 - 14 Hz
β	14 - 30 Hz

Alpha waves appear when the individual is still awake but is becoming more relaxed, there is a slowdown in both rates of respiration and heartbeat. As sleepiness increases, N1 begins and involves a marked decrease in both overall muscle tension and body core temperature.

The transition of alpha waves into theta waves occur [20] [18]. During N2, theta waves still dominate the activity of the brain, but they are interrupted by brief bursts of activity known as sleep spindles which are related to the replenishment of the learning ability [2] and K-complexes, that can occur in response to environmental stimulation [20].

The REM phase it is impossible to differentiate from the wakefulness state using the EEG alone since the spectral and morphological content is highly similar in both states. Therefore, EOG and EMG are also recorded. The EOG allows the identification of the periodic flicking of the eye muscles during the rapid eye movements of REM sleep. The EMG records the muscle movements, at this phase it is expected a drop in the muscle tone, resulting in a muscle atonia [18].

The appearance of the brainwaves recorded in different sleep stages during an EEG exam is shown in the figure, 2.4

Electrocardiogram (ECG) is a test that measures the electrical activity of the heart. The heart is a muscle that produces electrical impulses in order to pump the blood.

A normal heartbeat is composed of "P wave", blood passing from atria to ventricles, "QRS complex", blood pumped out from ventricles, and "T wave" which is the muscle electrical recovery, when the ventricles are in a rest phase.

Through this exam is possible to detect the heart rate variability (HRV), which revealed to be an important parameter in detecting Obstructive Sleep Apnea (OSA). This parameter is going to be discussed further.

50% of patients with OSA were detected with nocturnal arrhythmias, meaning that the individual is presenting resting heart rate values outside the normal range. The most common type arrhythmias diagnosed were premature atrial contractions (PACs) and premature ventricular contractions (PVCs), but atrial fibrillation and tachycardia were also reported [37].

The normal range for the heart rate is between 60 to 100 beats per minute (bpm), yet during sleep, 40 to 50 bpm is also considered normal. Actually, presenting lower rest heart rates (HR) during sleep is better, it means that your heart does not need to work as much to keep a steady beat. According to Oura, a company that focuses on sleep telemonitoring, the common value for the lowest heart rate reported by the data of its users is 55bpm [38]. It is important to note that

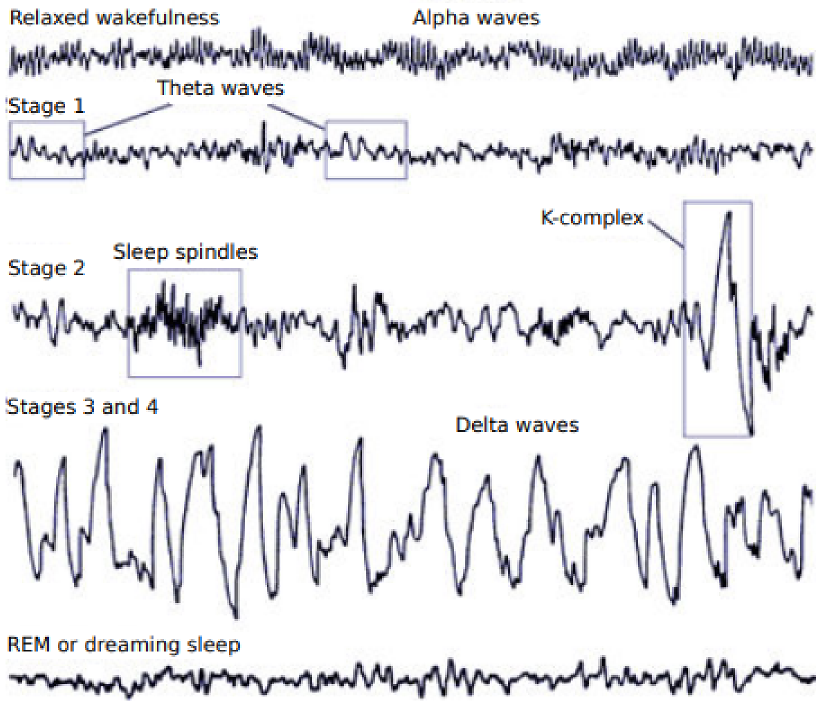

Figure 2.4: The different types of brain waves recorded in each sleep phase. There is a similarity between wakefulness and REM state. NREM is characterized by a gradual decrease of voltage, brain activity is reduced. In N2 there are transient sleep spindles and K-complexes (taken from [4]).

heart rate is influenced by several facts like age, stress, anxiety, and how physically active someone is [39].

In the table 2.5 it is summarized the differences noticed in each sleep stage during the electrical exams involved on a PSG.

2.3.1.4 Ballistocardiography

Ballistocardiography (BCG) is a non-invasive technique that allows the creation of a graph based on the repeated body motions that result from the ejection of the blood at each cardiac cycle. In diastole, there is the relaxation phase, and in systole, the contraction phase occurs.

BCG follows the Newton laws of movement, the contraction of the arteries causes the blood to move, and that acceleration, as well as the heart activity, translates into a force of the same magnitude but in opposite direction [1].

In the 2.5 is illustrated an example of what a BCG waveform looks like. It starts when the atria contracts, right before the ventricular systole. H-K waves correspond to the ventricular contraction. L-N waves correspond to the diastole of the heart. BCG waves are a combination of heart rate and blood flow. 'I' wave occurs right before the blood is sent from the ventricles to the aorta artery, occurring an acceleration of the blood that starts to drop after J wave, when the blood passes the arc of the aorta, changing its direction and decelerating.

Table 2.5: Differences shown in the bioelectrical signs recorded in a PSG - EEG, EMG, EOG.

Sleep Stage	EEG	EOG	EMG
Awake	α waves	Self control	Tonic activity relatively high; voluntary movements
N1	Relatively low voltage; mixed frequencies; θ waves may be highly present	Slow eye movements on sleep onset	Tonic activity weaker than awake stage
N2	Low voltage; mixed frequencies; presence of sleep spindles and K-complexes	Slow eye movements on sleep onset	Weak tonic activity
N3	$20\% \leq \Delta$ waves $\leq 50\%$ with variable amplitude	No activity	Tonic activity
N4	Δ waves $> 50\%$ with variable amplitude	No activity	Tonic activity
REM	Low voltage; mixed frequencies; presence of θ and slow α waves; absence of Δ waves	Rapid eye movements	Atonia; muscular twitches

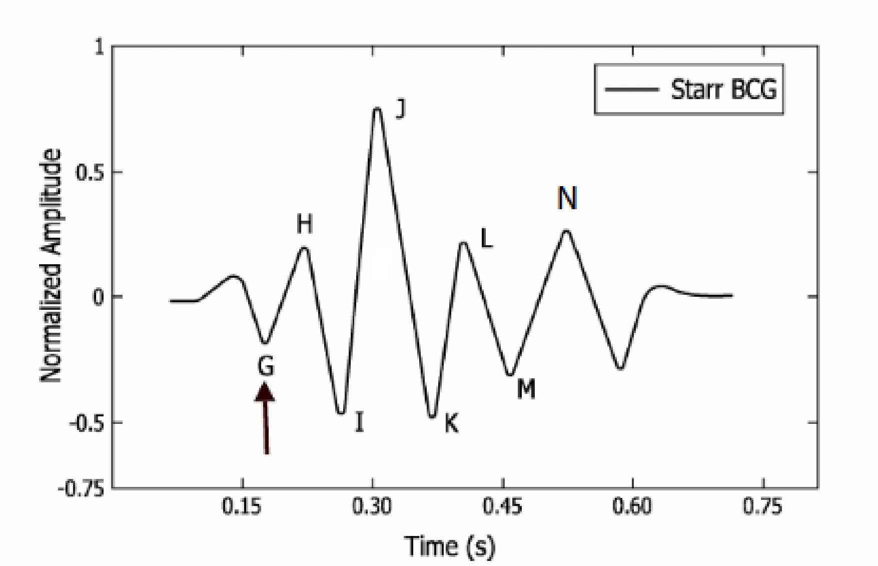

Figure 2.5: Example of BCG pulse, with the maxima and minima denoted with letters from H to N. G corresponds to the moment right before ventricular systole ('QRS' complex in ECG waveform) (taken from [5]).

This method has been a discovery in the late 19^{th} century, however, its application was not approved due to several reasons like a misunderstanding of the BCG waveform, not providing sufficient accurate diagnosis for clinical situations, and a lack of standard methods of measurement. Nowadays, a focus on this technique has been recover due to the emergence of a lot of hardware where BCG sensors can be easily inserted and software solutions that can produce algorithms able to reach meaningful information, like the respiration rate, heart rate, and body movements. This accessibility and ready-availability of information makes it a potential solution for sleep telemonitoring [40] [41].

2.3.1.5 Airflow

Measuring airflow and respiration patterns are useful to check if there any reductions of the air through the nose that can be the cause of sleep breathing problems.

The most precise exams are pneumotachography and body plethysmography, neither techniques are suitable for a routine PSG since they require complex environments that can be intolerable for the patient.

There are alternative options to measure the airflow such as thermistors that produces sinusoidal waves that represent the inspiration and expiration based on the temperature differences of the air. Although they can not provide quantitative measurements, they are a reliable source to determine complete airflow cessations [18]. Overall, this is a parameter quite complex and invasive to measure accurately outside clinical labs, requiring the use of masks or devices attached to nasal passages.

2.3.1.6 Respiration Rate

Respiration rate (RR) is the number of breaths a person takes per minute. For a healthy adult, the rest values are normally between 12 and 20. It can be obtained by counting the number of times the chest or abdomen arises using methods that report movements in these zones like strain gauges, piezoelectric belts, intercostal EMG [18].

There is another method to infer the respiration rate through the analysis of the heart rate. HR increases when inspiration occurs and decreases when the expiration happens. Wearable devices are using optical sensors to capture the heart rate variability through the measurement of the inter-beat-intervals, that correspond to the intervals between each heartbeat, and with this, they normally infer the RR.

2.3.1.7 Oximetry

This test examines the peripheral oxygen saturation (SpO_2), which represents the level of oxygen in the blood. It helps to identify if there are any drops of the supply of oxygen during respiratory-related events [18].

Pulse oximetry provides a non-invasive method to estimate SpO_2, uses the transmission red and infra-red lights through the vascular tissue. The amplitude of these waves changes with the different quantity of hemoglobin present in the blood. From the ratio of these amplitudes is possible to infer SpO_2, at the same time can provide HR estimation [42]. This parameter can support the detection of sleep breathing disorders [43].

2.3.1.8 Audio

This a practical and inexpensive method, audio recordings are useful to identify normal breathing, snoring or obstructive events. It is very common that mobile applications use this feature through internal or external microphones to record the breathing sounds [35].

2.3.1.9 Actigraphy

This technique allows to detect movements and it is normally done by piezoelectric wearable sensors too. The segmentation of sleep-wake happens by scoring the non-movement events as sleep and movement as wake state. It is a simple and non-invasive method commonly present in sleep telemonitoring approach but does not offer the same specificity that PSG offers, for example is not possible to display the different sleep stages with this type of measurement [18]. It gives satisfactory results in detecting sleep from wakefulness, when comparing to PSG in terms of accuracy, the total number of 30s epoch of sleep correctly classified by actigraphy were 86%. The sensitivity, correctly classifications of sleep, was above 90% for almost every participant of the study. The specificity, correctly classifications of wakefulness, the worst result with only 33% . The authors pointed that is still a valid method for estimating the total sleep time and WASO[44] [45]. The most common problem is that since it relies on movement detection it can be easily masked by the lack of movement during a period of quiet wakefulness in the bed, this leads underestimation of sleep onset latency (SOT) and overestimation of total sleeping time (TST) [45].

The results obtained with this method can vary with the type of actimetry sensor used and where is placed, wrist, waist, etc.

2.3.1.10 Video

Video recording appeared as a complementary method to PSG, and it allowed us to detect body and respiration movements at the same time. It's a useful parameter to assess the quality of sleep or to check if the sleep disturbance was real or not. Usually, the recording environment has low light conditions, infra-red-sensitive cameras are normally employed [18].

2.3.1.11 Body Core Temperature

Body core temperature is regulated by the circadian rhythm, increasing during arousal, reaches its peak on the late afternoon, after that continues to decrease through the night, reaching its low point in the second half of the night, between 5-6 hours after sleep onset and before 1-3 hours of awakening. Therefore, the drop in body temperature helps to initiate the sleep process.

Problems like insomnia can be related to a delayed circadian core body temperature rhythm, causing higher temperature values [2] [18].

2.3.1.12 Heart Rate Variability

This parameter has a correlation with the stages of sleep, awakenings, and body movements.

While heart rate focus on the average heart beats per minute, Heart Rate Variability (HRV) measures changes in time between successive heart beats. The time between these changes is referred as "R-R interval" or "inter-beat interval(IBI)".

The heart rate fluctuates, it normally follows a circadian curve similar to that of body temperature. A gradual decrease in heart rate is noticed since the person enters the NREM phase, this is explained by the depression of the sympathetic activity that occurs in NREM. The increase in heart rate occurs when the REM phase is taking place.

HRV analysis consists in assessing the duration it takes between each beat and if there is a variation in this duration overtime. The time interval between 2 beats it is known as R-R interval, or N-N interval, where R is the peak of QRS complex, and N is a normal R peak, it is used just to emphasize that were not recorded unusual situations during the measurement, like arrhythmic events [34].

Some recent wearable devices are using this parameter to score sleep, and even detecting sleep breathing disorders. There is a cyclical variation of the heart rate that is modulated by each breath, making it possible to estimate sleep apnea events by analysing the pattern. To extract that pattern, several methods can be used, the most widely spread are time domain and frequency domain methods. The latter has normally shown better results in scoring sleep stages. It is important to take into consideration that is common to have noise in this electrical signal, especially when it is used devices that do not have direct contact with the person. However, R peaks are the waves that have the highest amplitude and they tend to remain detectable. This is the reason why HRV computation and the analysis of R-R peaks remain feasible in unobtrusive devices [46] [47] [34].

2.3.2 Subjective Measurements

For a good comprehensive sleep evaluation, subjective sleep measures should be included in order to fulfil possible gaps in the understanding of the objective measures recorded.

In this section, sleep diaries appear as the gold standard. Although there is a lack of uniformity in these diaries, they are commonly used in a long-term and large-scale assessment of sleep quality and disturbances [45].

One of the most known model of self-report to assess sleep quality and disturbances in a time frame of 1-month is The Pittsburgh Sleep Quality Index (PSQI). It discriminates poor and good sleepers.

Contains 19 self-rating questions that reflect 7 components - subjective sleep quality, sleep latency, sleep duration, habitual sleep efficiency, sleep disturbances, use of sleeping medication, and daytime dysfunction [48]. In resume, it evaluates [3]:

- Sleep onset;
- Sleep latency;
- Total sleep latency;
- Awakenings;

- Drugs assumption;
- Sleepiness during the day;
- Sleep quality;

As approached in the next chapter, a lot of diagnosis methods of sleep disorders include sleep diaries. One of the drawbacks of this method is that it requires the ability of subjects to remember their past accurately, which can be a challenge especially among the elderly, due to age-related cognitive changes. However, this is something that telemedicine can mitigate. In chapter 4 it is possible to conclude that sleep telemonitoring strategies already calculate the first 4 items with their algorithms. This is typically done by mobile apps and helps in obtaining more accurate sleep diaries.

Regarding the other 3 items, since they are related to the daily life behavior of each person, the best way is to incentive a consistent fill of a questionnaire every day. Nowadays is typical the usage of mobile phone multiple times during the day so a good tool to keep remembering the person to fill the questionnaires would be through notifications.

Overall, the implementation of sleep diaries in form of an app can bring the following advantages:

- Reduce fill time;
- Greater incentive to fill in each day (avoiding the person to fill retrospectively information about previous days at the same time);
- Automatic scoring;
- Automatic recording of the time when the person filled the form;

In a study that compared actigraphy with sleep diaries, there was a poor agreement between sleep quantity and quality, as well as the number of awakenings. The tendency was for participants to subjectively underestimating the number of awakenings. This proves the point that electronic questionnaires help to achieve an improved data collection [49].

Another known standardized questionnaires used for the detection of sleep disorders are Epworth Sleepiness Scale(ESS) and STOP-BANG Questionnaire (SBQ). The first one measures excessive daytime sleepiness and the overall likelihood of a person to fall asleep in several situations. The second one is specific for screening Obstructive Sleep Apnea (OSA). STOP stands for snoring, tiredness, observed sleep apnea, and high blood pressure. BANG stands for body mass index, age, neck circumference, and gender [45].

Due to the existence of many different sleep diaries, sleep specialists have come together to identify the most essential components for sleep self-evaluation and propose a new improved sleep diary. The Consensus Sleep Diary (CSD) was the product of this joint effort [49].

2.4 The Influence of Sleep in the Health Context

Sleep has a big influence on our health, both mental and physical. During a night of sleep, our mind is improving its ability to learn, memorize, make logical choices, and preparing to go through another day of social and psychological challenges, recalibrating our emotions. At the same time, our body is enriching is the immune system, the metabolic state is refined by adjusting the balance of insulin and glucose levels. It helps to develop our gut microbiome which has a very important role in controlling our food digestion. Till the date, there is not known a biological function that does not benefit from a good sleep. This way, sleep is one of the most relevant factors with influence on physical health, covering its influence in the major physiological systems of the human body: cardiovascular, metabolic, immune, reproductive [2]. Sleep related problems are the second biggest cause of seeking medical services, only behind the feel of pain [50]. Sleep deprivation and sleep disorders are associated with chronic diseases, like type 2 diabetes, hypertension and, can lead to heart failure by stroke. Sleep complaints and looking for medical attention are usually associated with poor quality of sleep or insufficient amount of it. Continuity is the indicator that reveals more impact on sleep quality, it is measured by sleep latency, number of awakenings (more than 5 minutes), wake after sleep onset and sleep efficiency [51].

2.4.1 Sleep Disorders

The International Classification of Sleep Disorders (ICSD) has identified over 80 different sleep disorders that are divided into 7 categories [52]:

- Insomnia, persistent difficulty in falling asleep or staying asleep;
- Sleep-related breathing disorders, inside this category there are obstructive sleep apnea (OSA), and central sleep apnea (CSA). OSA is the most common one, making it different from CSA because although the person stops breathing, there is still respiratory effort. In CSA cases, the airflow cessation is caused by the stop of neurotransmitters responsible for the activity of the muscles involved in breathing function meaning that there is no respiratory effort [53];
- Central disorders of hypersomnolence, narcolepsy fits in this category;
- Circadian rhythm sleep-wake disorders, these are further classified as delayed, advanced or irregular sleep-wake phase disorders, jet-lag disorder, and shift-work disorder [54];
- Parasomnias, disorders caused by the activation of nervous system during sleep, they can be categorized by NREM-related parasomnias, REM-related parasomnias, and other parasomnias [54];
- Sleep-related movement disorders, the most common disorder in this category is restless legs syndrome;
- Other sleep disorders that ca not be classified by ICSD. [54]

The most common sleep disorders are OSA, narcolepsy, REM sleep behavior disorder, non-REM parasomnias, restless legs syndrome/periodic limb movement, insomnia, and circadian rhythm disorders [8]. Delayed sleep-wake phase disorder (DSWPD) and shift work disorder are the most commonly seen sleep circadian rhythm disorders. The diagnosis of these disorders is sometimes difficult, requiring a more accurate assessment of the subject's circadian phase. In research situations, body core temperature and the quantity of melatonin in the body is measured [8]. DSWPD appears mainly in adolescents and young adults, is also thought to be account for 10% of patients with chronic insomnia. DSWPD is often misdiagnosed with insomnia. In both situations there is a difficulty in falling asleep but the difference is that in DSWPD, the patient normally reports that he/she is going to bed for environmental reasons, e.g., the need to wake up early for work, and not because they are feeling sleepy [55][56].

