CIRCADIANSENSE – A PROTOTYPE WEARABLE DAY AND NIGHT PATIENT MONITORING SYSTEM

by

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ABSTRACT

The 24-hour circadian cycle maintains physiological, biochemical and behavioural variables, and regulates sleep. Modern lifestyle and behavioural factors such as shift work, sedentariness, social interaction, substance abuse, and medication can affect cycle rhythms and sleep quality. Sleep and circadian rhythm disruptions are also observed in large patient cohorts with psychological and neurodegenerative disorders. Health improvements and the reduction of symptoms are achieved when these multifactorial factors are understood and addressed with a positive effect on sleep quality, mood, learning, memory and functioning. However, the lack of objective data provided by the patient and the limited measurements at the moment of the appointment with the doctor limit support in respect of clinical decisions. This extends the time for a correct diagnosis and evaluating treatment efficacy to the detriment of the patient.

There is a general consensus in the literature that patient-monitoring systems capable of recording in the real-world and during the activities of everyday living, where problems are more evident, have the potential to provide much richer and more informative objective accounts of patients‘ well-being, sleep problems, circadian cycle disruption, and symptoms for a better diagnosis, prognosis and treatment of diseases than those of assessments made in the clinic or laboratory.

The literature review reports a number of wearable health-monitoring systems. However, many of these devices record only during waking hours or sleeping hours, record a limited number of variables, are used in controlled environments, are confined to hospitals or some areas of the home, and do not include environmental or behavioural data. Moreover, but unfortunately, most of these wearable health-monitoring devices are characterised by the lack of participation of clinicians during their development. The opinions of clinicians are generally limited to the final stages of development of the system to assess data presentation and device appearance. Poor clinical participation in the stages of the design can lead to having a device not accepted for clinical applications, with the device collecting and presenting irrelevant and meaningless clinical data. Furthermore, thus far there has been little discussion in the literature surrounding

how multisource and multirate physiological, environmental and behavioural data can be collected, combined, analysed, visualised and summarised to extract information for monitoring, diagnosis, prognosis and treatment.

This thesis describes the design of a proof-of-concept wearable device with which to record physiological and environmental variables relevant to the circadian cycle, sleep and, in general, for health monitoring (including chronic diseases). These objective measurements taken in the daily life of the participant are combined with their behavioural data for offline analysis and visualisation. The design of the wearable device took into account important features for wearable health-monitoring devices discussed in the literature. These features were complemented and discussed with the participation of clinicians in interviews and focus groups who identified potential issues and barriers regarding the use of medical prototypes in their clinical practice, in addition to those reported in the literature. Issues reported were disinfection and hygiene of the system, no trust in the data recorded, irrelevant data recorded, no compliance with safety and medical regulations, risks to patients, data not being presented in the format of medical standards, accuracy and validation of the device, and the time in which to process and extract conclusions from the data recorded, which were some of the barriers to adopting this technology.

The first system, called CircadianSense, is a 24-hour patient-monitoring system prototype with broad application in patient care. CircadianSense comprises a set of recording systems for waking hours and sleeping hours. CircadianSense records the pulse rate, body temperature, energy expenditure, electrodermal activity (EDA), environmental temperature, light, and noise. In sleeping hours, rapid eye movement (REM) and body movement for monitoring human rest–activity cycles (known as actigraphy) were recorded. CircadianSense is aimed at recording physiological and environmental variables where patients perform their activities. Objective data collected was processed and combined offline with behavioural information reported by the patient in a daily log. In the one-on-one interviews with four clinicians from Queen Elizabeth Hospital Birmingham (QEHB) it was found that complementing the proposed variables recorded with other physiological signals, such as respiratory rate, pulse oximetry, blood pressure, glucose levels and laboratory tests, could help in monitoring chronic diseases such as diabetes and

hypertension to extend its application to obesity, preoperative and postoperative evaluation, and rehabilitation.

The second prototype, called PatientSense, was the evolution of CircadianSense. PatientSense design was undertaken in an iterative design process with a rich participation of 23 general practitioners who participated in four focus groups and a final assessment of the evolved device. More detailed issues and barriers in adopting wearable health-monitoring technology in these focus groups were explored. Themes and issues of accuracy, reliability, validation of the device, data presentation with medical standards, and usefulness of the data recorded were discussed in more detail.

Ethical issues were investigated by inviting a researcher who is secretary of the Committee of Medical Research. Ethical issues arise when physiological signals or behavioural data of people is recorded. Any research involving the collection of data of people should include in the research protocol, with detailed information of the procedures to follow, a description of participants and consent forms informing of possible risks (even if it is a skin irritation). Privacy of data should be a priority because as algorithms progress it could be possible in the future that analysis of physiological signals will be used to detect the development of chronic or degenerative diseases. If this data is not properly handled it could have future implications for the participant, e.g. if this data is accessible to employers or insurance companies. Participation of clinicians and users in different stages of the design of PatientSense identified important features, issues and barriers in adopting wearable health-monitoring systems. Among all features presented in the literature, validation of the device with different cohorts of patients, clinical hygiene, data privacy, and compliance with safety and medical regulations should be followed. Participation of clinicians in the design provides direction for the selection of variables for medical application and for the target population. There are multifactorial causes of diseases in which behavioural data and emotional states of the patient play an important role in the condition and might explain symptoms of the patient without apparent causes. These factors, again, can only be chosen with the participation of clinicians so as to produce a clinically relevant system. Visualisation of data is an important task in order to deliver useful and meaningful information to clinicians. Both in the interviews and focus groups it was recommended visualisations that enable comparing and observing trends of data. Variability of physiological signals depends on a

number of factors, such as, age, disease and its severity. Clinical participants suggested that reliability, accuracy and meaningfulness can be observed and assessed when the device is validated with a broad number of patients with different diseases and severities. Visualisation would be used to determine whether there are visual differences between the data of patients with different diseases and severities. Moreover, anaesthesiologists recommended visualisations of different patients to observe how data behaves and to determine the presence and severity of a disease. Furthermore, visualisation of different patient cohorts would be used to train clinicians by comparing how data behaves. The assessment of a wearable health monitoring device should not be generic as the features and characteristics depend on the application of the device. Themes discussed with clinicians provide useful features necessary to consider for the development of similar solutions to PatientSense.