In the table 2.6 is summarized a description of these disorders, the symptoms of each one them and possible parameters that can help the diagnosis.

Table 2.6: The most common types of sleep disorders, a description of what they are, their symptoms, and possible parameters that might help in their diagnosis. Based on [8] .

Sleep Disorder	Description	Symptoms	Diagnosis Strategies
Obstructive Sleep Apnea	• Blocked nasal airflows due to the relaxation of the throat muscles.	• Snoring • Hipoxaemia • Gasping or choking • Excessive daytime sleepiness • Large chest motions • Arousals from sleep	• Respiratory Effort (to distinguish types of apnea) - microphone can be used [57] • Sp02 measurement [58] • Airflow - microphone can be used [57] • Body Position - actigraphy can be used [58] • Heart Rate Variability[58] • Diagnosis Requires: Apnea-Hypopnea Index >5/h with symptoms Index > 15/h regardless of symptoms
Narcolepsy	• Neurological disorder that affects the control of sleep and wake periods. • People with this disorder go directly to REM sleep after sleep onset and sometimes when they are still awake.	• Cataplexy, muscles that suddenly became weaker or paralyzed • Excessive daytime sleepiness • Hallucinations when awakening or falling asleep	• Sleep Staging, in particular REM phase. • Sleep Latency, people with normal sleep take 10-20 minutes to fall asleep. With this disorder it can take less than 5 min [59]. • Multiple Sleep Latency Test: Latency < 8 min 2 sleep-onset REM

Continuation of Table 2.6			
Sleep Disorder	Description	Symptoms	Diagnosis Strategies
Insomnia	• Difficulty in falling or staying asleep • It can be acute, happening from a night to a few weeks • Or it can be chronic, where it happens > 3 times/week and > 3 months • It can be linked with other sleep disorders like sleep apnea or restless legs syndrome.	• Sleepiness during the day • Concentration impairment • Mood Disturbance	• Sleep diary • Time in Bed • Total Sleep Time • WASO • Sleep Latency
Periodic Limb Movement Disorder	• Rhythmic movements of the limbs, usually of the legs • Difficulty in initiating sleep due to the above sensations and the urge of moving • Partial or full awakening resulting in a fragmented sleep	• Sleepiness during the day • Insomnia	• EMG - 15/h leg jerks that are accompanied by symptoms.
REM behavior disorder[60]	• Abnormal behaviours during REM phase: talking, screaming, punching, kicking • Occur in later parts of the night • Muscle atonia absent in REM phase, making people to act-out their dreams	• Motor activity during REM phase	• Sleep diary • Actigraphy • Video • EMG

Continuation of Table 2.6			
Sleep Disorder	Description	Symptoms	Diagnosis Strategies
DSWPD	• Sleep occurs systematically later than needed • Sleep length is normal, but sleep pattern is delayed to what is desired or what is considered socially acceptable	• Delay in the sleep pattern compared to the desired sleep schedule • Trouble in falling asleep in the desired time • Difficulty in being awake in desired or socially acceptable time • Having a normal duration and quality of sleep in their own schedule • Report this stable but delayed schedule for > 7 days • Treatment should be sought when the person's lifestyle can't match with the sleep schedule	• Sleep Diary
Shift Work Disorder	• Conflict between the body's circadian rhythms and the work schedule	• Excessive sleepiness • Difficulty in staying or falling asleep • Fatigue • Concentration impairment • Headaches • Mood disturbance	• Sleep Diary

PSG is the traditional diagnostic tool for this sleep disorders but there is a growing development in less expensive and more convenient ways to study sleep, a lot of portable devices capable to measure sleep at home are appearing in the market. The major target of the clinical home testing is sleep breathing problems, but it can be beneficial for other disorders [61].

Most of the sleep related researches has OSA and insomnia as central themes. Insomnia hits approximately 30% of adults, being the most common sleep disorder among the general population, the symptoms normally reported are difficulty in staying asleep, long sleep onset latency, waking up too early, non-restorative or poor quality sleep [62] [63].

OSA is the most common sleep breathing disorder, and is normally associated with other medical complications like hypertension, atherosclerosis, stroke and insulin resistance [64]. The characteristics of people that are more prone to be affected by this condition are suffering from obesity, having more than 40 years old, having a large throat diameter, having tonsils, suffering from gastroesophageal reflux, allergies or sinus problems. It is also more prone to happen in men. This disease is caused by the relaxation of the throat muscles which block the airways. It is characterized by partially, hypopnea, or completely blocked airways, apnea. The first scenario is considered if there is a airflow reduction of more than 50 % comparatively to the baseline, and a drop of blood oxygen saturation of at least 4%. In case of apnea, the person stops breathing for at least 10 seconds, this results in multiple awakenings in order to recover muscle control in the throat to reopen the airway [65] [66]. It is common in the presence of snore because the airways become narrower. The sound of snoring can be similar to a choking sound when there is a complete cessation of breathing. The pattern after each sleep apnea event is a drop in blood oxygen and high activation of the sympathetic tone. Concomitant, blood pressure, and heart rate increase. The event ends with an activation of the central nervous system, which allows the recovery of the control over the respiratory system.

The Apnea Hypopnea Index (AHI) and oxygen desaturation levels are the metrics used to measure the severity of this disorder. AHI is obtained by dividing the number of apneas and hypopneas by the total sleep time (TST) per hour. According to ICSD, OSA is defined by an AHI ≥ 5 with evidence of respiratory effort during partial or total part of the event, followed by symptons of excessive daytime sleepiness, unrefreshing sleep, gasping or choking during sleep, loud snoring; or an AHI ≥ 15 with evidence of respiratory effort during partial or total part of the event [52]. In resume, a person is considered as not suffering from apnea if $0 \leq$ AHI < 5, as suffering of mild apnea if $5 \leq$ AHI < 15, moderate apnea if $15 \leq$ AHI < 30, and severe apnea if $30 \leq$ AHI [67].

The most efficient treatment for this disorder is Continuous Positive Airway Pressure (CPAP), where it is used a device that sends continuously air pressure into the airways through a mask to prevent apneic episodes. This is a just a palliative treatment because OSA is a chronic disease, therefore regular adherence to CPAP can be a challenge. A study concluded that TM is relevant to support the follow up of this treatment and is well received by the patients, decreasing the risk of stopping the therapy [68].

TM is been also used as a way to assess the severity of sleep apnea. In a study, it was used BCG to analyze HRV to diagnose sleep apnea disorder. The authors explained that in cases of apnea, it occurs a disproportion of the oxygen demand and supply, also known as cardiac hypoxia. In this situation, there is an induction of the production of reactive oxygen species, leading to a sympathetic hiper-activation that leads to alterations of the heart rate [66].

Another study used BItalino hardware to collect ECG signal, the smartphone built-in microphone and accelerometer to diagnose OSA and stroke. These signals allowed to estimate heart rate, audio, sleep pose, and the number of apneas while asleep [69].

A study analysed the detection of sleep apnea based on heart rate analysis. The authors concluded that it is possible to estimate sleep stages and sleep apnea events with heart rate noctural recordings. The possibility of using this method with patients that suffer from cardiac or autonomous nervous system disorders still needs to be studied. Overall, it is a good methodology that requires simple and inexpensive hardware. Research studies shown that it can be improved when combined with pulse oximetry [46].

A method for sleep apnea monitoring was proposed in another study by using a polyvinylidene fluoride (PVDF) film. PVDF is a thin and flexible piezoeletric sensor allows to measure and identify where mechanical loads are applied. The PVDF was inserted in a pad and placed between the bed mattress and the bed cover. None of the participants felt that the sensor interfered or provoke an uncomfortable feeling during sleep. The respiratory signal is estimated by the different levels of pressure that result from the volume changes in the subject's body when breathing inspiration and expiration occur. BCG and body movement are also obtained in the PVDF output signal. Signal extraction methods are applied to obtain only the respiration signals. Principal component extraction and data segmentation is performed over the breathing signals, thresholds are established, and an algorithm determines apneic events. PSG data was used to determine the correlation with the results obtained with the bed-sensor. The estimated AHI obtained from the study was highly correlated with the PSG data [70].

In another study [71] it was developed a product called Smart-Bed. It is a smart mattress designed to assess the sleep quality in order to early identify signals of sleep disorders and insomnia. It processes data from the environment, body motion and position, heart rate and breathing rate. The mattress integrates a pressure mapping system and several tri-axial accelerometers. The first technology allows to extract the ballistocardiograph signal that gives the cardiac activity of the subject. Multiple accelerometers are used to reduce the noise and to detect more accurately artifacts by averaging the signals of the different sensors. The data collected is then analysed by a machine learning algorithm that identifies four behavioral conditions, no bed occupancy, non-REM, REM, and wakefulness. Besides that, it calculates an environmental index that indicates how appropriate is the room for sleeping. The criteria used to classify the environment is:

- Sound intensity - continuous noise level should be bellow 35dB and no more than 45dB for single noise events;
- Temperature - should be within 17ºC and 28ºC;
- Relative humidity - should be within 40% and 60%;
- Luminosity - should be at maximum 10 lux;

Another study used a pillow with embedded pressure sensors, wireless network devices, and software that classified posture movements. Their system evaluates breathing quality and sleep efficiency using the detection of the head movements. They found out that sleep quality can be determined by the breathing rates that are classified with upper and lower movements of the chest. The diagnosis of sleep apnea is based on moments where the person stops breathing for several periods. The results of the prototype were compared with PSG, it was shown a high correlation for sleep efficiency and sleep latency (>0.80). They concluded that the system is able to determine breathing rates and patterns, that can be used for the detection of sleep breathing disorders [72].

Measuring sleep outside the lab appears also as a good alternative for diagnose and treatment of insomnia. A study was done with the belief that insomnia detection can be fully automated and performed at home, by implementing subjective and objective measurements to assess sleep. The study methods required a single EOG electrode that was placed on the subject's left eye to measure the epochs in SWS sleep and a smartphone. A mobile application was developed to collect the data from the electrode via WiFi, and to keep a sleep diary. The sleep diary was composed by questions that were placed in 4 categories, assessment of sleep pattern (time in bed, sleep latency, etc.), substances taken before going to sleep (alcohol, drugs, caffeine doses, etc.), mental health and medical conditions (stress, anxiety, and mood), sleep conditions and others questions (noise, snoring, alarm clock, etc). This helps creating a sleep history that can be sent to the clinic. A machine learning algorithm is used to evaluate SWS epochs from non-SWS epochs, only this sleep phase was considered because previous research found that the amount of time passed in this stage is what it reflects more in a subject's sleep quality. It was achieved a 90% agreement of the assessment of SWS epochs when compared with the evaluation done with a sleep expert. It was shown that is possible to reduce the number of electrodes to assess deep sleep, and by providing a sleep diary it is possible to reduce the number of interviews between the patient and the health professional [73].

Another study was carried on based on the analysis of deep sleep. It was proposed an algorithm for the insomnia diagnosis. They took EEG data from good sleepers and patients that suffer from insomnia to identify which features could discriminate these two groups better. The algorithm achieved 91% of accuracy with a kappa value of 0.81. By using only one EEG channel, the computational overhead is reduced and it turns more practical to do the diagnosis in a home environment [72].

There is a study that evaluated the performance of sleep trackers in measuring sleep before and after a cognitive behavioural intervention in insomnia disorder. The sleep trackers used were a research-grade actigraphy device Actiwatch Spectrum Pro and a commercial actigraphy device Fitbit Alta HR. The device performance was compared regarding the sleep continuity parameters, TST, SE, WASO and sleep latency for two non-consecutive weeks. To identify insomnia cases, it was used sleep diaries filled by the participants and Insomnia Severity Index questionnaire. In the sleep diaries it was asked questions regarding sleep habits such as bedtime, wake time, time in bed, number and duration of awakenings and naps. It was concluded that Fitbit Alta HR provided similar estimates compared with the research-grade device. Fitbit identified 86% of the insomnia pretreatment cases and 69% of changes in the case status after the treatment. These results were based on the measurements obtained for SE, being the only recorded parameter that showed clinical importance. However, the authors considered that using only the devices is not sufficient to identify insomnia as the sleep diaries, yet the fact that there was not significant differences of sleep estimation in and out of laboratory support the use of the tracker as a home measurement option. Therefore, a combination of both could be a better option [74].

A lot of home monitoring devices measure HRV, therefore it is important to understand if this parameter alone can be decisive in insomnia diagnosis. In a study, it was used time and frequency analysis of heart rate, it was concluded that with insomnia patients there was an increased activity of sympathetic activity. The authors noticed high values on the low-frequency band during the N3 phase, which corresponds to 0.04Hz - 0.15Hz interval, and it reflects the sympathetic activity of ANS. However, this biomarker ca not be used alone because there are other sleep disorders, like sleep apnea, that influence HRV [75].

Chapter 3

Home Sleep-Monitoring Devices

Polysomnography is the gold standard method to measure sleep stages, being widely used in clinics. However, as mentioned in the PSG section in the chapter before, it requires a lot of sensors that can be disruptive in the person's sleep, a PSG unit is very expensive and there is a need for an expert technician to evaluate each physiological signal recorded and correlate it to sleep stages. All of these factors make this method very complex and impractical for long-term monitoring. The growing availability of new technologies allowed the emergence of portable devices with the aim of tracking sleep outside of clinics. These devices appear as a less expensive and invasive alternative to evaluate sleep at home, combining them with good software it can lead to a positive impact on sleep health. Plus, home monitoring offers a more realistic way to provide data by recording it for multiple days, since sleep is a dynamic process that changes daily. This option of having a larger dataset makes it useful to correlate sleep with variable events, like exercise, food, alcohol, caffeine, naps, and stress that can influence someone's rest. So, the major advantage of sleep telemonitoring is giving long-term feedback that helps people realizing their sleep patterns, serving as a resource for improving sleep health. The following section aims to review devices that are already developed and some of them ready for purchase in the wellness market. According to the American Sleep Disorders Association, standard PSG must be the reference used to compare the performance of all the wearable devices. [61] Actigraphy based devices represent the biggest portion of ambulatory monitoring, thus more research has been done to validate this type of sleep measurement, making them the most appropriate device to use outside the laboratory. [76] [77] There is also been a growing development of these type of devices, therefore most of the actigraphy based health trackers have now additional sensors, making it possible to record more parameters than body movement. In table 3.1 it is possible to see what type of sensors the sleep health trackers can normally include and what physiological information about the human being it's possible to track with them. In this study, the goal is to find a good option for one or more devices to integrate into the Diani system that will then constitute allies for the detection of sleep disorders. The choice will relay in these principal conditions - availability in the market, low cost, low invasiveness, and API availability provided by the brand for easier integration. Invasiveness is one of the major factors because the comfortability is important for long-term monitoring. Therefore, the devices more carefully reviewed are going to be in the shape of rings, in-bed based sensors, and wristbands. These type of devices are normally based on cardiac activity or movement of the user. Nowadays, is getting more typical the combination of both as it is going to be seen in the next subsections. The best option would rely on a device that could extract brainwave information, cardiac activity, body movement and respiration events.

Table 3.1: Commonly used sensors found in wearable devices that can track sleep. Adapted from [9]

	Functions	
Sensor	Physiological Monitoring	Activity Monitoring
Accelerometer	Heart Rate	Body Acceleration Detection
Gyroscope	-	Motion and Gesture Detection
Infrared	Heart Rate, Body Temperature	Proximity Detection
Optical	Temperature, Blood Oxygen Saturation	-
Photo Conductive	Heart Rate, Body Temperature, Blood Sugar, Blood Pressure	-
Piezo-electric based	Blood Pressure	Motion and Gesture Detection
Thermistor	Body Temperature	-
Thermoelectric	Body Temperature	-

3.1 Brainwave-based devices

iBrain (Neurovigil) and Zeo are two devices based on EEG signals. The first one uses 3 electrodes that represent a single channel of EEG, data can be streamed in real-time or stored in the device's mini-USB to be transferred later into their analysis servers. An algorithm is performed to create a brain map that can reveal low power, high-frequency components, or fragmentation patterns [78]. A study lead with zebra finches concluded 84% accuracy in scoring sleep-awake [79]. Zeo was a company that launched a device consisting of a headband with sensors that are able to collect a combination of EEG, EMG and EOG signals. They used a neural network model that streamed the data every 30 seconds, classifying it in the states wake, light NREM, deep NREM, and REM. The algorithm operating along with the data collected by the device has shown some analysis gaps such as classifying that more time in NREM state means better sleep quality, however, there is not much literature evidence about this and combining phase N1 and N2 into a single category when they are marked with physiological differences [61]. A further study compared the device's accuracy with 2 PSG lead by different laboratories, it was concluded that: agreement of sleep/wakefulness was between 91% and 93%, and for sleep scoring it was between 74% and 76% [80]. NeuroOn is a sleep mask that includes a 3-axis accelerometer, temperature sensor, EOG and EEG sensors, and a pulse oximetry sensor. It is able to readout sleep stages and may help to detect sleep apnea using the pulse. Yet, no researches were found using this device [81].

Table 3.2: Brainwave-based devices found in the market study with the information about the sensors included, their format, monitored parameters, the most relevant information found in studies to support their reliability and their cost.

Device	Sensors	Format	Monitored Parameters	Reliability (Research Conclusions)	Cost	Medical Device
iBrain (Neurovigil) 	EEG electrodes	Headband	Brain Activity	84% accuracy sleep-wake scoring (tested in zebra finch birds)	Not available for consumer market	Yes (FDA approval)
Zeo  [82]	EEG electrodes	Headband	Brain Activity	82% accuracy sleep-wake scoring	Not produced anymore	No
NeuroOn  [81]	EEG, EOG, Temperature, Pulse Oximeter, Accelerometer	Sleep Mask	Brain Activity, Physical Activity, eye movement, pulse	No studies have been found	Price point of €449.99[81]	No

Although these devices are very complete in the number of physiological parameters that they can extract, they are too invasive or too expensive. For these reasons they are out of the options list of devices that can be integrated into the Diani system.

3.2 Movement-based devices

Devices that track sleep based on movement continue to have a high grow in the market, most of them are in the shape of wristbands, making it easy to use on a daily basis. They offer low-cost continuous monitoring during a long period of time, providing an exhaustive picture of sleep/wake cycles. There are two techniques able to exploit the body movements:

- Noise detection
- Actigraphy

Actigraphy is the most used one and is well accepted. The mechanism behind it, is based on the quantification of the limb movements, when it records high values it associates with a wake state, when there is a progressive reduction it means that the individual is approaching deeper stages of sleep.

Several actigraphy devices are available on the market having different levels of agreement with PSG, which mainly depend on the scoring algorithm used.

Several studies compared the accuracy of these type of trackers with PSG, the typical metrics involved are:

- TIB;
- TST;
- WK;
- WASO;
- SOL;
- SE;
- Sleep Stage Scoring, normally done considering 30 seconds epochs where is checked if there was a correct detection of the sleep stage (light sleep, deep sleep, and REM sleep).

The most common problem was overestimating sleep and underestimating wake[83] [76]. For the devices that were able to report the different sleep stages, they showed poor specificity, i.e., limited ability to detect WASO, marked with a decrease in accuracy for a higher amount of wake time.However, they showed good sensitivity, i.e, good detection of sleep stages[84].

The main advantages of these type of devices are:

- Low-cost;
- Low-impact on the user daily life.