ACKNOWLEDGEMENTS

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I would like to thank Luis and his family, who helped me and my wife very much, even before we met. His support made everything easier in the UK.

It is time to answer a question that my supervisor, Dr. Sandra, asked me some time ago. What have you learnt, David, in this PhD? I can list research skills and technical things: I know now how to read a paper, how to be critical and how to extract relevant information. But the most important thing that I learnt was not in a journal paper. I am also a lecturer and the way in which she supported me during the PhD has changed the way in which I lecture and supervise in Mexico. She is an incredible supervisor who knows a lot about research, but as a person she is even more special. I learnt from Dr. Tim that I have to explore other options in research. If 20 researchers use the same method, Tim explores a different solution. When I read a paper, instead of thinking about how to improve the method used, I now think about what other possible solutions there are.

I would like to thank the examiners, Prof. Bob Stone and Dr. Price, for all of the recommendations that they made, all of the time that they spent on these recommendations for improving the thesis, and guiding me in respect of critical thinking in research. Furthermore, I would like to thank the University of Birmingham for their support during my health problems.

I would also like to thank my family, especially my mother and all of my siblings. Finally, I would like to thank God for the amazing wife that I have.

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ABBREVIATIONS

AASM	American Academy of Sleep Medicine
ADC	Analogue to Digital Converter
ANN	Artificial Neural Network
BPM	Beats Per Minute
CBT	Core Body Temperature
CKD	Chronic Kidney Disease
COPD	Chronic Obstructive Pulmonary Disease
CPAP	Continuous Positive Airway Pressure
ECG	Electrocardiography
EDA	Electrodermal Activity
EDR	Electrodermal Resistance
EEG	Electroencephalography
EMG	Electromyography
EOG	Electrooculography
GSR	Galvanic Skin Response
HRV	Heart Rate Variability
IIR	Infinite Impulse Response
IRAS	Integrated Research Application System
IDE	Integrated Development Environment
LDR	Light-Dependent Resistor
MHRA	Medicines and Healthcare products Regulatory Agency
NHS	National Health Service
OSAS	Obstructive Sleep Apnoea Syndrome
PIR	Passive Infrared Sensor
PLMD	Periodic Limb Movement Disorder
PPG	Photoplethysmography
PTSD	Post-Traumatic Stress Disorder
QEHB	Queen Elizabeth Hospital Birmingham
RCSQ	Richards–Campbell Sleep Questionnaire
REM	Rapid Eye Movement
SD	Secure Digital Card
SWSD	Shift Work Sleep Disorder
TBI	Traumatic Brain Injury
UoB	University of Birmingham

CHAPTER 1

INTRODUCTION

1.1 Background

The circadian cycle is the 24-hour biological process by which sleeping and waking periods are regulated. It is entrained by external cues known as zeitgebers (translated from the German for *"time givers"*). The main zeitgeber is natural light and its light and dark cycles. Other zeitgebers include patterns of eating and drinking, physical activity, and social interaction (Grandin et al., 2006). The circadian rhythm can be disrupted by the misalignment of zeitgebers and resynchronised by realigning them (Arendt, 2009).

Sleep and circadian rhythm disruption is common in many large patient cohorts, e.g. in people with cancer (Dickerson et al., 2014), and it is widely observed in neurodegenerative and psychiatric diseases and in abuse disorders, e.g. in Alzheimer's disease (Gagnon et al., 2006), Parkinson's disease (Arnulf and Oudiette, 2008), Huntington's disease (Morton et al., 2005), schizophrenia (Cohrs, 2008), multiple sclerosis (Bamer et al., 2008), post-traumatic stress disorder (PTSD) (Schoenfeld et al., 2012), seasonal affective disorders (Tsuno et al., 2005) and alcoholism (Roehrs and Roth, 2001).

The past decade has seen a rapid development of wearable health-monitoring devices. For example, Lopez et al. (2010) developed a vest with sensors for monitoring physiological signals of patients in the hospital. Bellos et al. (2013) developed a T-shirt with embedded sensors and combined laboratory information and behavioural data of the patient for chronic obstructive pulmonary disease and chronic kidney disease management. Bonmati-Carrion et al. (2014) recorded wrist temperature, activity, and body position with sensors on a wristband and on the body to assess circadian rhythms based on patterns of activity, rest, and body temperature.

Long-term recordings in the environment wherein the patient lives have been recommended to understand the behavioural, physiological and environmental factors that affect the circadian cycle and sleep in children with multiple disabilities (Tietze et al., 2012), children with Down's syndrome (Churchill et al., 2012) and shift workers (Wright et al., 2013). Even though improving sleep quality has been shown to reduce symptoms and improve life quality of people with psychiatric and neurodegenerative diseases, little effort has been made in the stabilisation of sleep and circadian patterns (Wulff et al., 2010). Long-term monitoring of physiological, environmental and behavioural variables can help clinicians to better diagnose and assess treatment efficacy not only for sleep or circadian-related problems but also for better managing of chronic diseases.

Despite the amount of research into wearable health-monitoring devices, there is little discussion in the literature surrounding relevant features that the device should have. Much of the discussion has focused on the assessment of issues of comfortability, data privacy, aesthetics, technical aspects of miniaturisations of hardware, extending battery life, and the usability of interfaces for clinicians. The sparse participation of medical experts has led to producing devices not medically accepted with irrelevant data collected. Most of these studies have tended to focus on user needs such as usability and wearability with little clinical involvement (Bergmann, and McGregor, 2011). Moreover, as McAdams et al. (2011) suggested, "*the necessary sensor-related technologies are often not as advanced as may first appear; certainly they are generally not adequate for the robust, long-term monitoring of patients under real-life conditions*".