The major weaknesses are:

- Overestimation of sleep, due to the limitation of distinguishing if lack movements are caused by sleep or not;
- Sleep stages can not be scored.

Fitbit is a brand that started the business of smartwatches and bands with this type of technology to automatically record sleep, based on movement. Their algorithms classify wake/sleep based on the following, if a person does not move for more for about 1 hour, the device assumes that is on sleep mode. The length of the movements that happen while sleeping, like turnover, help to confirm the sleep mode. It also provides two modes, normal and sensitive, the first one only counts significant movements as being awake while the second takes into consideration nearly all movements for that classification[85].

Another really big company in this field is the Chinese electronics company Xiaomi that appeared with the Xiaomi Mi Band in 2014. Since the first version of this model, it came with not only the physical activity tracking feature but also sleep monitoring, always retrieving the TST of the user and dividing the sleep into light and deep stages. Plus it presents a smart alarm clock, that wakes up the user during light sleep in order to be easier. However, just in its following versions, the heart rate sensor was integrated, which is the case of Xiaomi Mi Band 2.

Currently, the Diani application supports Fitbit and Xiaomi devices to track the physical activity and classify the sleep periods. During this work, it was used Fitbit Charge 2 and Xiaomi Mi Band 2 to get information regarding each night's sleep.

The first one provides more detailed sleep insights due to its functionality of continuously measuring the heart rate, the Xiaomi Mi Band 2 also has a heart rate sensor along its accelerometer to classify sleep, however is insights are less detailed, on Mi Fit, the mobile app that can be connected with the Xiaomi band it is only possible to see a sleep score, the amount of time deep and light sleep, not referring the REM phase, the total sleep time, the time awake. It provides some statistics that compares the user's sleep over the week, and it also compares the user to the other users from the same age group that own a Xiaomi device that tracks sleep.

In Diani, Xiaomi is the primary tracker choice, taking into consideration that it was used with a focus on physical activity monitoring and it was shown that it has high validity for step measurement while being a low-cost option[86]. Despite the fact that it can provide sleep information is not the most complete source to get sleep data. Even though the tracker comes with heart rate sensor helping to get more accurate sleep measurement, it's still a more side functionality, requiring the user to turn on the HR sensor on Xiaomi App to keep measuring during all night for better sleep results, having consequences in the battery. Fitbit Charge 2, it is a wristband that came out in 2016, it provides all-day stats like the number of steps, heart rate, calories burned among other parameters. Once is connected with the Fitbit dashboard, that can be accessed via mobile or web, the user can start to have access to its sleep history and patterns. It can give the user reminders when it is bedtime for them to improve the sleep routine. In the same way, as Xiaomi does it compares the user data with the one from other users that are in the same age and gender group. Differently to Xiaomi, Fitbit can show information about all sleep stages by using a combination of the user's movement and the heart rate variability, which fluctuates during stages transitions.

To have sleep data is required to sleep at least 3 hours, so in the case of naps, this device does not provide any information.

Even though this wristband is more complete than Xiaomi Mi Band, it can turn uncomfortable to keep wearing a wristband during the night. Also, both Fitbit Charge 2 and Xiaomi Mi Band 2 are already discontinued, being imperative to an update of the tracker chosen and the Diani system.

Still, regarding Fitbit, one of the biggest brands in this field, it is possible that its new generation of devices can outperform clinical actigraphy, as they leverage multiple streams of biosignals for sleep staging, some of them are addressed in the next section. To visualize the sleep data, Fitbit offers a website and mobile application. The trackers can synchronize to smartphones via Bluetooth and/or to Bluetooth-equipped computers running Windows or macOS. As explained before, users have access to a whole night's sleep hypnogram, a graph that represents the sleep cycles in function of time, among other parameters such as TST and the ratio of each sleep stage.

Their devices are often present in several studies. Fitbit Ultra is one of their models that was analyzed and showed an underestimation of TST and SE in the sensitive mode and an overestimation in the normal mode [87].

Fitbit and Actiwatch (Philips Respironics, USA) when compared to PSG, constantly misidentify wake as sleep and both overestimate TST and SE. It was also noted that Fitbit has a lack of configuration options to support more accurate records for disordered populations and different age groups [88].

Actiwatch 64 and GT3X+ (Actigraph, Pensacola, Florida, USA) were subjected to a study where GT3X+ showed overall best results in epoch-by-epoch agreement with PSG, however, both revealed high sensitivity but low specificity [89]. Actiwatch 64, Actiwatch 2, and Actiwatch Spectrum in a comparison study it was analyzed that all of the models calculated similar sleep statistics [90].

SenseWear Armband (BodyMedia, USA) was an actimetry device provided with a 2-axis accelerometer that was placed around the arm instead of the wrist. It calculated the total energy expenditure, TST, and circadian rhythm. Compared to wrist actigraphy devices it could benefit from removing the influence of extraneous small movements recorded in the wrist that lead to underestimation of TST [64].

Sleepwatch (Ambulatory Monitoring, USA), Actiwatch (Philips Respironics, USA) - wrist actigraphs and Actical (Philips Respironics, USA) - chest actigraph, were under a validation study where they were compared to PSG, it was reported good correlations related to TST but poor estimation for SE, algorithms of scoring and sensing should be analyzed in order to improve accuracy [91].

All of the models mentioned above are research-grade devices and used only in medical clinics. One of the most accurate device in this field is the SomnoWatch, that can be incorporated with other electrodes in order to measure other parameters besides movement. In a study done with young adults, PSG and SomnoWatch plus EEG were compared side to side, there were not reported significant differences in SOL and sleep stage scoring. The biggest differences were found in the

TST, WK, WASO, and SE, but without big effects. Therefore, the authors concluded using this device plus EEG is a valid option for self sleep assessment [92].

Some of other options, available for home usage, besides Fitbit or Xiaomi, can be the Vivago Care Watch (International Security Technology, Finland). In a study using this watch, it was demonstrated a high correlation between user's self-reports about their sleep time and TST measurement in detecting wake and sleep periods. Although, it was discussed that this device can have its accuracy improved by adding information about bedtime, illumination, and sleep logs [93].

This device has a recent model called Vivago Move, but there is not research about it. Not only wristbands can fit in this category, Zeeq Smart Pillow (REM-Fit) has a gyroscope and an accelerometer, as well as eight wireless speakers. It comes with an app that shows how good the user slept, the average snoring level, how loudly the sound was, and a graph with the movements during the night. There are other options that rely only on sound capture, such as mobile apps, as it is going to be covered next.

Table 3.3: Movement-based devices found in the market study with information regarding the sensors included, their format, monitored parameters, the most relevant information found in studies to support their reliability, their cost, if they are approved as a medical device, the type of connection used, and if they provide API for developers access.

Device	Sensors	Format	Monitored Parameters	Reliability (Research Conclusions)	Cost	Type of Communication	Medical Device	Developers access/API
Fitbit Ultra and Fitbit One [94]	Accelerometer	Clip/Sleep Wristband	Sleep-Wake score, TST, Motion	Overestimation of sleep quality metrics in normal mode and underestimation in sensitive mode. High inter-variability	Discontinued models	WiFi	No	Yes
Vivago MOVE (Vivago, Finland)  [95]	Accelerometer	Wristwatch	Sleep-Wake score, TST, Motion	High-correlation between TST and user-self reports. Accuracy could improve with light sensors and sleep logs.	-	Bluetooth	No	No
GT3x (Actigraph)	Accelerometer	Wristwatch	Sleep-Wake score, Motion , TST	High sensitivity and low specificity, Reasonable epoch-by-epoch agreement with PSG	Only available for research	WiFi	Yes	No
Actiwatch2, Actiwatch-64 (discontinued model), Actiwatch Spectrum (Philips)	Accelerometers	Wristwatch	Motion, Sleep-Wake classification, TST	Good TST correlation with PSG estimation but poor SE estimation	Available only for clinics/research	USB to Infrared connection	Yes	No
SomnoWatch (SOMNOmedics)	Light Sensor, Accelerometer, 1 External Optional Sensor can be added: Pressure Sensor for Nasal (Oral) Flow + Snore, Pressure Sensor for CPAP (0 to 15 cm HO), EEG Electrode, ECG Electrode, EMG Electrode, EOG Electrode, Temperature Sensor	Wrist/Leg/Bodyband	Circadian Rhythm, PLM detection, Tremor Analysis, Body Temperature, Respiratory Screening with Flow, Snoring, Body Position, Sleep/Wake Score	Good correlation between PSG in sleep scoring and SOL	€5522	USB local storage	Yes	No
Zeeq Smart Pillow (REM-Fit)  [96]	Accelerometer, Gyroscope, Microphone	Pillow	Snoring, Motion, Sleep Score, TST	No studies have been found	€46.61	Bluetooth	No	No
Xiaomi Mi Band 2  [97]	Accelerometer, HR sensor	Wristwatch	Snoring, Motion, Sleep Score, TST, Light and Deep Sleep Stages	Underestimation of WASO, overestimation of TST [98]	From €25	Bluetooth	No	Yes

3.3 Cardiac activity-based devices

The tendency for the movement-based devices is to include more sensors that allow not only score the state of awake or sleep but also the sleep stages. There are studies that found correlation between EEG and HRV, hence with sleep stages. The cycles of these stages are accompanied with electro-cardiac changes, making it possible to assess sleep with HRV[34]. Some of the current technologies used by the devices to extract these signal are [3]:

- Ballistocardiography;
- Piezoelectricity;
- Impedancemetry;
- Photoplethysmogram.

One of the major companies in wearable devices, Fitbit, already presented in the section before, released in 2017, the Fitbit Alta HR. This model came as an upgraded version of the Flex line, by adding to the accelerometer, another sensor, an optical heart-rate tracker, allowing to classify the different sleep stages. Later on, other lines of trackers emerged, like Charge and Inspire. The first tracker of the company enabling heart rate recording was Fitbit Charge HR in 2015. One of the most reviewed trackers was Fitbit Charge 2, integrating several studies where its performance was compared against polysomnography. This model is now discontinued, giving place for its successor, Fitbit Charge 3. This most recent model is lighter and it has changes on the software that improve the sleep tracking [99]. However, most of the studies found, use older models of Fitbit, yet knowing that they still maintain there core features it is worth to review the conclusions found in these studies.

As mentioned before, Diani supports Fitbit, and its model Charge 2 was used during this work. It was chosen because it has a large dataset of heart rate measurements, while a long battery duration that goes up until five days of usage.

In a comparison between Charge 2 and PSG done with adults, it was concluded that this product has satisfying performance in measuring TST and SE but fails to produce accurate results in classifying sleep stages, there is an underestimation of the sleep stage transitions. The accuracy in detecting sleep, sensitivity, was 96%, the accuracy in detecting wake epochs, specificity, was 61%, and the correlation accuracy for sleep staging was 81%, 49%, and 74% for light sleep, deep sleep, and REM, respectively. WASO outcomes did not differ between the tracker and PSG[100]. Fitbit Charge HR performance was compared to a research-grade actigraph, Actiwatch Spectrum Plus (Philips Respironics). The results showed a good TST correlation but less good results when compared to the ratio of TST/TIB, i.e, sleep efficiency. Plus, it detected an overestimation of sleep. The authors do not recommend this device when clinical accuracy is needed but is good to provide qualitative metrics, for example, to test the effect of an intervention [101]. Nevertheless, other studies were conducted, one reported a good agreement between PSG and Charge HR when measuring HR and sleep of healthy adolescents. The overall accuracy was of 91%, sensitivity of 97%, specificity of 42%. The average HR tracked with Fitbit was 59.3 $\pm$ 7.5bpm and 60.2 $\pm$ 7.6bpm from ECG, it was a negligibly lower value [102]. Another study used Fitbit

Charge HR to create a sleep quality evaluation model based on the heart rate sleep classification, concluding that objective measures help to create a more truthful sleep quality insight than subjective measures, and Charge HR provides good outcomes [103]. In another study, participants with type 2 diabetes were asked to fill self-reports about their physical activity and sleep patterns. These patient-reported outcomes showed a higher correlation with the Fitbit results in the case of physical activity. The conclusions of the study reported that this tracker applies better to measure physical activity than sleep. The most likely reason behind this is that there are parameters not covered by device settings that vary from subject to subject and have an influence in sleep quality [104], as well as an under-reporting of sleep disturbances[105]. Whereas, physical activity can be more easily standardized by adjusting settings like weight, height, and stride length. From the above studies, it is possible to conclude that Charge HR and its successor, Charge 2, provide a fair assessment of sleep, although it produces more accurate results for measure the physical activity. Sleep is a more complex activity that can be affected by external events that are harder to be captured by the Fitbit software.

Fitbit One and Beddit Pro (acquired by Apple in 2017) are two devices that were analyzed in a study. The first one is based only on actigraphy while the second its an under-the-sheets sensor strip that records temperature, light intensity, sound, and presence in bed using a piezoelectric sensor. In this study, it was verified that Beddit Pro produced more accurate results, whereas Fitbit One overestimated sleep quality metrics. However, the estimation's result varied between individuals promoting that calibration is needed for each subject[106]. This result, emphasizes that accuracy is higher when the heart rate is an input for sleep assessment. At the same time, it alerts for the fact that HR and HRV are subjective biomarkers, hence a calibration setup is needed before starting the data collection[106].

From a study that used the following 5 devices - Basis Health Tracker (2014 edition; Intel Corp, Santa Clara, CA, USA), the Fitbit Flex (Fitbit, USA), the Misfit Shine (MisfitWearables, USA), the Withings Pulse O2 (Withings, France) and the Actiwatch Spectrum (Philips Respironics, USA) it was concluded that Actiwatch revealed the highest correlation of the SE value compared with PSG. However, all trackers had good correlation results for TST. Only Basis, Misfit, and Withings reported sleep stages but none of the devices provided reliable staging data. In this study it was considered deep sleep as SWS + REM. For deep sleep, the algorithms tend to have a higher fail rate due to the fact that both are characterized by low movement. Withings and Misfit showed a moderate correlation with PSG on scoring light sleep. For deep sleep, only Withings showed correlation, however not very strong. Basis Health Tracker showed a good detection of deep sleep [107]. It is noteworthy that the models used in the above study are no longer available, and SWS was combined with REM phase, which are two sleep phases remarkably different. The Misfit Shine evolved to Misfit Shine 2, but this line is now discontinued [108]. Basis Health Tracker can still be purchased through third-parties, but the wearable division of Intel was shutdown [109]. Withings continued to upgrade their Pulse line, in 2014 to Pulse OX where pulse oximetry was added with the reflexive method [110][111]. Currently, the device of this line available from their website is Withings Pulse HR, yet the tracking features are similar to their predecessors[112].

EarlySense (Ltd., Israel) is a contact-free monitoring system that combines an under-the-mattress piezoelectric sensor with an application to calculate sleep patterns using a collection of vital signs such as HR, body movement, and RR, that sensor obtains by software conversion of the pressure changes applied over the mattress. For sleep analysis, it performed an algorithm that uses RR, RR variability, HR, and HR variability. When side to side with PSG performance, the TST estimation of EarlySense showed a high correlation, good sleep staging and the values of accuracy, specificity, and sensitivity were all higher than 80%. However, it presents some disadvantages - a bed used with more than one person can lead to estimation errors, it doesn't have internal storage so if the Bluetooth connection with the smartphone fails the data is lost [113][114].

M1 (SleepImage) is a device that has a 4 channel recorder that captures actigraphy, ECG, body position and snoring. M1 must be attached to the chest, data signals are stored locally and analysed after sending through any PC computer to the SleepImage website. The system assess sleep not through the conventional PSG but with a computational method called cardiopulmonary coupling (CPC). It is based on the ECG record, then combines the heart rate variability, and the fluctuations in the R-wave amplitude. This fluctuations represent the oscillation of the position of the heart and lung tissue relative to the skin surface resulted from the respiration [61]. The algorithm classifies sleep in "stable" stage, represented by high-frequency coupling (HFC), 0.1 - 0.4Hz and "unstable" stage, represented by low-frequency coupling (LFC), 0.1 - 0.01Hz [115]. Therefore, CPC method is used to classify N1, N2, N3 and REM phases, instead of brain, eye and muscle activity. Translating this way of classification to the approach of NREM and REM phases: Stable is associated mainly with stage N3 with some portions of N2, and is associated with a coupling frequency in the range of the normal respiratory rate, which is around 0.3Hz. The unstable stage is associated with N1 and some portions of N2, especially when this phase is fragmented. REM is not distinguishable from wakeful state due to the same breathing irregularity, both exhibit very low-frequency coupling (VLFC), 0.1 - 0.001Hz. In situations of sleep apnea, the algorithm increases the relevance of LFC component, translating in elevated LFC (e-LFC) situation. When the frequency of e-LFC metric is variable it is associated with obstructive sleep apnea situation. This conclusion is based on the fact that in this type of sleep disorder, apnea situations have variable duration. When the e-LFC values are similar its associated with central sleep apnea, its events are normally short and happen in regular intervals of time. However, this device is not approved for sleep apnea diagnosis, is possible for sleep apnea patients to have some assurance in distinguish there disorder phenotype between these existent two. This system is approved by the Food and Drug Administration (FDA) to aid in the evaluation of sleep disorders, measure sleep quality, and sleep duration. When used with the oximeter, it can give SleepImage Apnea-Hypopnea Index which helps the diagnosis of sleep apnea. To evaluate the performance of this device, a study was done by collecting data from healthy participants, people with insomnia, and sleep apnea, during multiple nights. In people with sleep apnea, therapeutic effects could be tracked. Regarding the results of insomnia participants, there were consistent patterns regarding the variability in sleep times and sleep quality that is expected with this disorder. Disassociation between self-reports and the data collected with M1 can help identify individuals that have a misconception of their sleep, providing insomnia insights. Overall, the authors concluded that this device provides clinically meaningful data. Participants adherence to the device was high, yet most of them said they were unlikely to continuously use it after the study, this suggests that this device might still be invasive for a long-term evaluation [116].

There is a growing interest in making the sensors the less invasive possible, thus other formats of devices are appearing, like rings or under-the-mattress sensors. Oura ring collects motion, body temperature, pulse rate, pulse amplitude, and heart rate variability. A machine learning algorithm is combined with the collected physiological parameters in order to detect the sleep stages, classified in their system as light sleep (N1 + N2), deep sleep, REM sleep, and awake stage. It is one of the first devices measuring the variation of the skin's body temperature instead of the environment. They display the temperature variation value of the individual compared to its baseline. This is possible due to the integration of an NTC sensor that tracks the temperature from the skin rather than the body's core temperature. As soon as the device collects sufficient data from the person the baseline is established. In sleep studies, body core temperature is the parameter often measure, however, skin temperature is also associated with the body core temperature, normally they change in opposite directions when one is high, the other becomes lower. In addition to this parameter allowing the detection of stress, how well is the body recovering, it is also related to sleep disorders, like insomnia [117]. A recent study compared Oura ring performance with PSG. The results concluded that there was an underestimation of N3 (20min) and overestimated REM (17min). The sensitivity to detect sleep was 96%. The agreement detection of light sleep, deep sleep, and REM sleep was 65%, 51%, and 61%, respectively. The specificity to detect wake was 48% [118]. Another example of rings is GO2SLEEP, made by the SLEEPON company. The designers claim that is the smallest sleep apnea detection ring, yet there is still no FDA approval. The device comes with a mobile app and it records motion, heart rate, blood oxygenation level, perfusion index. As the heart rate increases and the blood oxygen levels drop to abnormal values, GO2SLEEP will vibrate to alert the person. It can not measure airflow or respiratory effort, so is not possible to differentiate the type of apnea. There were not found articles that used this device or that evaluate its accuracy. One of the smallest devices that appeared in the market is Beddr SleepTuner. It has an accelerometer and a PPG sensor inside a chip that is placed on the forehead, a place that is thin, flat, and high-vascularized making it possible to measure SpO2 and the heart rate. Some of the disadvantages are that it requires the purchase of stickers continuously for the device to stick in the forehead, and it does not provide an API. Nevertheless, it offers an interesting feature, besides showing the percentage of SpO2 it shows in which body position the person was, this gives a useful insight to understand if there is a sleep position that the person might need to fix [119].

Table 3.4: Cardiac-activity based devices found the market study. Information about the sensors they have, their format, monitored parameters, the most relevant information found in the studies to support their reliability, their cost, type of communication, if they are considered a medical device and if there is an API available. PPG: Photoplethysmography, HR: Heart Rate, NTC: Negative Temperature Coefficient, RR: Respiratory Rate, RHR: Resting Heart Rate TST: Total Sleep Time, WASO: Wake After Sleep Onset, SOL: Sleep Onset Latency

Device	Sensors	Format	Monitored Parameters	Reliability (Research Conclusions)	Cost	Type of Communication	Medical Device	Developers access/API
M1(SleepImage, MyCardio LLC)  [120]	Chest electrode, accelerometer, gyroscope	Small processing unit and wire electrode	ECG, Actigraphy, Body Position, Snoring vibrations, SpO2 (optional)	Useful tool to evaluate insomnia symptoms, detecting the different types of apnea and track treatment [116]	Used for clinics	WiFi	Yes (FDA approval)	No
Beddit Sleep Monitor (Model 3.5), (Apple)  [120]	Piezoeletric, Humidity (USB plug), Temperature (USB plug)	Under-the-sheet	Snoring (using the app), HR, RR, Sleep Time, Room Temperature, Room Humidity	More work is needed to calculate TST. [121] Underestimated WASO, overestimated TST and SE, High inter-variability; failed in sleep stage scoring. it was concluded that is not a valid device to monitor sleep. [122]	$149.95	Bluetooth	No	No
Withings Sleep Tracking Mat (Withings)  [123]	Pneumatic sensor (with a microphone)	Under-the-mattress	TST, SO, Sleep Stages, HR, Snoring, WASO, Sleep Quality Score, Sleep Disturbances (breathing pauses)	No studies have been found	€ 99.95	Bluetooth	No	Yes
Beautyrest (Fullpower Technologies Inc.)  [124]	Piezoelectric	Under-the-mattress	HR, RR, Movement, Sleep Stages, WASO, TST, Wake up time	No studies have been found	$199	WiFi	No	No
Xiaomi Mi Band 4  [125]	Accelerometer, Gyroscope, PPG HR, Capacitive proximity sensor	Wristband	HR, Body Movements, Sleep Stages, TST	No studies have been found	from € 25.90	Bluetooth	No	Yes
Vivosmart 4 (Garmin)  [126]	PPG HR, Accelerometer, Pulse Ox, Ambient Light Sensor, Barometer	Wristband	HR, Sp02, Sleep Stages, TST	A study used the previous version, Vivosmart 3 and it was obtained 70% of accuracy in the sleep stages detection and Cohen's kappa of 0.54 +/- .12.[127]	€ 99	Bluetooth	No	Yes
Oura Ring (Oura)  [128]	PPG HR, NTC thermistor, Accelerometer, Gyroscope	Ring	Interbeat Interval (IBI), Pulse Amplitude Variation, RHR, HRV, Respiratory Rate, Body Temperature, Movement, Sleep Stages, WASO, SOL, TST	Underestimation of N3, overestimation of REM. 96% sensitivity in sleep detection. Agreement detections of light sleep, deep sleep, and REM sleep were 65%, 51%, and 61%, respectively. 48% sensitivity in wake detection. [118]	from € 314	Bluetooth	No	Yes
Motiv Ring (Motiv)  [129]	PPG HR, Accelerometer	Ring	HR, RHR, TST, WASO, Activity Intensity	No studies have been found	$199.99	Bluetooth	No	Yes
GO2SLEEP (SLEEPON)  [130]	PPG HR, Vibrator, Accelerometer	Ring	HR, Sp02, Motion, Perfusion Index (Pulse strength), Sleep Stages, Sleep Apnea Times, TST	No studies have been found	from $99.90	Bluetooth	No	No
Beddr Sleep Tuner (Beddr)  [130]	PPG HR, Accelerometer	Forehead Chip	HR, Sp02, Movement, Number of stop breathing events	No studies have been found	$149.00	Bluetooth	Yes	No
Fitbit Charge 2 (Withings) 	PPG HR, Gyroscope, Accelerometer	Wristband	HR, Physical Activity, Sleep Stages, TST	Good TST, SE and WASO detection; Underestimation of sleep stage transitions; 96% sensitivity, 61% specificity; The correlation accuracy of sleep stages face PSG: 81% for light sleep, 49% for deep sleep, 74% for REM sleep [100]; Good HR measurement [102].	From 99$	Bluetooth	No	Yes

3.4 Mobile Applications

Mobile sleep applications have a place in the sleep telemonitoring market, typically using the built-in smartphone sensors and structures like the camera or microphone. The biggest advantage of using applications is that by the time of access of the application can accurately note the time when the user went to bed and due to their high sensitivity can record the initiation sleeping time. These metrics are useful for making a more precise sleep diary. A review article showed that every application did not have scientific support nor information about the algorithms used to determine the sleep structure. There were two applications that underwent a study to compare their performance in comparison with PSG. Starting with Sleep Cycle App, available for android and iOS. It tracks sleep patterns using sound and movement analysis. It comes with a smart alarm feature that detects light sleep periods to wake up the user within 30 minutes till the final alarm [61]. When compared to PSG, there was not correlation between the two in the calculation of total sleep time and sleep latency. A lack of correspondence of the sleep stages was also noted. So, although it can provide higher awareness about sleep patterns, the use of Sleep Cycle App with clinical purposes is not recommended [131]. In the study with Sleep Time (Azumio), researchers did not find correlation with the polysomnogram when comparing the estimations of sleep efficiency, light sleep percentage, deep sleep percentage or sleep latency. They reported high sensitivity, accuracy in detecting sleep but poor specificity, the accuracy in detecting awake phases. Sleep On Cue (SOC, by MicroSleep, LLC) is an iPhone application that requires the use of headphones in order to send a low-intensity tone stimulus every 30 seconds that the user must respond by gently moving the phone. If two consecutive responses to tones are failed, the application assumes that the user has fallen asleep. In a study that compared this application with PSG records, it was detected the overestimation of SOL [131]. There should be more studies to validate sleep app algorithms and higher encouragement for more development on it, since its a possible way to have sleep data in an inexpensive format [131]. It is interesting to review the possibilities only when the user has a smartphone as an option. As expected the results are less outstanding keeping in mind that there is the limitation of using only the sensors that the smartphone has to offer. This option fits for those who want just to have a rough estimation of their sleep patterns and to keep a simple sleep diary. Diani has research purposes, requiring more detailed sleep insights, therefore this solution is out of this scope.

Chapter 4

Sleep Monitoring System Proposed for the Diani

The market study done in the previous chapter covered devices that use diverse types of physiological signs to track sleep, more specifically, brainwave activity-based, movement-based, and cardiac activity-based devices.

Due to the complexity of human sleep, an ideal sleep monitoring system is difficult to be achieved and even the use of dedicated equipment in the lab is prone to provide errors.

The closest to ideal to have as a home sleep-monitoring system would include all the physiological inputs that the devices analysed before are able to detect, brainwave activity, body movement, and cardiac activity. Nowadays it is easy to find a tracker with at least these last two signs. Even the devices that used to rely only on the body movement have new successors that include heart rate sensors. Therefore, what will make them different and better will be their software and the capacity that their algorithms have to analyse physiological data, in order to produce the most accurate sleep analysis they can, and this is continuous work in progress.

By adding the capacity to read brain activity to those devices, they are getting access to the most important input to classify the different sleep stages the person goes through during the night.

As seen in chapter 2, the brainwaves show remarkable differences between the sleep stages, with the exception of REM and awake phases. However, the other two inputs can help to spot the REM phase, since the heart rate increases during this period, and the body movement should be low, due to muscle atonia, to prevent people to act up their dreams during this phase.

However, there is still not a non-invasive and comfortable option to incorporate EEG analysis in home sleep-monitoring devices. One of the most accurate devices found is SomnoWatch. When used with an EEG module it has shown really good results in comparison to the ones obtained with PSG, yet the EEG module includes electrodes that must be attached to the head, which is not a familiar environment. Also, its price turns this device into a hard option for the majority of people.

Not yet having an easy solution to include brain activity analysis into the devices as an ideal option, the best option is to use a device with movement and cardiac activity as inputs, and taking this into consideration the choice of the device for Diani has been done.

As observed before, the Diani system is currently using Xiaomi Mi Band 2, which is an actigraphy-based technology and it has been used with a focus on physical activity not really in the sleep data. With this tracker, it can only be seen in Diani the time the user stayed asleep, based on the intensity of movements. At this time, with more offers in the digital health device market, it is possible to find trackers that can give more detailed sleep insights than this model from Xiaomi.

After reviewing several alternatives of sleep telemonitoring devices, the option chosen to be integrated within the Diani application is the Withings Sleep Tracking Mat. The reasons that lead to this final option are:

- Product obtained easily;
- Low-cost;
- Low invasiveness, the sensor does not need to be attached to the person;
- Easy integration and data extraction, Withings provides API documentation that uses OAuth protocol, which means that only with an access token it is possible to extract the server information;
- It uses Ballistocardiography, a method that when combined with actigraphy had shown to increase the accuracy in detecting sleep/awake states as well as identifying sleep stages [132].
- By implementing their API, Diani can easily integrate more Withings devices, and this brand has been showing an incredible grow in this field, just during the period of this work, they launched two other devices that got medical certification for sleep apnea detection in Europe.

The next steps involve the creation of a console application in C# to automatically extract data collected from my Withings Sleep Tracking Mat. For this, it is necessary to work with the Withings API.

4.1 Withings Sleep Sensor

The model acquired is the Withings Sleep Sensor - Model WSM02 - V1.0. Figure 4.1 shows the different components inside the sensor. The comprising parts are:

- A - Air Bladder, Withings Sleep is a pneumatic sensor, which means that requires a soft air bladder connected to an electrical pressure sensor responsible for reading air pressure changes due to the different bladder deformations;
- B - Textile Cover;
- C - USB Cable, this device does not contain a battery to prevent the fire risk that can come with the lack of air circulation under the mattress. This limits where it can be used, however, this was never a challenge during the experiments because the cable is very long;
- D - USB power adapter;

- E - Microphone, it can isolate the snoring sound from other environmental sounds. It does not store any audio recording, only detects if there was a snoring period and shows the average value at the bottom of the sleep graph. Whereas snoring detection is based on the sound crossing with respiratory patterns, it can make the distinction between individuals, in cases of not sleeping alone.
- F - Setup LED, it can present 7 different colors to provide feedback to the user. The colors are:
  - Flashing Blue: The sensor has not been paired with a mobile device;
  - Solid Blue: The sensor is in the setup mode and has been paired with a mobile device;
  - Flashing Red: The inflation has stopped or there is an air leak;
  - Solid Red: The internet connection ca not be established;
  - Solid White: The deflation process is occurring;
  - Solid Green: It can appear in 3 situations if the factory reset was successfully done, if the device is ready for WiFi configuration, and if the user is trying to setup a device already installed;
  - Flashing Purple: It shows up if the 30 minutes time window for the sensor installation is over, not being discoverable by Bluetooth anymore. For trying the setup again, it is required to unplug and plug the sensor again.

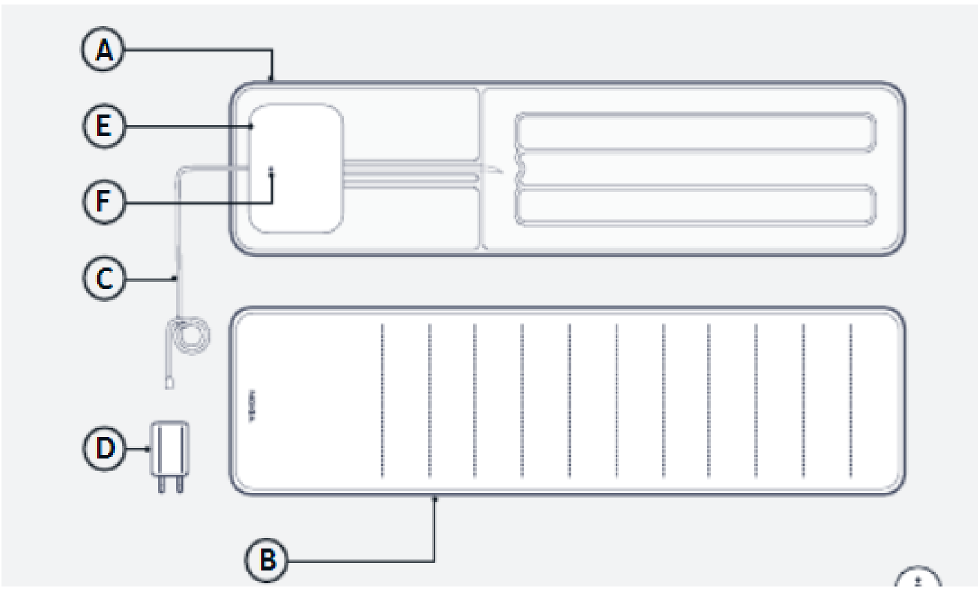

Figure 4.1: Overview of the sensor components. A - Air Bladder; B - Textile Cover; C - USB Cable; D - USB power adapter; E - Microphone; F - Setup LED. [6]

The whole sensor should be placed horizontally under the mattress near where the user lands the chest. It can be placed between the mattress and the mattress pad. It is compatible with several type of mattresses, like spring, foam, latex and memory foam [133].

The device has not been FDA approved, it only has CE certification, meaning that it follows the EU standards for health, safety and environmental protection.

Figure 4.2 shows how the sensor was placed during my dissertation experiment. It was set between a spring mattress and a piece of cardboard over the bed frame. The cardboard is needed because the sensor needs to lay in a sturdy surface. The mat fits one person, when using it on a double bed, it should be placed on the side the person lays down or in the middle of the bed is not shared.

Figure 4.2: Photos of the sensor placed during the experiment. The sensor needs a sturdy surface to be on, so it was placed cardboard over the bed frame. The sensor is in contact with a spring mattress.

After positioning the sensor it is necessary to plug it into an outlet using the provided adapter. The next step was to install the Health Mate app on my smartphone and create a Health Mate account. The information about age, height, weight, and gender should be included.

The following step is to connect to a WiFi connection and pair the sensor with the smartphone using Bluetooth. After this setup, it is required to wait nearly 10 minutes until the user can lay on it. This time is required for calibration and for the sensor to recognize the characteristics of the bed (e.g. mattress, base). Once finished it emits a soft whirring noise [123][133].

A calibration check is done every day to ensure that the nights are properly tracked. After calibration, the mat can automatically gather data every time the user sleeps.

In case of a WiFi issue, Sleep has an internal memory of 1 day, corresponding to the former night. Depending on the internet connection, data is normally sent to the app shortly after waking up. It can be visualized in the web Dashboard or the Timeline of the mobile app [6].

The screenshots 4.3, 4.4 show how data is presented about each night:

- Sleep stages (defined with colors):

  - Gray: time spent awake;
  - Light Blue: duration of REM sleep;
  - Medium Blue: duration of light sleep;
  - Dark Blue: duration of deep sleep.

- Sleep Score: provides a simple way to understand how good was the sleep night by rating it in a system of 100 points based on 6 factors:
  - Duration: total time spent sleeping;
  - Depth: time spent in restorative sleep phases, REM and deep sleep;
  - Regularity: consistency of the times to go to bed and to get up (it needs a minimum of 3 nights data for its calculation);
  - Interruptions: number of awakenings;
  - Time to sleep: time it took till falling asleep;
  - Time to get up: time it took to get out of the bed.
- Resting Heart Rate: the average resting heart rate is shown at the bottom of the sleep graph, but is possible to see each bpm value per minute;
- Breathing Disturbances: Withings algorithm retrieves in this section a qualitative evaluation. It refers to interruptions in sleep breathing patterns and it can be associated with conditions like sleep apnea. It is required a minimum of 5 hours of sleep to get data about this, and the snore recording must be activated;
- Snoring: using the microphone incorporated in the sensor, it retrieves the time spent snoring, which is calculated by crossing with respiratory patterns, thus it can distinguish from the snoring of a sleeping partner.

The sleep mat introduced recently a new feature, the sleep apnea detection. It was approved by the CE European medical certification and clinically validated. The feature can be activated if the device firmware is up to date (firmware 1991). It estimates the average of sleep apnea episodes per hour using as parameters, snoring, thoracic activity, and heart activity. The algorithm was trained and validated with data from apneic patients at Hôpital Béclère (France). It provides also an estimation of sleep apnea severity.

The connectivity of the sensor is done with Bluetooth Smart Ready in order to pair it with a smartphone. In the case of this study, an android phone was used. It is compatible with any android BLE (Bluetooth Low Energy) device. It requires WiFi 2.4 GHz to store and retrieve data from the sensor to the Withings servers[6].

4.1.1 Comparison with other Sensors

To understand the reliability of the Withings Sleep sensor, a study comparing with a PSG exam should be the ideal. However, none of related studies were found and the lack of time plus the nonexistent availability of a sleep lab made it impossible to be conducted during this dissertation.

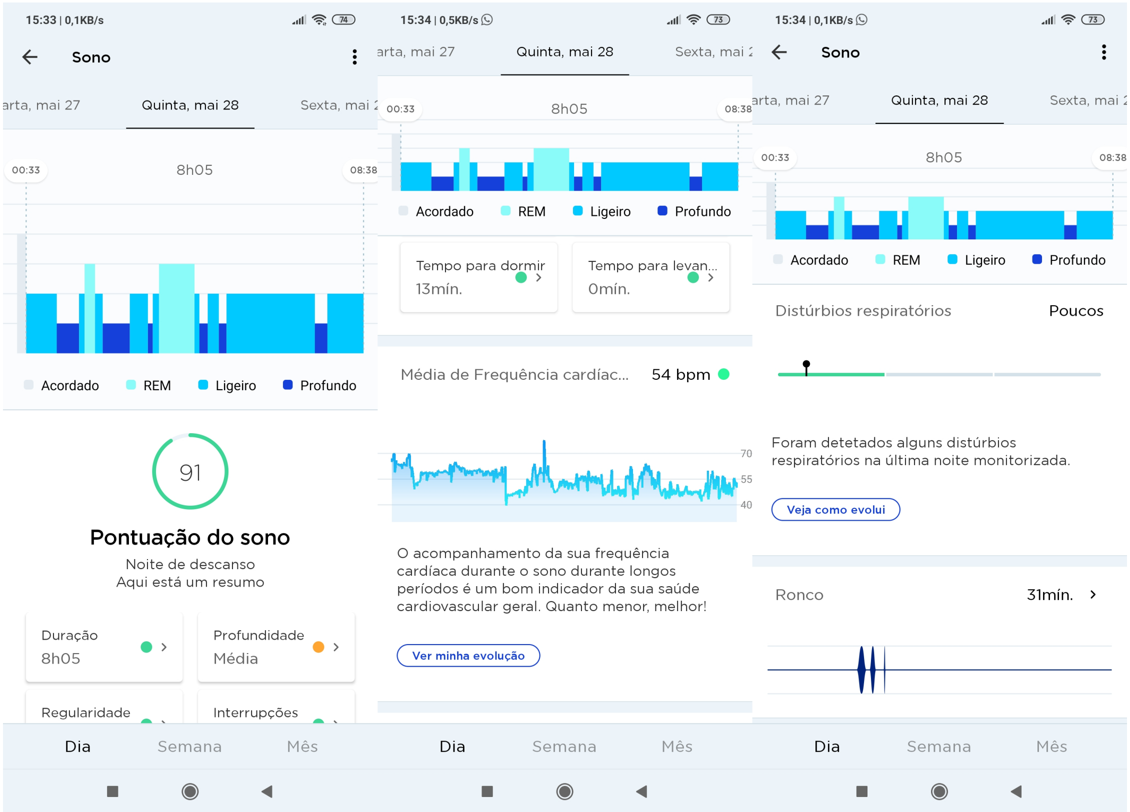

Figure 4.3: Screenshot from the Health Mate app of the main sleep page. When checking the daily information about the last sleep night, this is how the app looks like. Starts by showing the sleep score, scrolling down, it is possible to see the area about the heart rate variation and finally the information about breathing disturbances and snoring.