1.2 Motivation

The literature review reveals that patient-monitoring systems capable of recording in the real world and during the activities of everyday living have the potential to provide substantially richer objective accounts of patients' well-being than those of the limited observations and measurements made in the clinic and in the laboratory environment. Furthermore, data recorded at home or in the environment wherein the patient lives and performs their daily life activities might reveal problems that are not evident in the office of the clinician.

Circadian cycle problems are observed in the deterioration of sleep quality, but also affect memory, learning, mood and functioning. Circadian rhythm disruptions are also present in a number of neurodegenerative, psychological and chronic diseases. The stabilisation of circadian rhythms, in turn, can improve the symptoms of the patient and general well-being. Moreover, long-term environmental, psychological and behavioural recordings can provide information for monitoring and better management of a number of health conditions.

A group of four anaesthesiologists of QEHB who were interviewed and 23 general practitioners (GPs) who participated in four focus groups pointed out that diseases have multifactorial causes and recommended gathering long-term recordings of physiological, environmental and behavioural data of the patient. Clinical participants reported that long-term information on these factors could bring about many benefits, such as a better understanding, diagnosis and treatment of diseases, monitoring patients in their homes so as to reduce the cost of health intervention, and better administration of hospital resources. However, much of this information is not available at the moment of the appointment or the patient forgets to report it.

It was found to be necessary to work with clinicians in all stages of the design of the wearable health-monitoring system (WHMS) in order to identify desirable features or characteristics of the system and determine the set of physiological and environmental variables and behavioural and activity-related information of interest for clinicians. Of course, objective accounts cannot and should not replace subjective patient reports. Ideally, both objective and subjective reports would be combined together to create more complete and detailed patient pictures.

Even though the literature review reports a great number of wearable devices used for recording physiological signals with applications in health monitoring, there is little discussion surrounding issues that could prevent their use in clinical applications. Much of the work has focused on improvement of technical aspects, such as reducing power consumption and wireless networks, and aspects of comfortability, appearance, cost, data privacy, and easy-to-use devices. Additional features were discussed with clinicians and users that are necessary for the design of the device and analysis of the data. In particular, ethical, hygiene and accuracy issues, validation of the device, and relevance of the data recorded were discussed with clinicians and their importance.

The lack of relevant behavioural and activity-related information on the patient and long-term objective measurements of the environmental and physiological signals of the patient that can lead to extending the time to diagnosis and providing a better treatment were the issues that motivated the design of CircadianSense. Furthermore, the decision to work with clinicians of QEHB and GPs in Mexico gave the opportunity to identify from the beginning of the research features and characteristics of the device. Some of these features and issues can be used in the design of future wearable health-monitoring systems so as to produce clinically relevant devices.

1.3 Novelty of the Research

The participation of four anaesthesiologists in two interviews and 23 GPs who took part in four focus groups opened areas of discussion surrounding themes relevant to the selection of physiological and environmental variables, and the design of a daily log for registering behavioural information. The literature review shows features and issues to take into account for wearable health-monitoring devices; however, the inclusion of clinicians from the early stage of the design enabled exploring these issues in detail and exploring more themes with a greater number of general practitioners in Mexico. Working with anaesthesiologists of QEHB and GPs in Mexico gave the opportunity to explore topics from different perspectives. Anaesthesiologists have experience in intensive care in hospitals and GPs provide primary healthcare to any type of patients. Participation of the secretary of the Committee of Medical Research identified more ethical issues that need to be anticipated and informed to the people involved in the project and that need to be addressed by informing all parties involved in the project and the study thereof.

In particular, the evolved CircadianSense prototype in this research is a novel patient-monitoring system for patient care in the real world with possible application in monitoring chronic diseases, sleep and circadian cycles. The research defines a combination of physiological and environmental data and behavioural information selected for clinical relevance and system feasibility. This was achieved through participation of users who wore the system and clinicians who participated in the first stages of the research.

The recorded data provided novel real-world datasets that included behavioural and activity-related information and physiological and environmental recordings. Different visualisations were explored and discussed with clinicians for their possible applications in summarising data,

comparing trends and in different health conditions of patients. The research proposes an amended approach to wearable health-monitoring assessment and recommends additional features important for the design of a WHMS for clinical applications and real-world patient use.

1.4 Contribution

Patient assessment by a clinician is generally limited to the information provided in the clinician‘s office. The measurements of vital signals of a patient do not necessarily reflect trends, states or complications of the disease in the daily life of the patient. The first contribution is the design of a proof-of-concept system for real-world 24-hour patient monitoring with broad application in patient care, general well-being, circadian and sleep disruptions, and monitoring of chronic diseases. The clinical relevance of signals recorded by CircadianSense and behavioural data were given by participation in the design of a group of anaesthesiologists of QEHB and a group of Mexican GPs. These clinical participants helped in the specification of the variables to be recorded and the subjective data to be registered.

The second contribution is the identification of issues, barriers and features in the clinical adoption of a wearable system for patient monitoring as a result of the involvement of clinicians in different stages of the research for variable selection, system construction, risk assessment, system testing, system assessment by both users and clinicians, and data analysis, visualisation and summarisation.

1.5 Research Flowchart and Thesis Organisation

In this section the research process followed and the organisation of the chapters of the thesis are explained. The research idea started with a meeting with a clinical collaborator who has experience in research projects related to the feasibility of exploiting interactive technologies for rehabilitation, pain management, sleep, and psychological well-being. In the initial meetings with the main clinical collaborator it was explained that in the hospital the conditions are not adequate to promote good sleep, patients have disturbed circadian rhythms, environmental conditions can trigger crises in inpatients and, in general, there is a lack of information on physiological, environmental and emotional states to explain the behaviour of diseases.