It was possible to compare this device to other devices already available on the Diani System, like in this case, the Fitbit Charge 2, that was already analysed in the chapter 3. During two different weeks, the sensor was used alongside the Withings Sleep Sensor, and the results are going to be presented and discussed in this section.

During six days, I wore the Fitbit Charge 2 band to compare the results obtained. The results were taken from the Withings Sleep Web Dashboard and the Fitbit Mobile App, they were compiled in table 4.1, and refer to the days between 31 of August and 5 of September. The parameters available for comparison were the sleep score, the total sleep time (TST), awake, REM, light, and deep sleep stage duration.

There was a significant synergy between the two devices, the TST was often similar, Withings has frequently shown longer duration in this parameter, as well as for light sleep. REM and deep sleep were harder to compare, varying more often, Fitbit showed several times longer periods of REM phase.

Overall, the TST was coherent with the two, the differences came in the algorithm of sleep stage classification, with Fitbit giving more weight to REM periods, and Withings to light sleep periods.

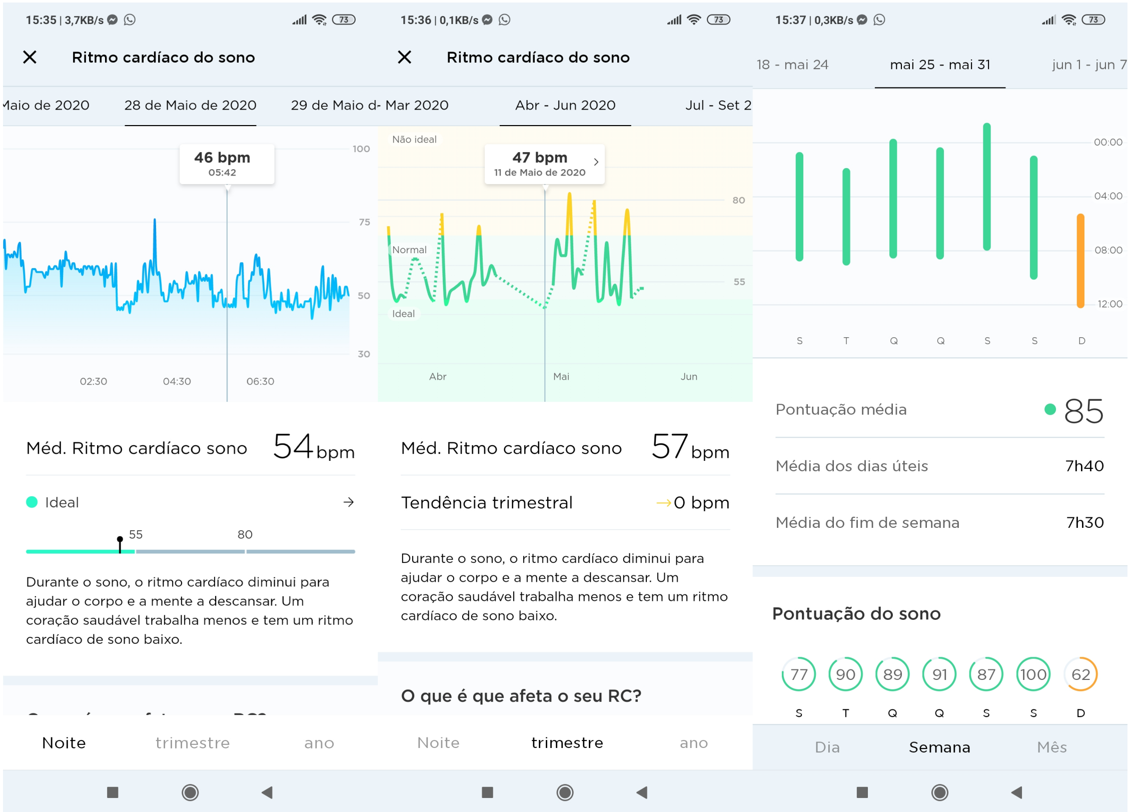

Figure 4.4: Screenshots from the Health Mate app. On the first one, it is possible to see in more detailed the night's HR variation graph. In the middle is how the statistics of HR variation in 3 months look like. Lastly, there are the statistics of the sleep score over a week.

The sleep scores were in line in both devices, although they differ a bit in the way that they are computed. Withings takes 4 inputs: the TST, the regularity of bed and rise times, the time spent in deep sleep and REM, and the time spent awake. Fitbit has the same inputs with the exception of the regularity one, instead, it takes into consideration the sleeping heart rate and the restlessness, lower heart rate values, and a quiet body help getting a better score. The similarities shown helped to trust Withings data.

4.2 Diani Telemedicine System

Diani was originally created with the purpose of providing a remote way to monitor diabetic patients.

The system functions are collection, visualization, and analysis of data extracted from multiple devices used on patients that suffer from chronic pathologies, such as, diabetes and hypertension.

At the moment, it is used for education and research purposes related to the self-management of these patients. The architecture of the Diani system can be unfolded into two parts, Server side and Patient/User side. In the server side, there are 4 components:

Table 4.1: Results extracted from Withings Web Dashboard and Fitbit Mobile App regarding the days between 31 of August and 5 of September. The data collected represents the Total Sleep Time (TST), the amount of time passed in each one of the sleep stages, and the sleep score given to each night according to each algorithm of the brands. The trackers wore Withings Sleep Tracking Mat and Fitbit Charge 2.

Parameters	31/08/20		01/09/20		02/09/20		03/09/20		04/09/20		05/09/20	
	Withings	Fitbit	Withings	Fitbit	Withings	Fitbit	Withings	Fitbit	Withings	Fitbit	Withings	Fibit
TST	09H45	08H49	07H04	06H45	07H25	07H20	08H06	7H23	08H05	08H02	06H56	06H43
REM	02H40	01H49	07H04	01H08	01H22	01H30	01H31	01H16	00H58	02H15	01H05	01H48
Deep Sleep	02H00	01H59	01H17	01H08	01H03	01H39	01H23	01H10	00H22	01H08	01H31	01H24
Light Sleep	05H05	04H59	05H06	04H29	05H00	03H53	05H12	04H57	05H45	04H39	04H20	03H31
Awake	01H06	01H05	02H09	00H45	00H53	00H44	01H18	00H57	00H45	00H47	01H15	00H53
Sleep Score	89	84	65	74	79	80	81	75	82	83	73	74

- Diani Web Application:
  - Presents a graphic display of the measured data;
  - Generates reports;
  - Includes a more detailed analysis of the records;
  - Allow the management of users and patients;
  - Data can be exported.
- WiFi Router;
- Hospital Information System;
  - Connection via FHIR HL7 interface;
- Diani Telemedicine Server:
  - Presents a centralized model for data storage;
  - MS SQL and .NET databases framework;
  - Communicates with the rest of the system via secure web services.

From the Patient/User side, the components can change regarding the aim of the study. For sleep monitoring the scheme would be with the following components:

- Fitness Bracelet:
  - Collects information about physical activity: Number of steps/min, sleep duration and heart rate values;
  - Automatic data transfer to the mobile application;
  - Automatic data transfer to the Diani web application;
  - Xiaomi MiBand and Fitbit support.
- Under-the-mattress Sensor:
  - Withings Sleep is the sensor that is going to be integrated into the system with this work;

  - Sleep score, continuous sleep heart rate tracking, apneic episodes, sleep duration, amount of sleep in each sleep phase, sleep interruptions and snoring.

- Mobile Application
  - Diabetesdagboka, allows to insert daily logs, keep in track levels of glycaemia, amount of carbohydrates, insulin, and stores the periods of physical activity.
  - Diani MiBand, an app for automatic reception and data transfer from Xiaomi MiBand.

Future ambitions for this system include a better sleep analysis and possible expansion to the use of patients with sleep disorders, that could help in their diagnosis and treatment control. The scheme shown in figure 4.5 illustrates how Diani is built and the communications that occurs between the different components.

4.3 Sleep Telemedicine System

The purpose of this work was to design a new sleep telemedicine system that could be implemented into the Diani System.

As the first phase of work, there was a need to understand what biological features influence our sleep most and how they can be tracked.

In the second step, an overview over the main sleep disorders was done. This allows to realize the importance of sleep tracking and for which circumstances the new sleep telemedicine system can have a purpose. Most of the articles reviewed focused on insomnia and sleep apnea, which are the disorders with more impact in the society.

For the third step, it was necessary to do a study over the existing home sleep-monitoring devices in the market. A survey was made to conclude which are the sensors typically found in the devices and what features they allow to monitor. All the devices reviewed could fit one of three categories, that were based on which physiological parameter they focus on during the sleep tracking: brainwave-based, movement-based, and cardiac activity-based. The last category was more framed on what the Diani system was looking for. Those devices provided a more complete understanding of sleep in a less obtrusive way. The final choice landed on a Withings device. Withings provides a public API making it possible to integrate any of their sensors into Diani.

The general use case of the sleep telemedicine system is shown in figure 4.6. As actors, there are the researchers/healthcare professionals that should have access to the sleep diary and sleep dashboard that contains the data from the patients or the participants of the research. These last ones are also actors and they can do everything the researchers/healthcare professionals do, and extra functionality that is editing their sleep diaries. Both of these two actors can also export the data to .csv files. The other two actors are part of the Withings system, which is their sensor responsible for the data collection, it communicates with Withings Server to synchronize the new data with the already existent one. After that, the Withings Server synchronizes with Diani Server, turning the data available for display.

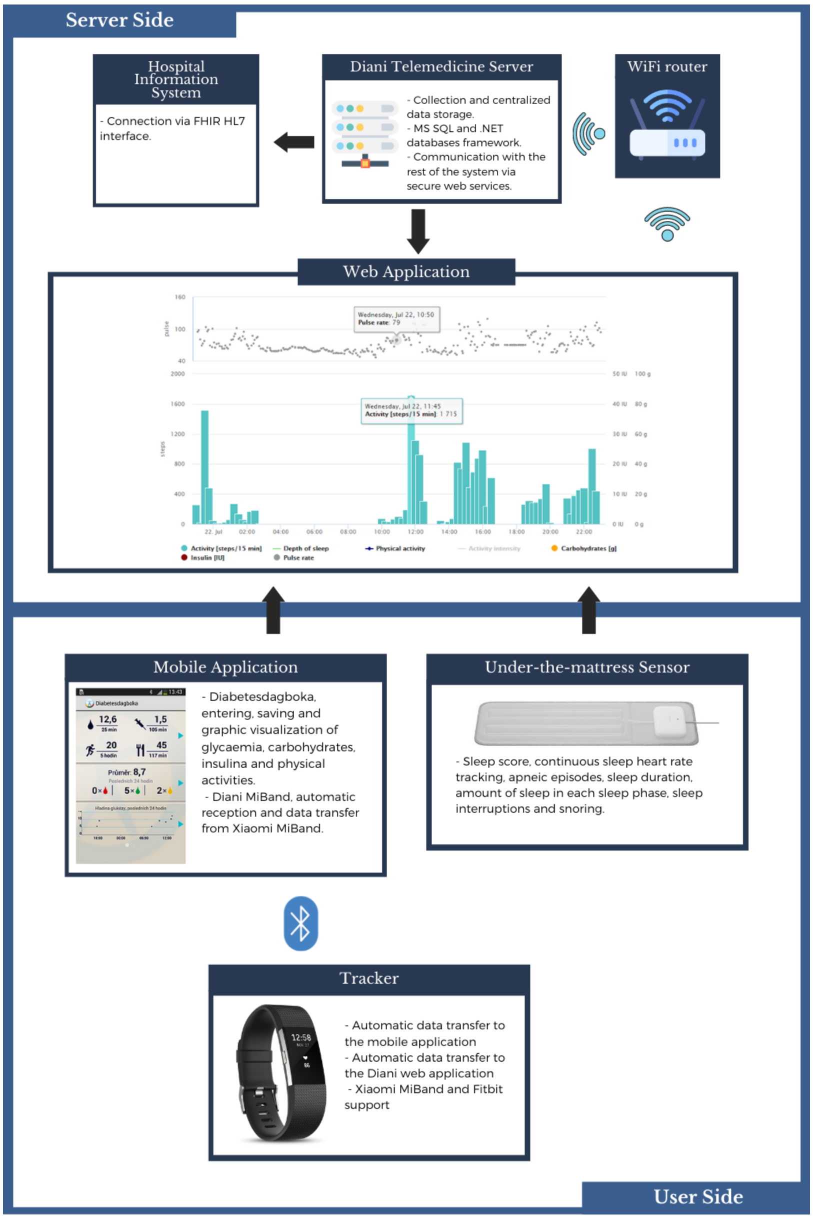

Figure 4.5: Scheme of Diani telemedicine system architecture and the communication means between the components.

The following subsections focus on the work that was developed to create a program in C# that used Withings API to collect the data analysed by the sensor every day. This program will be part of the Diani system, giving it a new and more detailed sleep telemedicine system.

4.3.1 OAuth 2.0

The Withings API is a public interface that allows developers to get access to Withings dataset from their devices.

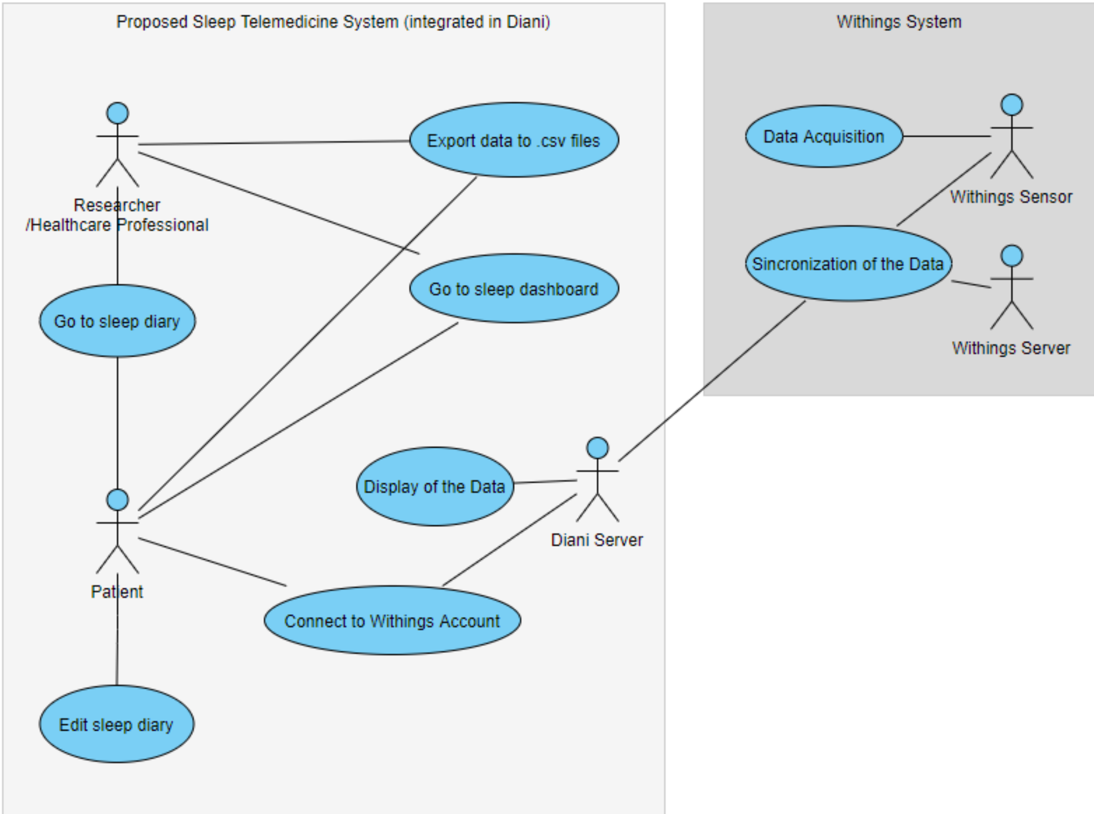

Figure 4.6: Diagram of the general use case. There are two systems involved: Withings System and the Proposed Telemedicine Sleep System. In the first one the actors are the Researcher/Healthcare professional, the patient and the Diani Server.

The API is implemented using OAuth 2.0, an authorization structure that enables to get user data without knowing their Withings' password account. This structure defines 3 role papers, resource owner/user, resource/authorization server, and client.

The resource owner/user is the user that authorizes an application to use their data, in this case, it is the person that has a Withings account.

The resource/authorization server is the API, this server is the host of the Withings accounts. It recognizes the user identity and emits access tokens for the application. It also provides the data, so it can be considered as a resource server as well. The client is my application that wants to access the user's Withings account. The access to the data is granted after the user accepts it and this authorization is validated by the API.

The diagram shown in figure 4.7 represents the flow between these 3 role papers.

The first step is to register my application providing its name, description, and a callback URL. This URL is to where Withings is going to redirect the users, after their authorization (or denial) to my application, and it is how Withings can communicate with the application every time that there is new data. Once my application is registered, a Withings API key and a secret key is provided. The API key is public and allows Withings API service to recognize my application. It will be also

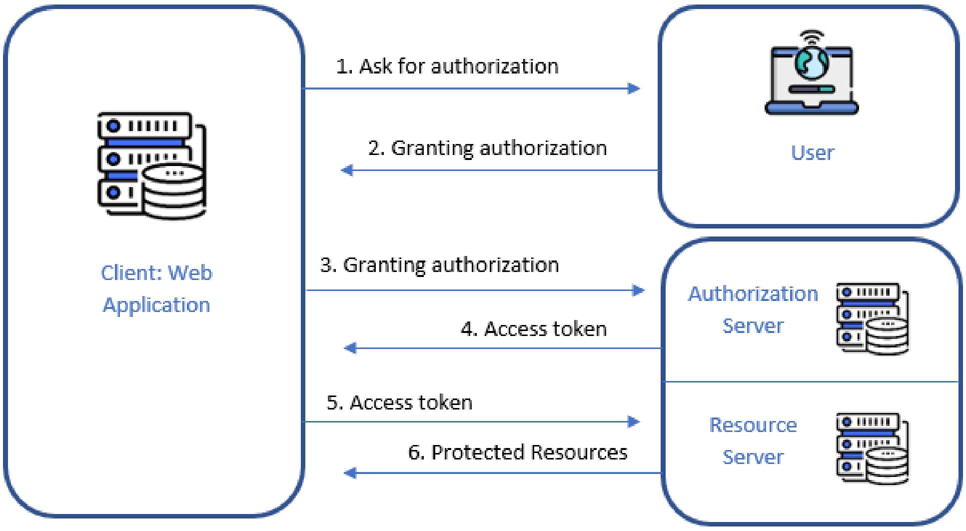

Figure 4.7: Diagram that represents the interaction between the user, the client and the API (Authorization/Resource server) in OAuth protocol.

used to build authorization URLs that are shown to the users. The secret key should be maintained between the API and my application. It is used to authenticate the identity of my application to the API when the application asks access to user's Withings account.