The literature review in Chapter 2 was performed on the circadian cycle, sleep problems, and stabilisation of circadian rhythms. The literature summarises the effects of circadian disruption on different neurological and psychological conditions and general well-being. It shows that there is a consensus in respect of the need for long-term measurements of physiological and environmental variables and for behavioural and activity-related information. The summary of wearable health-monitoring systems reveals a lack of clinical involvement in the design of the medical prototypes, which can lead to producing a device that is not clinically relevant.

System construction of the wearable health-monitoring system was called CircadianSense. The design of CircadianSense is discussed in Chapter 3. CircadianSense was informed by both the literature and the clinicians whose continuous feedback was used to select and make changes to variables of clinical interest, data analysis and visualisations. Short-term testing regarding wearing CircadianSense was conducted by the research team to assess and improve comfortability and data reliability in various scenarios, such as sitting, walking, running at different speeds, and climbing steps. Modifications to placement and used materials were made based on the results and feedback of the short-term testing. These modifications are also shown in Chapter 3. Following the short-term trials by the research team, a protocol and risk assessment were provided to the Science, Technology, Engineering and Mathematics Ethical Review Committee of the University of Birmingham (UoB) to be included in the study‘s recruited participants. Permission for testing with recruited clinical participants of the National Health Service (NHS) and the hospital was sought. A protocol evolved and, again, a risk assessment was made and approved. In the risk assessment the main collaborator and a technician of the UoB participated in finding possible issues in anticipating possible scenarios with participants wearing the system in the hospital. The University of Birmingham acted as an insuring sponsor and all of the necessary NHS permissions and approvals were obtained via the online Integrated Research Application System (IRAS). After the assessment of the IRAS it was required to apply for approval from the R&D department of Queen Elizabeth Hospital Birmingham. The clinical collaborator recruited three participants, all of whom are anaesthesiologists working in the intensive care unit of QEHB. The relevant documents for this study are in appendix A. The origin of the research and the stages of gaining approval for the study are shown in Figure 1.1.

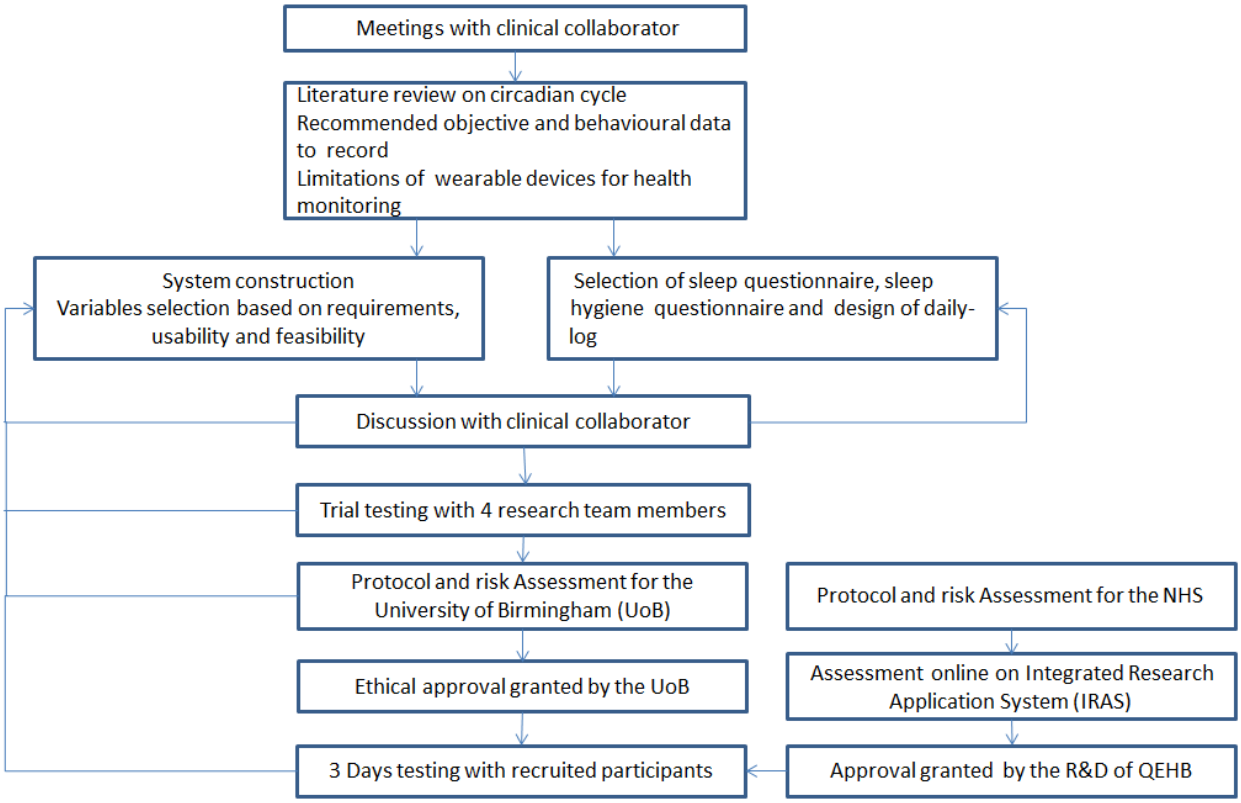


Figure 1.1 Origin of the research, permissions and approvals for the study

Data Preparation and Visualisations

Three days of wearing CircadianSense was undertaken by the researcher, supervising academics and recruited participants. Data recorded was processed offline in Scilab, which is a free software for numerical computation. Data analysed and processed was exported to Excel to create databases and visualisations. Different visualisations were generated to display the data recorded and shown to clinicians for an assessment. These visualisations comprised scatterplots with different data averages, histograms of data, dynamic visualisation using Google's ~~"~~Motion Chart", and heat maps with a graphical representation of variations of signals recorded (represented as tones of colours). Heat maps also included annotated information of the daily log represented with icons. The first assessment and modifications were provided by the main clinical collaborator, who recommended changes in the visualisations, icons and information to be registered in the daily log. This stage of the research is shown in Chapter 4 and the sequence of activities for data preparation and visualisations is shown in Figure 1.2.

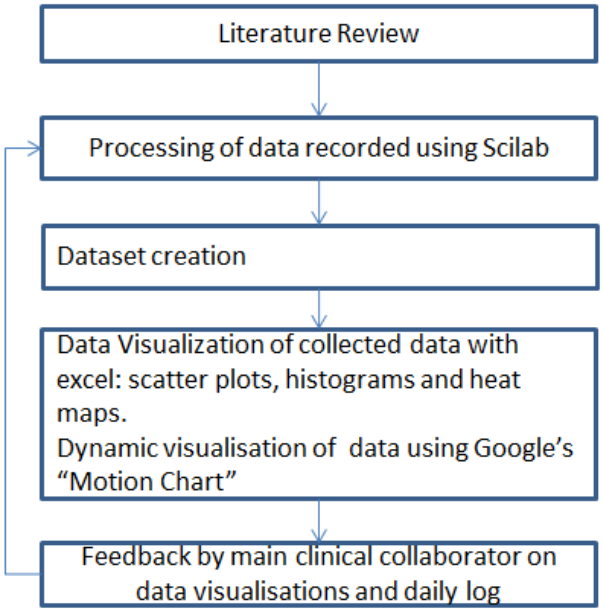


Figure 1.2 Data preparation and visualisations

Clinical Interviews and CircadianSense Assessment

Two one-on-one interviews were conducted with four anaesthesiologists. The objectives of the set of questions of interview I were to explore the experience of clinicians with wearable medical devices, possible scenarios, benefits, and features desirable for a wearable health/patient-monitoring system. Suggestions and feedback were used to make improvements to CircadianSense. In the second part of interview I, opinions and suggestions for the visualisations of data collected of participants were discussed so as to make improvements. These visualisations comprised scatterplots, histograms, heat maps, and dynamic visualisations. It was found that data collected by CircadianSense could be used for monitoring more diseases, including obesity, chronic diseases, and general well-being. These applications would require complementary information of laboratory tests and more physiological variables. Multivariable visualisations were also explored with clinicians. However, these were found to be complex to understand and were no longer pursued — they are not presented in this work.

The assessment of the features of CircadianSense was conducted by users and clinicians in interview II. In total, 10 users and clinicians wore CircadianSense. There was room for improvement of CircadianSense, as expressed in the responses and feedback from users and clinicians. Topics of reliability, comfortability, visualisation of data, and possible uses for monitoring, diagnosis and treatment for a broad number of diseases were taken into account for

an evolved system called PatientSense. The results and analysis of the two clinical interviews and CircadianSense assessment are presented in Chapter 5. Figure 1.3 shows the stages of organisation of the interviews and assessment of CircadianSense.

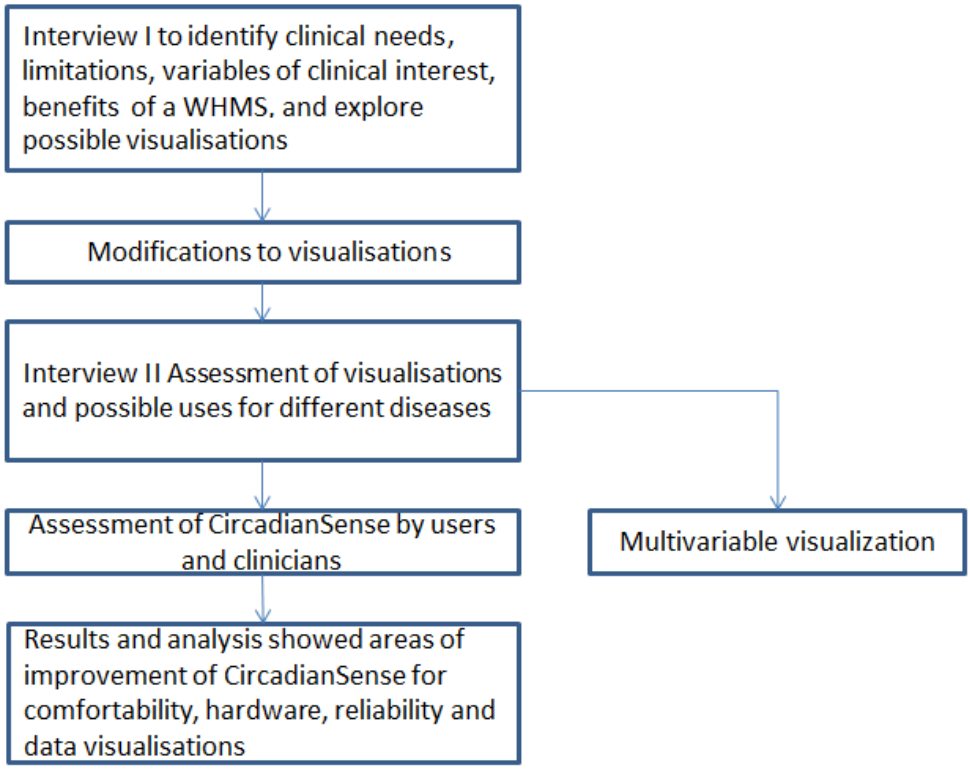


Figure 1.3 Clinical interviews and CircadianSense assessment

Focus Groups with General Practitioners

Themes and issues that arose in interviews I and II and in the assessment of CircadianSense by participants in the study of CircadianSense were explored with general practitioners (GPs) and users in Mexico. In total, 23 general practitioners were recruited, who participated in four focus groups. Two pilot studies were conducted with one clinician to identify confusing and repetitive questions, set the order of the questions and determine the length of time before conducting the focus group with more GPs. After these two pilot studies, the design of the questions of focus groups 1 and 2 was undertaken. Participants of focus groups were divided into three groups. Focus group 1 was conducted to find limitations and needs of information provided by patients, as well as variables of interest to be recorded. Focus group 2‘s objectives were to identify and discuss environmental, physiological and behavioural variables, as well as laboratory tests with which to explore possible applications if all of this data was available for monitoring different diseases. Questions for focus group 3 were designed after the analysis of the responses of focus

groups 1 and 2, and focused on a discussion surrounding a WHMS called PatientSense (which evolved from CircadianSense), visualisations of data recorded with CircadianSense, and the design of a daily log. More features desirable for the WHMS and their assessment were the central theme of focus group 4. Results and analysis of the first three focus groups are presented in Chapter 6.