4.3.1.1 Implementation

The C# program was divided in two projects, *DianiWithings* and *WithingsData*. The first one is where the authorization process occurs.

When using the program for the first time it is necessary to run *DianiWithings* first. It will start by popping a window with the callback URL. To perform the login it is required to add into the URL the endpoint *\login*. By adding that endpoint, the function Authenticate, illustrated in the figure 4.8 will trigger and the user is redirected to a Withings page with the API key attached. In this page the Withings username and password should be inserted. After that, it will tell the user which data the application is going to have access to and if the user allows the app to obtain it.

```
[HttpGet]
public RedirectResult Authenticate()
{

    try
    {
        string url1 = $"{_appSettings.AuthBaseUri}&client_id={_appSettings.AuthClientId}" +
          $"&state={_appSettings.State}" +
          $"&scope=user.activity,user.sleepevents&redirect_uri={_appSettings.AuthRedirectUri}";

        return new RedirectResult(url1, true);

    }
    catch(Exception e)
    {
        _logger.LogError(e.ToString());
        throw;
    }

}
```

Figure 4.8: Function that leads the user to the authorization process.

After the user's acceptance, the app will redirect back to the callback URL with an authentication token on it. If redirection is successful, the app will receive the user ID, an access token, the expiration time of the token, the type of token, the scope, i.e, the data that the app is allowed to have, and a refresh token, for requesting a new access token when this one expires, all of this is processed by the code shown in figure 4.9.

The data mentioned above is saved in a SQL Server Database in the *AuthResponse* table. After this, the app can ask for sleep data by using the access token.

4.3.2 Withings API

Withings API lays on OAuth 2.0 protocol, that was explained before. After the implementation of the protocol in the app, is important to become familiar with the functions of the API and its documentation.

For the scope of this work, only the section of sleep was used. This section provides two functions, both of them can retrieve data till 7 days:

- *Sleep - Get*: retrieves data about a night of sleep between the dates provided in the POST request. The data returned:
  - Start date;
  - End date;
  - State: 0 stands for awake; 1 for light sleep; 2 for deep sleep and 3 for REM sleep;
  - Heart rate: the value recorded and in which minute;
  - Respiration rate: the value recorded and in which minute;
  - Snoring: total snoring time;
  - Model: the type of sensor. 16 is for a tracker, and 32 for the sleep pad.
- *Sleep - Getsummary*: gets a more details about user's night. 17 parameters can be returned:
  - Start date;

```
var client = new HttpClient();
client.BaseAddress = new Uri(_appSettings.AuthRedirectUri);
var request = new HttpRequestMessage(HttpMethod.Post, "https://account.withings.com/oauth2/token");

var accessTokenMessage = new List<KeyValuePair<string, string>>();
accessTokenMessage.Add(new KeyValuePair<string, string>("grant_type", "authorization_code"));
accessTokenMessage.Add(new KeyValuePair<string, string>("client_id", _appSettings.AuthClientId));
accessTokenMessage.Add(new KeyValuePair<string, string>("client_secret", _appSettings.AuthClientSecret));
accessTokenMessage.Add(new KeyValuePair<string, string>("code", code));
accessTokenMessage.Add(new KeyValuePair<string, string>("redirect_uri", "https://localhost:44391/authorization/"));

request.Content = new FormUrlEncodedContent(accessTokenMessage);
var response = await client.SendAsync(request);
var authorizationJsonResponse = await response.Content.ReadAsStringAsync();

//deserialize our JSON into a AuthorizationResponse object
var authorizationResponse = JsonConvert.DeserializeObject<AuthorizationResponse>(authorizationJsonResponse);

try
{
    var authResponse = new AuthorizationResponse
    {
        UserId = authorizationResponse.UserId,
        AccessToken = authorizationResponse.AccessToken,
        ExpiresIn = authorizationResponse.ExpiresIn,
        TokenType = authorizationResponse.TokenType,
        Scope = authorizationResponse.Scope,
        RefreshToken = authorizationResponse.RefreshToken,


    };
    _context.AuthorizationResponses.Add(authResponse);
    _context.SaveChanges();
    return authResponse;
```

Figure 4.9: Function in the Authorization Controller, it receives the code retrieved in the URL after the user allowing the app to have access to its data. The code is used to ask for an access token, that is valid for 3h to ask for data to Withings server. Besides the access token, other information is returned and it is saved on a database in the table, AuthResponse.

- End date;
- Last update;
- Breathing disturbances intensity: for this to be computed correctly, the user needs to enter valid information regarding its age, eight, weight, gender. This is only calculated if the night of sleep is longer than 5 hours. From 0 to 30 is considered low, 30 to 60 medium and above 60 is high;
- Duration of deep sleep, light sleep, REM and awake phase;
- Time passed till falling asleep;
- Time to get up from the bed;
- Average, maximal and minimal heart rate;
- Average, maximal and minimal respiration rate;
- Sleep score;
- Total snoring time;
- Number of snoring episodes;
- Number of awakening times;

4.3.2.1 Implementation

The next phase of the code development is to prepare the program to receive the sleep data.

For that, a folder *Models* was created, it has the files *SleepResponse* and *SleepSummaryResponse*, which are the objects in which the JSON responses from the server will be deserialized to.

The project *WithingsData* is where the sleep data is received. It starts by going to the last row of *AuthResponse* table to get the last user who accessed into the application, and gets the access token.

After this, it is checked the date of the last data retrieved. This information allows the program to request for new sleep data. A POST request is done to *https://wbsapi.withings.net/v2/sleep?action=get* for the next 24 hours.

If the access token is not valid anymore, the response shows 401 in the status. In this case, another token request is done and the last row of the *AuthResponse* table is updated with the new token. If the response comes with 200 in the status parameter, the data was successfully retrieved. Therefore, it is stored in the *SleepDatas* table, which has the scheme illustrated in the screenshot, figure 4.10. A constraint was settled to make sure there is no repeated data stored.

```sql
CREATE TABLE [dbo].[SleepDatas] (
    [ID]             INT                IDENTITY (1, 1) NOT NULL,
    [UserId]         NVARCHAR (50)      NOT NULL,
    [DataType]       NVARCHAR (50)      NOT NULL,
    [Value]          INT                NOT NULL,
    [State]          INT                NOT NULL,
    [Date]           DATETIMEOFFSET (7) NOT NULL,
    [SleepDataID]    INT                NULL,
    [EndDateQuery]   NVARCHAR (MAX)     NULL,
    [StartDateQuery] NVARCHAR (MAX)     NULL,
    CONSTRAINT [PK_SleepDatas] PRIMARY KEY CLUSTERED ([ID] ASC),
    CONSTRAINT [UQ_codes] UNIQUE NONCLUSTERED ([Date] ASC, [DataType] ASC, [UserId] ASC),
    CONSTRAINT [FK_SleepDatas_SleepDatas_SleepDataID] FOREIGN KEY ([SleepDataID]) REFERENCES [dbo].[SleepDatas] ([ID])
);
```

Figure 4.10: Scheme of *SleepData* table in the database.

The content of the table is written on a .csv file after. The last function of *WithingsData* is another POST request, but to *https://wbsapi.withings.net/v2/sleep*. The data returned from that request is stored in *SleepSummaries* table, 4.11.

I used the Microsoft Team Foundation Server for the development team to always have access to the latest versions of my code, and to help me in case of code errors.

4.3.3 Front-end Proposed Implementation

As further work to be done in order to fully integrate this new sleep system into Diani, requires the design of how the data should be presented to the users.

In this section, it is going to be discussed the suggestions proposed for the visualization of the sleep telemedicine system.

```
CREATE TABLE [dbo].[SleepSummaries] (
    [ID]                          INT            IDENTITY (1, 1) NOT NULL,
    [Timezone]                    NVARCHAR (MAX) NOT NULL,
    [Date]                        NVARCHAR (MAX) NOT NULL,
    [BreathingDisturbancesIntensity] BIGINT      NOT NULL,
    [DeepSleepDuration]           BIGINT         NOT NULL,
    [DurationToSleep]             BIGINT         NOT NULL,
    [DurationWakeUp]              BIGINT         NOT NULL,
    [HrAverage]                   BIGINT         NOT NULL,
    [HrMax]                       BIGINT         NOT NULL,
    [HrMin]                       BIGINT         NOT NULL,
    [LightSleepDuration]          BIGINT         NOT NULL,
    [RemSleepDuration]            BIGINT         NOT NULL,
    [RrAverage]                   BIGINT         NOT NULL,
    [RrMax]                       BIGINT         NOT NULL,
    [RrMin]                       BIGINT         NOT NULL,
    [SleepScore]                  BIGINT         NOT NULL,
    [Snoring]                     BIGINT         NOT NULL,
    [SnoringEpisodeCount]         BIGINT         NOT NULL,
    [WakeUpCount]                 BIGINT         NOT NULL,
    [WakeUpDuration]              BIGINT         NOT NULL,
    CONSTRAINT [PK_SleepSummaries] PRIMARY KEY CLUSTERED ([ID] ASC)
);
```

Figure 4.11: Scheme of *SleepSummaries* table in the database.

In the tab menu, a sleep tab should be added, as represented in the figure 4.12. From here the user should use firstly the 'Connect to Withings Account' option, that should redirect to a Withings page, where the user can consent and accept the data that Diani will receive.

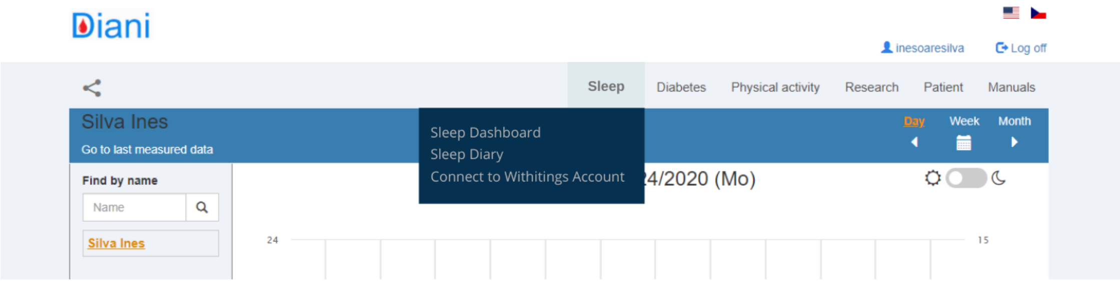

Figure 4.12: Sleep tab that should be added into Diani page.

In the 'Sleep Diary' option, the page illustrated in the figure 4.13 should be loaded. As explored in the chapter ref chap: sleep, the subjective measurements revealed to be an important source to compliment the objective measurements, filling the gaps that these ones might have. Overall, it helps to give a better picture of the user's sleeping habits. This diary was inspired by the Consensus Sleep Diary. Integrating sleep diaries in telemedicine solutions can help the sleep diary to be more accurate because a lot of the parameters can be automatically filled by the system.

The points 1, 2, 3, 4, 5, 6, 9, 10 can be filled automatically since Withings Sleep calculates them. However, here the user should be able to still edit them if the sensor gets some reading errors.

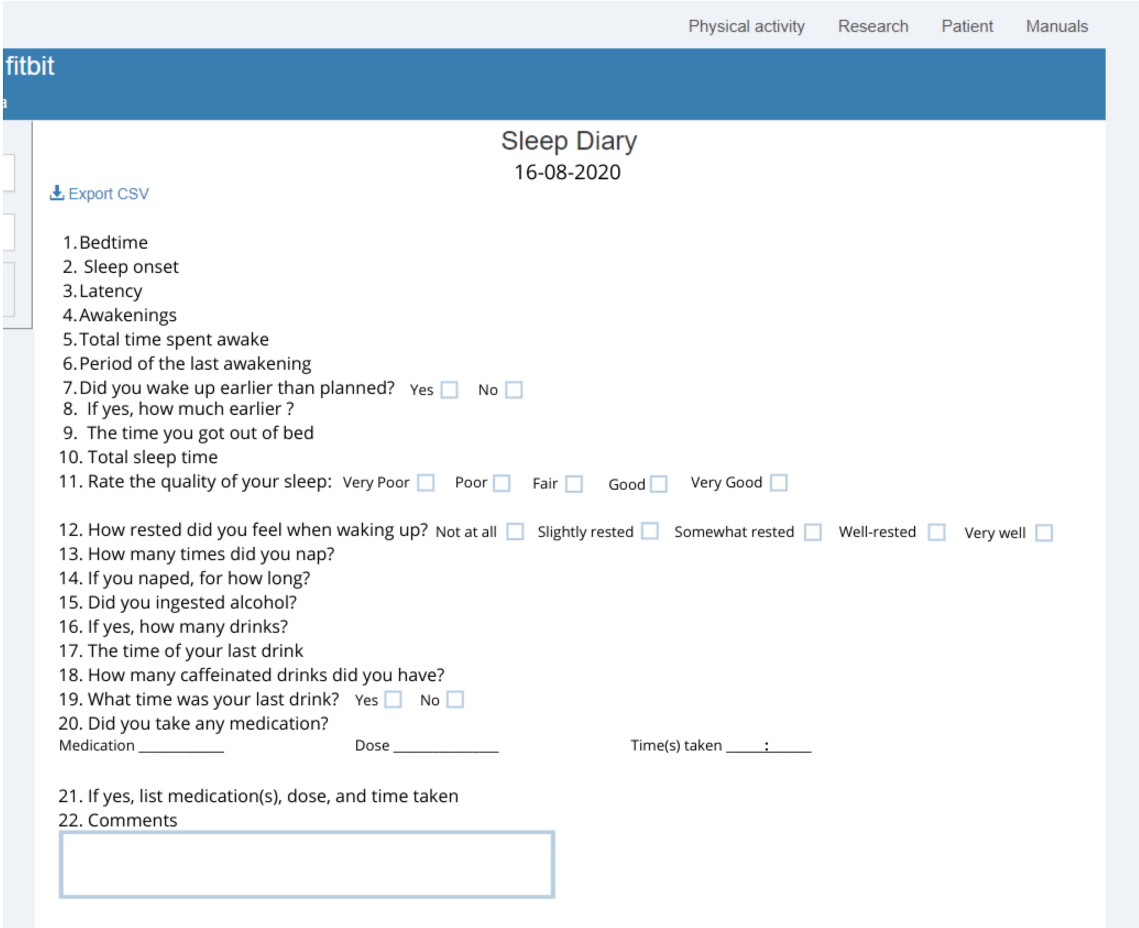

Figure 4.13: Sleep diary section that should be added into Diani. It is used the Consensus Sleep Diary.

In the 'Sleep Dashboard' is where the sleep information should be displayed, like in the format illustrated in this mockup, figure 4.14.

The hypnogram of the night should show up on the top, representing the different sleep cycles that the user passed through the night period.

Below, there is the pulse graph of the same period placed there to understand how the heart rate varied, with the average sleep HR value and the resting HR. This last parameter corresponds to the lowest possible heart rate while not sleeping. The best moment to extract it is when the patient first wakes up in the morning while laying down. HR during the day is not monitored with this sensor but is important to know that HR should be lower during sleep than during the day.

The next section of the page corresponds to the night statistics. On the left, there is the amount of time passed in each sleep phase. In the middle, the sleep score attributed by Withings algorithm, and already presented in the first section of this chapter, 4.1. On the right, the total sleep time, the time in bed, the efficiency, the latency, i.e, time the user took to fall asleep, and lastly, the time passed until the user got out of bed.

Finally, the section about respiratory events, how many snoring episodes and for how long they happen in total. The average respiratory rate should also be displayed, representing the number of breaths per minute.

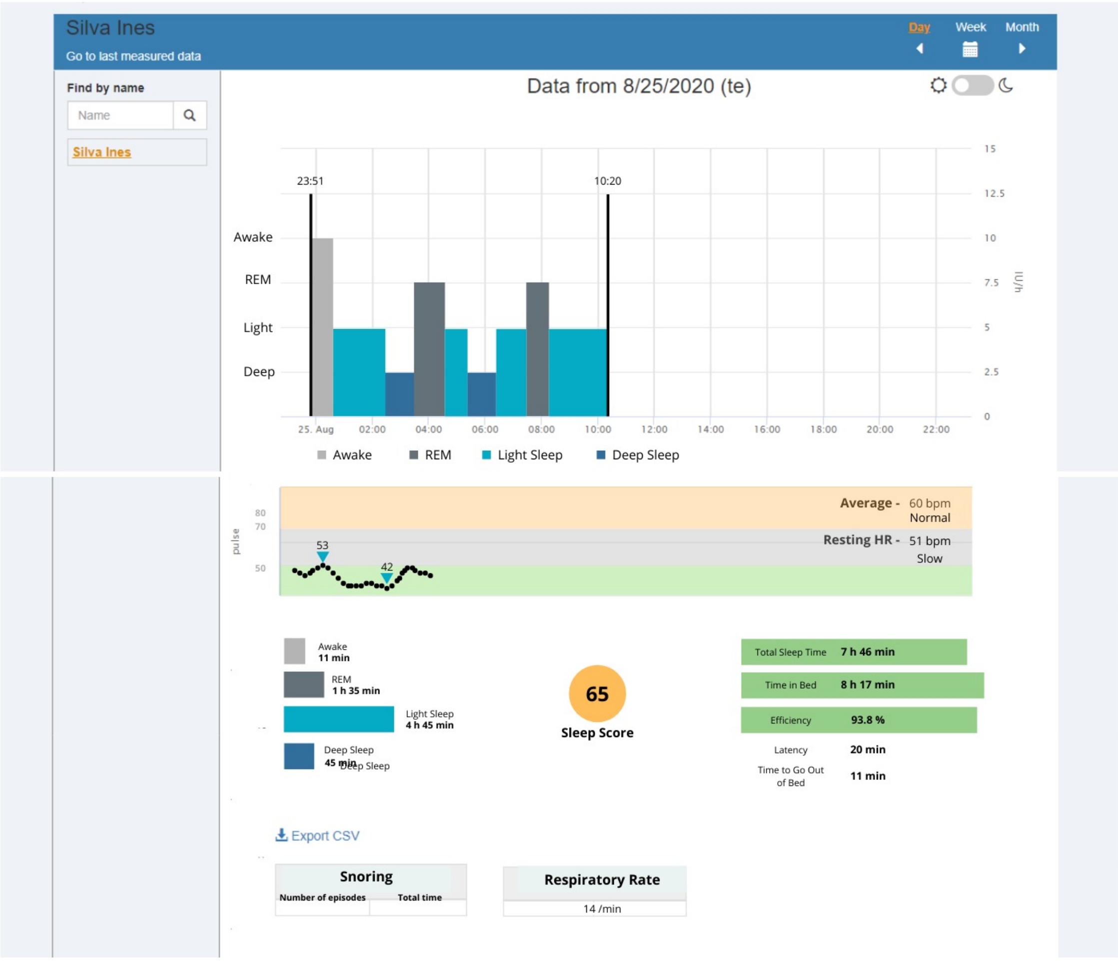

Figure 4.14: Mockup of the daily sleep overview.