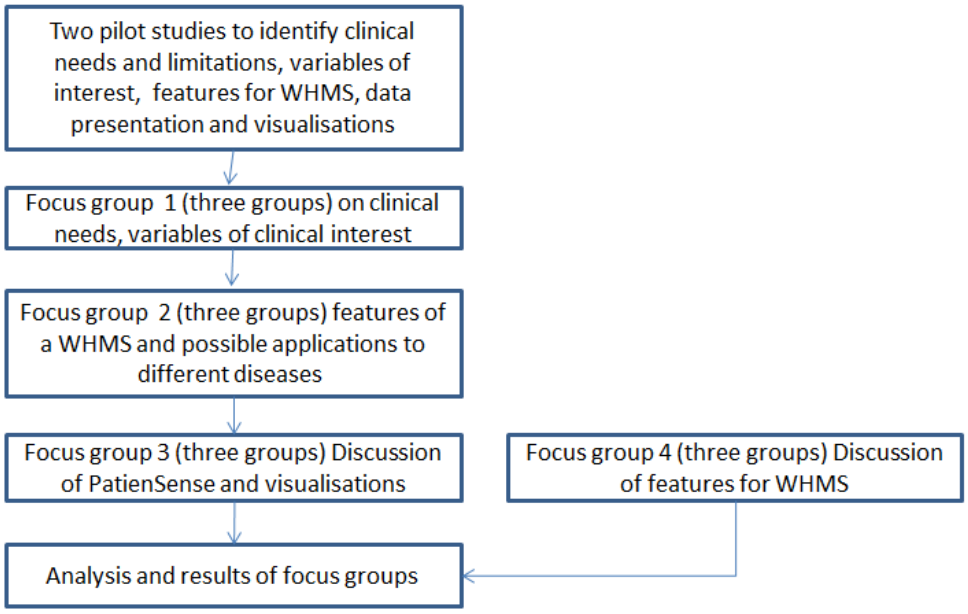


Figure 1.4 Focus groups with GPs

Design and Assessment of PatientSense

The evolved CircadianSense system was called PatientSense. The construction of PatientSense and the daily log design were informed by the analysis of the responses of the focus groups with GPs and the results of the assessment of CircadianSense. Suggested changes were carried out to hardware, software and the daily log. Sixteen recruited participants were asked to wear PatientSense for 36 hours (only 1 night). Data was collected and presented to clinicians in a final session, who assessed PatientSense based on the features discussed in focus group 4 and interviews. Wearers and GPs were asked to comment on how the features could be improved. A discussion with the secretary of Medical Research was conducted to explore features relevant to the WHMS and particular ethical issues. Results and discussions are shown in Chapter 7. Further work and conclusions are presented in Chapter 8. These activities are shown in Figure 1.5.