In the sleep dashboard, when switching from the day view to week or month, some statistical information should appear in the format like the one presented in this figure, 4.15. In the same format as the daily view, but the values displayed should be the average of all the nights of the week. Bellow, the average sleep score and an overview of all sleep scores through the week. The heart rate graph can display the average heart rate in each night. The strips of colors in this graph, help the user get a notion of the healthiest range of values. With this sensor the user can see its sleep heart rate, as well as, the resting heart rate which is normally %10 higher. As Withings explains, it is considered 50 to 85 bpm the more optimal range, however, in case of a really good cardiovascular health, the human can have 40bpm, like the case of many athletes. Below 40 may be a signal of a pathology.

The possibility of exporting to a .csv file is also relevant in order to show the doctor the information of a specific night.

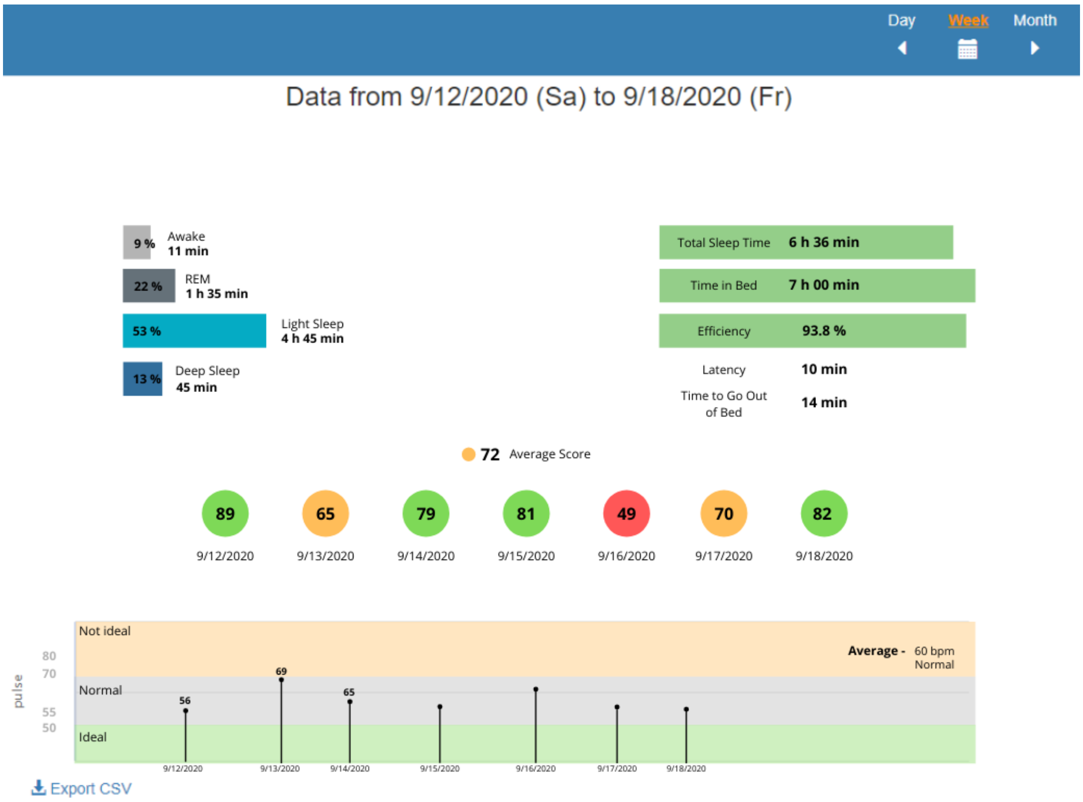

Figure 4.15: Mockup of the weekly sleep over view.

4.3.4 Results

The program developed in C# retrieves information about the sleep that is getting stored in a SQL Server Database, whose model is outlined in the figure 4.16.

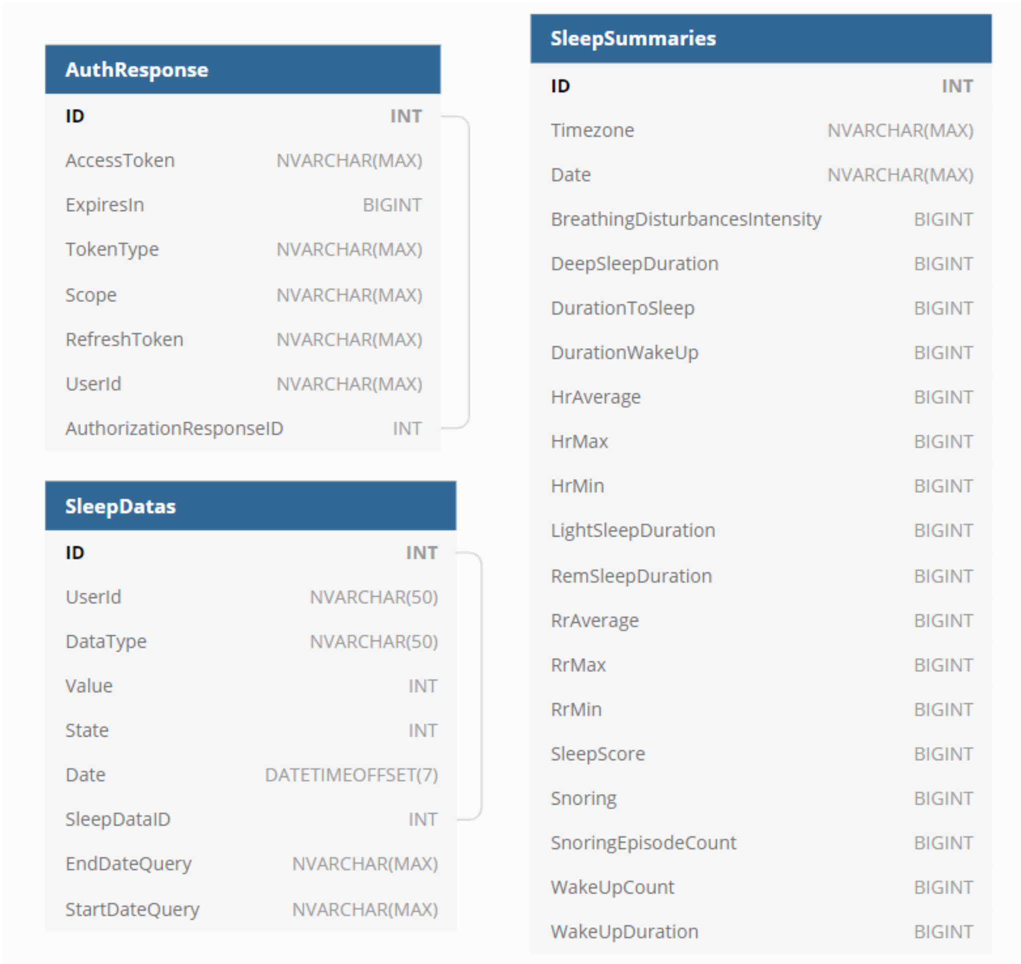

Figure 4.16: Database Model, representing the three tables, *AuthResponse*, *SleepDatas* and *SleepSummaries*.

There are some corrections in the relations between the tables. The connections ID to *AuthorizationResponseID* should be deleted as well as the ID connection to *SleepDataID*, they do not have any use. The tables miss a connection between them, that should be done be the UserId parameter. A way to do this could be changing the UserId as primary key in *AuthResponse* table, and make it as a foreign key in the other two tables. Nevertheless, let's analyse the content of each table. The first one stores information every time the *DianiWithings* project runs and a user does login on the Withings website. The columns of *AuthResponse* table, figure 4.17, are:

- *ID*, is an auto-increment primary key;
- *Access Token*, that is given by Withings after the user accept the access of my application to its information, it's very important since it allows doing the data requests to the server;
- *Expires In*, is the time in seconds that it takes till the access token gets expired. Normally is equivalent to three hours;

- *Token Type*, it is expected to be from the type 'Bearer', which is the predominant type of tokens used in OAuth2.0. It represents how the access token is generated and how is going to be presented for the resource calls to the server, not having much importance in this context;
- *Scope*, it stores a string with the type of data the user gave access to. In the case of this project, it is asked for:
  - *User.info*, which allows some functions like the creation of a new user and link of its devices;
  - *User.metrics*, this doesn't apply for the Withings Sleep Mat Sensor, but it is required for other products, like most of there smartwatches and smart-bands, which may be of the future interest of the Research Center;
  - *User.activity*, this gives permission to the utilization of several API services, which are, 'Sleep v2 - Get' and 'Sleep v2 - Getsummary'. These are the two services that are used in the project and the data retrieved from them is stored in two other database tables, that are going to be presented next;
  - *User.sleepevents*, this is for the API notification system. This system retrieves different parameters depending on the notification categories that are subscribed to. In this case, it was only subscribed to sleep-related events, and the actions that trigger the notifications are whenever the user lays in the bed, when the user gets out of the bed or when it finishes a new inflation of the sensor. When at least one of these events occurs, our server receives a POST call to our callback URL with several parameters in the body, like the user ID, the date, the device ID, and the data category.
- *Refresh Token*, this token allows to request for a new Access Token when this one is expired and enable to make requests again;
- *UserId*, it stores the ID of the user that logged in.

ID	AccessToken	ExpiresIn	TokenType	Scope	RefreshToken	UserId	Authorization...
5009	f3d10fae2e9516...	10800	Bearer	user.activity,us...	1b0ff8da2eab8f...	21112738	NULL
5010	58f6c110ea09f1...	10800	Bearer	user.activity,us...	98d7f6d618a32...	22891210	NULL
NULL	NULL	NULL	NULL	NULL	NULL	NULL	NULL

Figure 4.17: A screenshot obtained with SQL Server Object Explorer from Visual Studio of data stored in the *AuthResponse* table. It is composed by the following columns: ID as the primary key; *Access Token*; *ExpiresIn*; *TokenType*; *Scope*; *Refresh Token*; *UserId*.

Regarding the *SleepDatas* table, figure 4.18, the columns that compose it are:

- *ID*, an integer that represents the primary key;
- *UserId*, the identification number of the user from where the data belongs to;

- *DataType*, stores what type of information the row gives. It can be three different types, hr, heart rate, rr, respiration rate or snoring;
- *Value*, is the measurement recorded that has different meanings depending on the data type;
  - hr rows, represent the number of heartbeats per minute;
  - rr rows, represent the number of breaths per minute;
  - snoring rows, give the total snoring time.
- *State*, corresponds of the stage of sleep the user was during that measurement;
  - 0 - awake state;
  - 1 - light sleep state;
  - 2 - deep sleep state;
  - 3 - REM state.
- *Date*, stores the moment when the value was recorded, its format presents the date, the time and the UTC timezone from where the data was captured.
- *EndDateQuery* and *StartDateQuery*, in each of these columns an Unix timestamp value is stored, and it is the value used to request the data about the night sleep to Withings Server. It is used to make it easier to group the data for further analysis, to separate the data from each night.

ID	UserId	DataType	Value	State	Date	Slee...	EndDateQuery	StartDateQuery
17645	21112738	hr	62	0	02/09/2020 00:57:00 +01:00	NULL	1600103433	1600017093
17646	21112738	hr	56	0	02/09/2020 00:58:00 +01:00	NULL	1600103433	1600017093
17647	21112738	rr	16	0	02/09/2020 00:57:00 +01:00	NULL	1600103433	1600017093
17648	21112738	rr	16	0	02/09/2020 00:58:00 +01:00	NULL	1600103433	1600017093
17649	21112738	snoring	0	0	02/09/2020 00:57:00 +01:00	NULL	1600103433	1600017093
17650	21112738	snoring	0	0	02/09/2020 00:58:00 +01:00	NULL	1600103433	1600017093
17651	21112738	hr	59	0	02/09/2020 01:07:00 +01:00	NULL	1600103433	1600017093
17652	21112738	rr	14	0	02/09/2020 01:07:00 +01:00	NULL	1600103433	1600017093
17653	21112738	snoring	0	0	02/09/2020 01:07:00 +01:00	NULL	1600103433	1600017093
17654	21112738	hr	52	0	02/09/2020 02:49:00 +01:00	NULL	1600103433	1600017093
17655	21112738	hr	52	0	02/09/2020 02:50:00 +01:00	NULL	1600103433	1600017093
17656	21112738	hr	50	0	02/09/2020 02:51:00 +01:00	NULL	1600103433	1600017093
17657	21112738	hr	54	0	02/09/2020 02:52:00 +01:00	NULL	1600103433	1600017093
17658	21112738	hr	61	0	02/09/2020 02:53:00 +01:00	NULL	1600103433	1600017093
17659	21112738	hr	48	0	02/09/2020 02:54:00 +01:00	NULL	1600103433	1600017093

Figure 4.18: A screenshot obtained with SQL Server Object Explorer from Visual Studio of data stored in the *SleepDatas* table. It is composed by the following columns: *ID* as the primary key; *UserId*; *DataType*; *Value*; *Date*, datetime format with UTC timezone; *EndDateQuery* and *StartDateQuery*, unix timestamps of the interval of dates used in the query to get the sleep information.

Finally, the *SleepSummaries* table, figure 4.19, presents the following columns:

- *ID*, the primary key;

- *Timezone*, provides information about in which timezone the user was at the moment of the data collection;
- *Date*, the day when the data was collected;
- *Breathing Disturbances Intensity*, it represents an integer that is calculated by a algorithm from Withings to report the intensity of interruptions in breathing patterns. There are some considerations needed to make sure this value is well computed, such as correct profile information like age, height, weight, and gender. Also, sleep hours need to be longer than five. For shorter periods this is not computed and is stored as -1. Their values should be interpreted as the following:
  - low - from 0 to 30;
  - medium - from 30 to 60;
  - higher - more than 60.
- *Deep Sleep Duration*, the amount of time in seconds that the user spent on deep sleep stage;
- *Duration To Sleep*, the amount of time in seconds that it took the user to fall asleep;
- *Duration Wake Up*, it comes in seconds and represents the time the user took till getting out of the bed;
- *Hr Average*, the average heart rate during the night;
- *Hr Max*, the maximum heart rate measured during the night;
- *Hr Min*, the minimum heart rate measured;
- *Light Sleep Duration*, the amount of time in seconds that the user spent on light sleep stage, corresponding to N1 and N2 phases combined;
- *Rem Sleep Duration*, the amount of time in seconds that the user spent on REM stage;
- *Rr average*, corresponds to the average respiration rate, number of breaths per minute, during the night.
- *Rr Max*, the maximum respiration rate measured;
- *Rr Min*, the minimum respiration rate measured;
- *Sleep Score*, it is a value between 0 and 100, that aims to give a better understanding of how good was the user's sleep, it depends on several factors, that were presented in the section 4.1;
- *Snoring*, the total snoring time in seconds;
- *Snoring Episode Count*, number of snoring episodes during at least one minute;

- *Wake Up Count*, number of times the user woke up;

- *Wake Up Duration*, total time in seconds that the user spent awake.

ID	Timezone	Date	Br...	DeepS...	DurationToSleep	Duratio...	HrAver...	HrMax	HrMin	LightS...	RemS...	RrA...	RrMax	RrM...	Sleep...	Sno...	Snori...	Wak...	WakeU...
151...	Europe/Prag...	2020-07-21	-1	0	240	0	64	0	0	0	0	18	0	16	0	0	0	0	0
152...	Europe/Prag...	2020-07-22	6	4800	2580	540	59	0	0	0	5700	12	0	9	0	0	0	0	0
154...	Europe/Lisbon	2020-08-08	8	5340	720	0	68	81	47	13440	6660	13	19	10	91	360	2	0	720
154...	Europe/Lisbon	2020-08-10	6	5760	0	1800	58	78	44	13140	5040	13	18	10	75	3600	3	1	2220
155...	Europe/Lisbon	2020-08-14	-1	6720	1980	0	55	73	44	4200	1920	13	18	10	20	420	1	1	2400
156...	Europe/Lisbon	2020-08-20	8	5160	1140	0	51	73	43	16440	11100	12	17	9	100	1680	2	1	2640
156...	Europe/Lisbon	2020-08-21	7	3480	4260	0	51	81	41	15720	6780	12	19	9	80	180	1	1	5100
157...	Europe/Lisbon	2020-08-27	11	4860	5460	780	46	69	40	11520	4200	12	22	9	47	420	2	2	7020
157...	Europe/Lisbon	2020-08-28	9	4680	1560	0	58	76	47	16620	6900	14	25	9	78	180	1	2	5040

Figure 4.19: A screenshot obtained with SQL Server Object Explorer from Visual Studio of data stored in the *SleepSummaries* table. It is composed by the following columns, in order: *ID* as the primary key; *Timezone*; *Date*; *BreathingSleepDisturbances*; *DeepSleepDuration*; *DurationToSleep*; *DurationWakeUp*; *HrAverage*; *HrMax*; *HrMin*; *LightSleepDuration*; *RemSleepDuration*; *RrAverage*; *RrMax*; *RrMin*; *SleepScore*; *Snoring*; *SnoringEpisodeCount*; *WakeUpCount*; *WakeUpDuration*. All the time values are presented in seconds.

4.3.4.1 Graphic Visualization

The data mentioned and showed above is stored in a SQL Server Database that is then exported to .csv files, for further analysis and comparison with the data analysis done by Withings.

For the treatment of the data collected, two Python scripts were developed to generate graphs with the .csv as data input.

The software Spyder was used for code development. Several software libraries were included to help process the information.

The .csv data was converted to a data structure called DataFrame with Pandas library. Pandas DataFrame makes the approach to the data easier due to its two-dimensional size-mutable tabular data structure, following the same architecture as the database tables, having three main components, rows, columns and the data.

For the creation of the plots, the matplotlib library was used. In the first program, the *sleep-data.csv* file is analysed, and originates two plots, the hypnogram and heart rate variation of each night. For validation of the graphics generated, they were compared with the ones showed on the Withings Web Dashboard.

The results of the nights of two and three of September are illustrated in figures 4.20 and 4.21, respectively. Both images show firstly the two graphs computed with the python program using the data from the database of the proposed sleep system and bellow them, is placed the Withings data visualization for an easier comparison of the results.