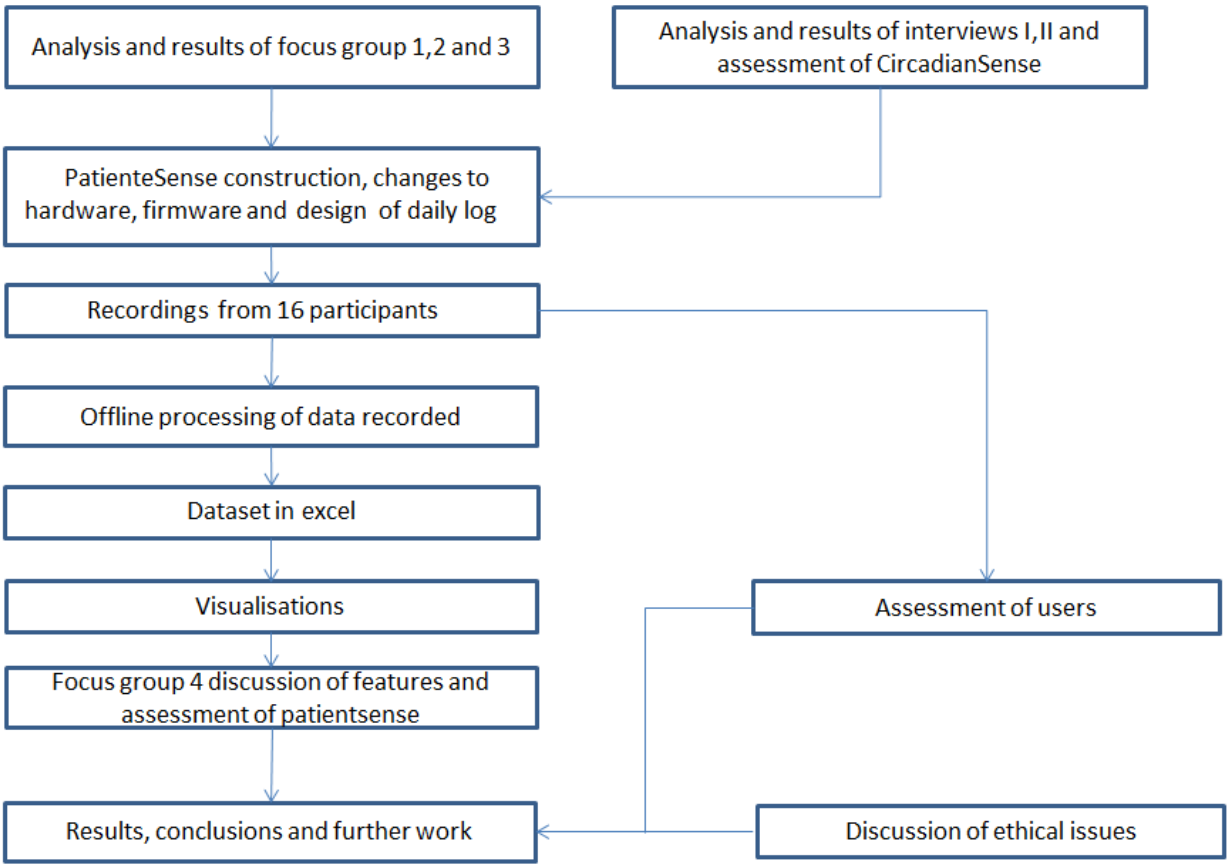


Figure 1.5 Construction and assessment of PatientSense

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter provides a review of the literature relevant to the main themes of the research. The chapter begins with a summary of the circadian cycle processes in various physiological signals, the effects of disturbed rhythms on health, and the benefits when the altering elements of the circadian cycle are controlled. It is followed by a review of sleep hygiene, sleep stages and sleep sensing. Physiological, environmental and behavioural information relevant to circadian rhythms both in waking hours and in sleeping hours, as recommended by the study‘s author, is also reviewed. Wearable health technology is summarised and issues related to maturity, assessment and features of these systems for medical applications are discussed.

2.2 The Circadian Cycle

The 24-hour circadian cycle maintains physiological, biochemical and behavioural variables, e.g. core body temperature, sleep wakefulness, alertness, mental performance, and the synthesis and secretion of hormones such as melatonin and cortisol (Rajaratnam and Arendt, 2001). Melatonin is a hormone that serves as an endogenous biomedical marker that controls the cycles of sleeping and waking hours (Rawashdeh and Maronde, 2012). External factors such as light exposure in sleep and medicine such as beta blockers used to treat high blood pressure can suppress melatonin secretion affecting the sleep–awake periods (Scheer and Czeisler, 2005) and increase the production of cortisol (Stevens et al., 2007) with long-term effects such as the production of glucose, leading to increased blood sugar levels.

Circadian cycles are observed in a number of physiological processes. For example, core body temperature (CBT) sleep patterns in healthy individuals are characterised by a maximum temperature at sleep onset, decreasing through sleep and then increasing again at the end of

sleep. Figure 2.1 contrasts normal CBT patterns with those of sleep onset and early morning awakening insomniacs (Lack et al., 2008).

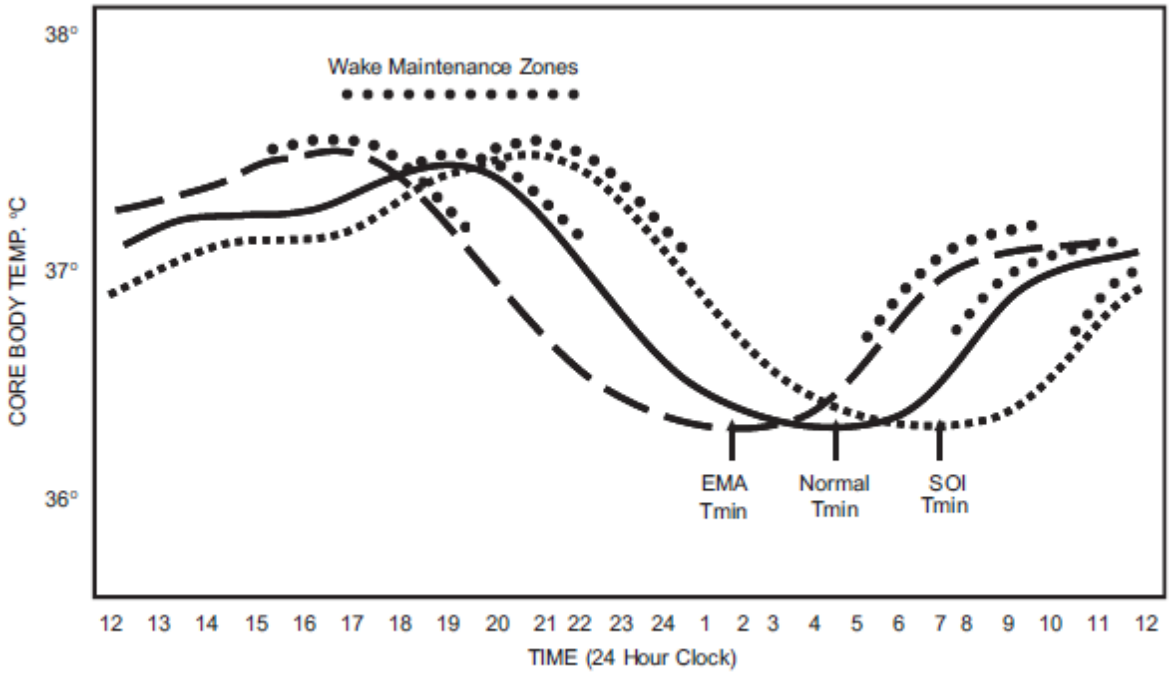


Figure 2.1 Typical circadian cycle of core body temperatures for i) early morning awakening (EMA) insomniacs, ii) normal sleepers and iii) sleep onset insomniacs (SOI), showing their temperature minima, wake maintenance zones, and morning wake zones (Lack et al., 2008)

Blood pressure also follows a circadian cycle that shows increased blood pressure at night, which lowers after awaking. Abnormal patterns characterised by lower blood pressure during the night and a surge in the early morning have been observed in cardiovascular events such as acute myocardial infarction and stroke. It is theorised that normalisation of blood pressure could prevent potential life-threatening events (Giles, 2006). Heart rate variability (HRV) also shows a circadian cycle pattern with higher HRV in healthy people during sleep than in people with some health conditions. For example, people with Parkinson‘s disease have shown abnormal patterns of HRV with lower variability during sleep than that of healthy individuals (Videnovic and Golombek, 2013). Lower HRV in alcoholics and diabetics during sleep has also been observed (Malpas and Purdie, 1990). These patterns of HRV are shown in Figure 2.2.