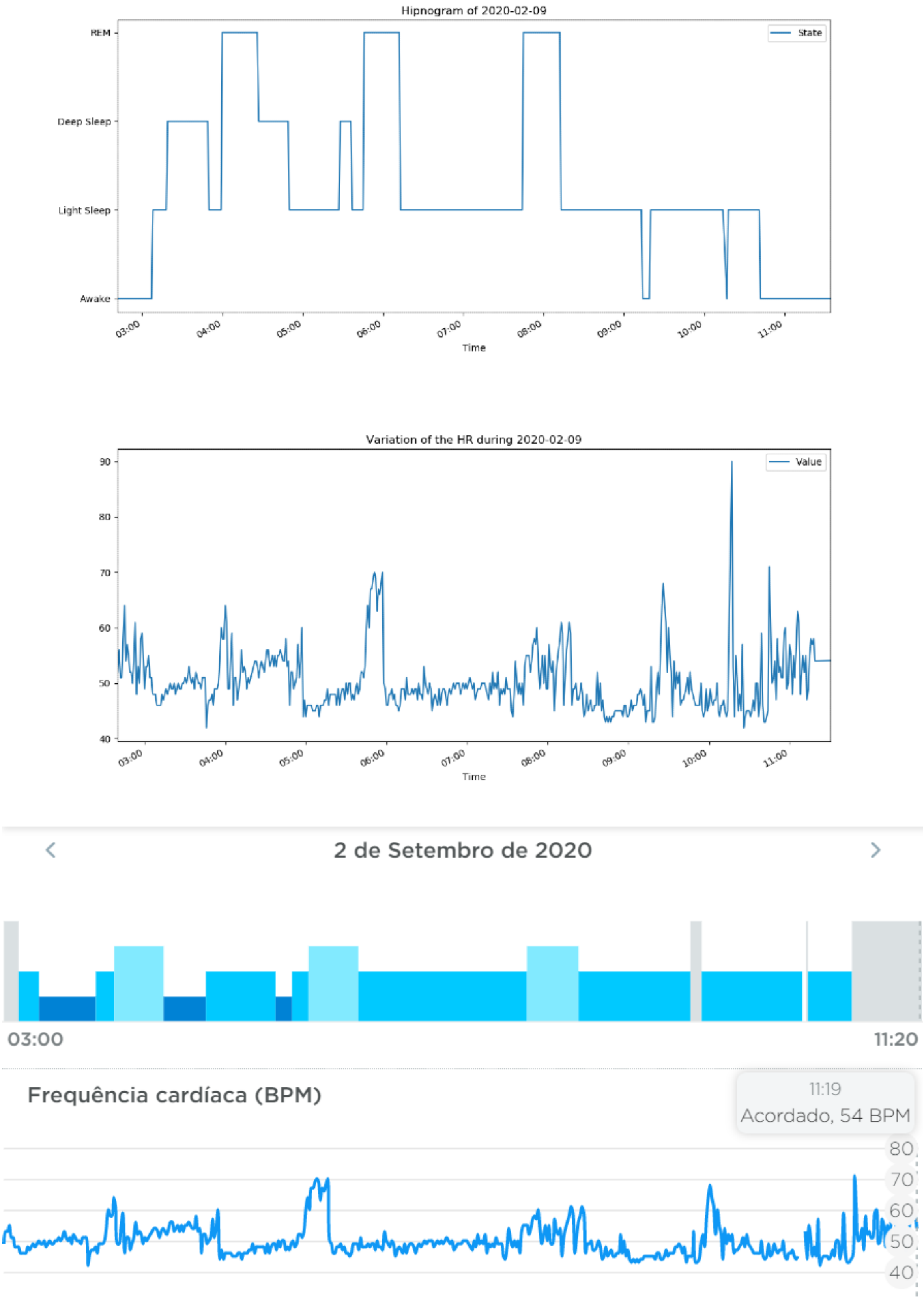

Figure 4.20: Comparison between the graphs plotted with the developed Python scripts (in the top) and the ones obtained directly from the Withings Web dashboard (at the bottom). Data taken on 3 of september of 2020. Note: meaning of the colors on the Withings hypnogram, light blue - REM; medium blue - light sleep; dark blue - deep sleep; grey - awake.

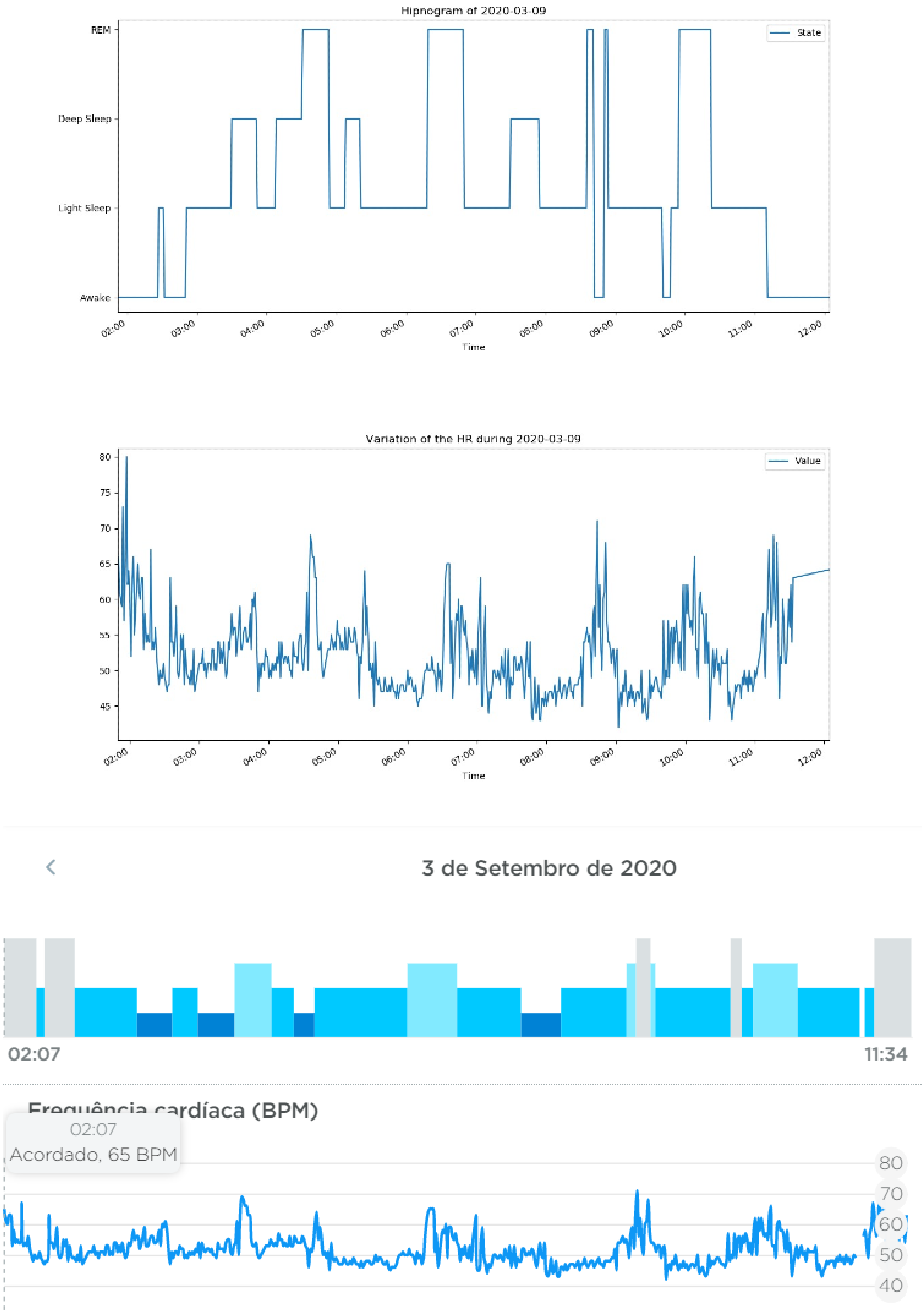

Figure 4.21: Comparison between the graphs plotted with the developed Python scripts (in the top) and the ones obtained directly from the Withings Web dashboard (at the bottom). Data taken on 2 of september of 2020. Note: meaning of the colors on the Withings hypnogram, light blue - REM; medium blue - light sleep; dark blue - deep sleep; grey - awake.

The results of the proposed system database are coherent with the ones plotted by Withings.

Monitoring the heart rate during sleep serves as an indicator of a person's overall health. This graph shows how the sleep heart rate varies during the night. While we are asleep, the heart rate drops to help our body to rest, low heart rate values reveal a healthy heart that needs to work less. A sudden increase of these values is commonly caused by lifestyle factors, like training, stress, caffeine ingestion, or it can be a sign of illness, like a viral infection. With the exception of this last factor, the other ones can be reshaped by the person The first factors can be controlled by the person, like exercise more, change the pre-bedtime routine, and having access to this metric can give better understanding if those changes are having a positive impact.

As it was analysed in the chapter 2 the heart rate increases during REM stage, similar to the awake phase, and after looking at the graphics it is possible to confirm that most of the peaks in the heart rate variation graph also correspond to a REM state or an awake state. Despite these spikes that are normal, the overall shape it should be like a hammock curve, i.e, going down reaching the lower points in the middle of the night and then start increasing till the wake up time. A curve like this shows that the body was relaxed during the night and is getting started to be ready for rising. In the case of these two graphs, both of them show a hammock curve, that is more notable in the night of 3 of September. These means a well rested night, in fact, the sleep scores of these days were 79 and 80, respectively, which is a good value.

There are two other possible formats of graphs, that are not ideal, those are, the downward slope format, i.e if the heart rate starts high and continues to drop till the moment of waking up. This shows that the metabolism of your body kept working overtime. Having a late meal, a late workout, or having alcoholic drinks can be factors behind this graph. The other one is when it looks like a hill, i.e, starts high and only drops before waking up, may reveal exhaustion. It may show that melatonin, a hormone that promotes sleep and reduce blood pressure [134], is present at high levels. This can be a signal that the person did not go to bed in its ideal bedtime window, or might have had long periods of snoring, which increases heart rate.

For the analysis of the hypnogram is noteworthy to review some concepts presented in chapter 2. A graph of a night with the recommended hours of sleep, from 7 to 9h, should present 4 to 6 cycles. A cycle is represented by the transition from NREM to a REM stage. and should be 4 to 6 cycles during a night

In the second night of September is possible to count 3 cycles out of a 7h25 time of sleep. Those cycles finish with the moment when the user reaches the REM stage. In the night after is already possible to count 4 cycles out of 8h06 of sleep, representing a better night of sleep.

There is a second program that analyses the *sleepsum.csv* file, which contains the data from the *SleepSummaries* database table. The graphs created from that program and presented below, figures 4.22 and 4.23, represent the night of 2 of September, while the figures 4.24 and 4.25 show the night of 3 of September.

Analyzing the cycles of the sleep and the quantities passed in each stage, as stated in chapter 2, the first REM episode occurs more or less 90 minutes after sleep onset. On the night of the 2 of September it occurs after one hour and on the 3, the sleep onset occurs almost at 3h, and REM happens at 4h30, going according to the theory explained before. It should represent 20% to 25% of the sleep. In the results obtained, in both of the nights REM represented 18% of the total sleep time. Though it should represent a longer period of the total sleep time, is still a satisfactory result.

As expected, we spend more time in the NREM phase, N3, or deep sleep, it accounts for 12.5% to 20% of the sleep, while the rest is for the light sleep. In the analyzed second and third nights of September, it stood for 14% and 18%, respectively, being inside the expected interval amounts. The third night was longer than the second and had better results, with more time passed in restorative phases, REM, and deep sleep. Overall the graphs plotted registered healthy and normal data from the nights of sleep.

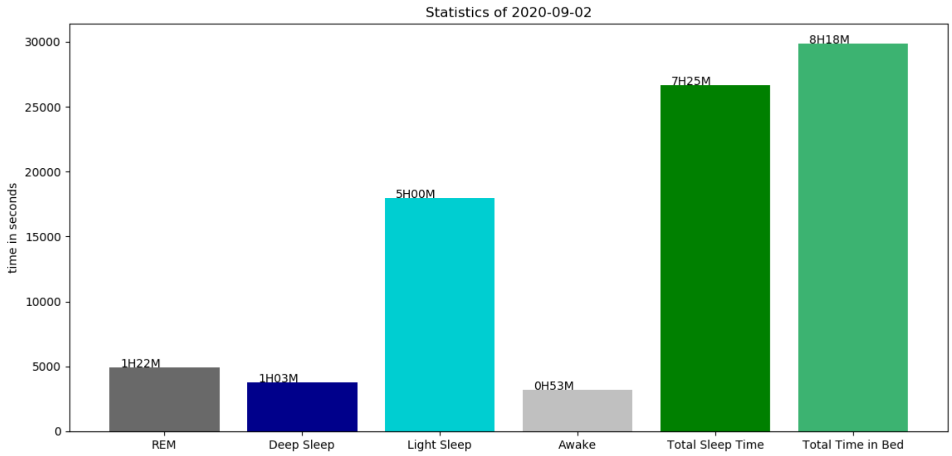

Figure 4.22: Night statistics of 2 of September 2020. Bar plot obtained using panda and matplotlib libraries of python. In the y-axis is illustrated time in seconds. Information of time spent in each sleep stage, total sleep time and total time in bed.

Figure 4.23: Night statistics taken from Withings Web Dashboard regarding 2 of September 2020. On the left, is shown the time spent in each sleep stage. On the right, information about total sleep time, total time spent in bed, sleep score, number of times the user woke up, and the average heart rate.

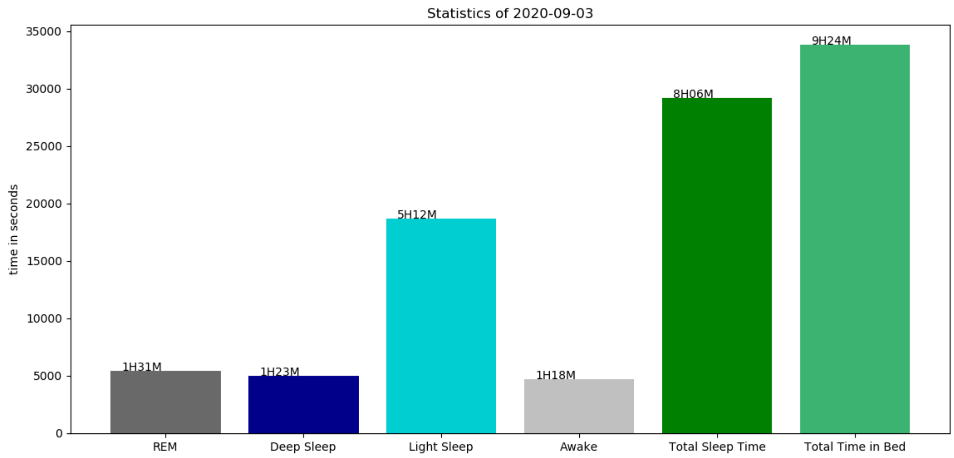

Figure 4.24: Night statistics of 3 of September 2020. Bar plot obtained using panda and matplotlib libraries of python. In the y-axis is illustrated time in seconds. Information of time spent in each sleep stage, total sleep time and total time in bed.

Figure 4.25: Night statistics taken from Withings Web Dashboard regarding 2 of September 2020. On the left, is shown the time spent in each sleep stage. On the right, information about total sleep time, total time spent in bed, sleep score, number of times the user woke up, and the average heart rate.

After plotting and analyzing these graphs, it is possible to conclude that the data was well extracted from Withings servers. The communication is well achieved using WiFi, the next step is to connect it with Diani, and for that their team must integrate the code developed in this work within their system.

Chapter 5

Conclusion

The complexity of human sleep turns it into an extensive field of study, and by combining it with technology makes sleep telemonitoring a topic that changes and improves at each moment.

This document presents the different stages that were required to achieve the main goal of the dissertation, i. e., the design of a sleep telemonitoring system capable of monitoring sleep to detect disorders based on the telemedicine system Diani. In chapter 2 the theoretical foundation is build to understand how a night of sleep can be translated into an hypnogram and how to analyse it. During the sleeping hours, humans experiment nearly 4 to 6 cycles of NREM and REM stages, and it is a challenge to classify exactly when these transitions occur. Polysomnography is the clinical test that is made to evaluate sleep and it involves the measurement of several physiological parameters. The bioelectrical signals, EEG, EOG and EMG, stand out for their importance on sleep staging. However, concerning the detection of sleep disorders, other exams are very crucial, such as the analysis of breathing pattern, oximetry and ECG.

Since sleep comes with an extreme influence on the overall health of the human being, it is of great interest to diagnose and understand better sleep disorders. Therefore, the Albertov Research Center would like to integrate and explore more this field in their telemedicine projects. This is how the aim of this dissertation gained place. The development of a sleep telemedicine system that could fit into their already on-going project, Diani, required several steps. The following step is framed in chapter 3, where a study of the home-monitoring devices currently available in the market is presented. The Diani system supports some wearable devices, such as Xiaomi Mi Band 2 and Fitbit Charge 2. However, both of them are now discontinued, and it was required to incorporate a device more focused on sleep monitoring. An ideal system would integrate brainwave inputs alongside movement and cardiac activity inputs. Brain activity is harder to measure and normally implies more invasive methods, which makes it impracticable for long-term monitoring situations like Diani. Other options were necessary to take into account that could give at the same time satisfactory results to Diani.

The Withings Sleep Sensor appeared has the chosen option and the reasons that lead to this choice are: the fact that it can be easily obtained; it is a low-cost option; non-invasive, not contacting with the person; it can be easy integrated into Diani, since Withings provides an API for the implementation of its sensors in third applications; and it uses Ballistocardiography, a method that when combined with actigraphy has shown to have higher accuracy in classifying the sleep stages.

After the choice of sensor, it was the moment for the development of the sleep telemedicine system itself. Chapter 4 explains the steps of the development of the proposed system. The sensor workflow and the architecture of Diani were reviewed, and the C# program to extract sensor's data started to be developed. The implementation started by handling authorization methods that followed the OAuth2.0 structure, in which the Withings API is based on. After dealing with this, the communication with Withings server could start. All the data from each night is obtained by doing two server requests. Then, the Withings server answers with the data, that is stored for its further processing and visualization. It is used the SQL Server database with 3 tables, one that stores authorization tokens and user information, the other two store sleep data. To visualize the sleep data collected, two scripts were developed with Python, with them is obtained an hypnogram, a graph of the heart rate variation along the night and a bar plot of some sleep statistics, like total sleep time and the time passed in each stage. Some mockups of how the sleep system should look like when fully integrated into Diani were also presented. There were some limitations in this work such as the lack of a clinical validation of the sensor's readings, it would be relevant to compare its performance with PSG exam. The sensor could provide more insights during sleep, like body core temperature and the levels of oxygen saturation in the blood. The first one could aid detecting circadian rhythm disorders and the latter one is involved in apnea events detection. Also, the time frame did not allow to fully integrate the system into Diani. However, looking at the big picture all the tasks proposed for this dissertation were successfully achieved, reaching a more detailed sleep analysis, yet leaving space for further improvements that are going to be discussed in the next section.

5.1 Future Work

The ambition of this telemedicine system is that it can be used with people that suffer from sleep disorders by helping the diagnosis or their treatment. The system designed adds a new section on Diani, just for the sleep analysis. However, it still needs to be integrated on it, so as next step, the merge of the code developed in this work with their code needs to be done. The scheme of the database done for this proposed system needs to be reviewed, there are some connections between the tables that should be modified and included. The connection of *AuthResponse* table to itself should be deleted. The same case happens in the *SleepDatas* table. Then, a relation between the three tables should be established, for that *UserId* should be the parameter connecting them. It should be the primary key in the *AuthResponse* table and foreign key in the other two. After these reviews and modifications, the tables can be integrated into the already existing database of Diani.

Front-end work needs to be done, to give the system an interface. A prototype of how it should look like at the end of integration was done and explained on section 4.3.3. The data displayed is limited to what the sensor can provide. As already seen, is still hard to find everything on one device. There are some physiological signs that would be relevant to track, such as body core temperature and SpO2. The first parameter can be a valuable information for circadian rhythm disorders and the last one for sleep apnea detection. So, it would had interest to use this system combined with other sensors besides Withings Sleep. Oura ring can provide information about body core temperature and the company has a public API, so a similar work could be done to integrate this device into Diani as well. Recently, Withings has launched an clinical validated sensor, that is an iteration of the Withings Sleep and is called Withings Sleep Analyser. It went through clinical experiments in direct comparison with PSG at Hôpital Béclère, giving it a CE approval as a medical device. This made possible for them to add a new feature into their Health Mate App that gives users a classification based on the AHI that tells them if they have apnea and how severe it is. However, their API still does not provide a functionality that enables getting this classification, but maybe in the future they will, and it should be something worth value to add into Diani. Other Withings devices can be used as well, like their most recent one, the ScanWatch. It has an oximeter, making it possible to add the SpO2 measurement into Diani. Finally, taking as example what was done in one of the studies analysed on the section 2.4, an environmental index could be added. For this a new market study should be done to look for a device that could measure the temperature, humidity, sound intensity and luminosity. This metric would be a way to evaluate how appropriate is the room for sleep.

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