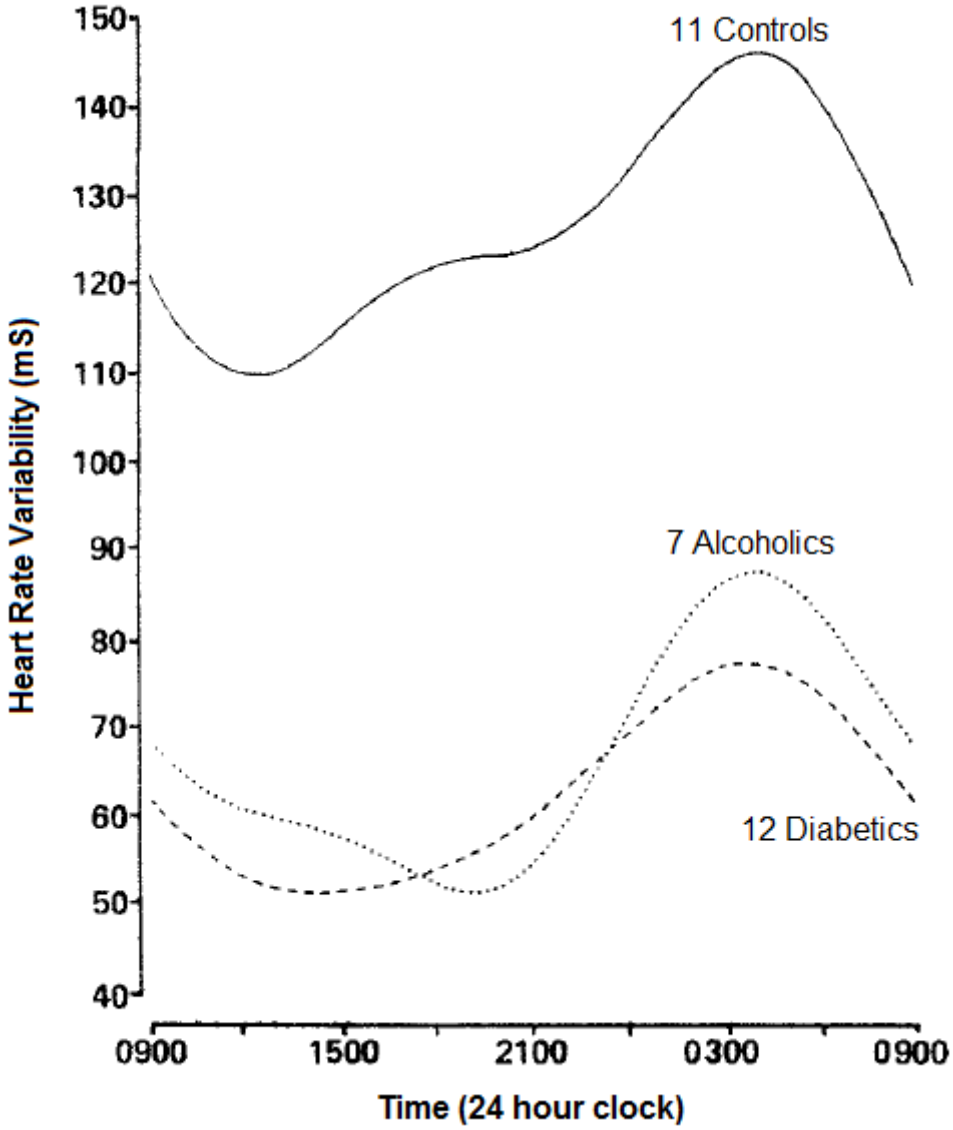


Figure 2.2 Heart rate variability for a group of 11 controls, 7 alcoholics and 12 diabetics (Malpas and Purdie, 1990)

The circadian cycle, although endogenous, is entrained by external cues known as zeitgebers (translated from the German for ~~–t~~ime givers"). The main zeitgeber is natural light and its light and dark cycles. Other zeitgebers include patterns of eating and drinking, physical activity, and social interactions (Grandin et al., 2006). The circadian rhythm can be disrupted by the misalignment of zeitgebers and resynchronised by realigning them (Arendt, 2009). Social and behavioural changes in modern life, such as shift work, nocturnal lifestyle, and feeding time, have been linked to a modification of metabolic functions. These metabolic changes can lead to

circadian cycle alteration, obesity, diabetes, and other medical problems (Arble et al., 2010). Circadian disruption impacts upon learning and memory processes and it is theorised that therapeutic treatments of melatonin could improve mental and cognitive deficits of people with abnormal sleep–wake cycles (Rawashdeh and Maronde, 2013).

Our understanding of the vital restorative functions of sleep is still evolving. Recent research points to sleep restoration as a consequence of the removal of neurotoxic waste from the central nervous system that has accumulated during wakefulness, which can lead to the reduction of cognitive function (Xie et al., 2013). Shi et al.'s (2013) adjustments of the biological rhythms could help to develop non-invasive therapies for metabolic disorders. Re-entrainment of social and feeding cues have been recommended to normalise the circadian rhythm and metabolic functions (Arble et al., 2010). Alcohol consumption, along with changes in food intake time, has a potent effect on circadian rhythmicity, which can lead to modifying behavioural patterns and increasing risk factors for chronic and metabolic diseases such as cancer, diabetes, and intestinal disorders (Voight, 2013). Furthermore, misalignment of the circadian cycle through either psychological or biomedical alterations has been shown to produce less efficacy of cancer treatments and insulin resistance in some patients (Sephton and Spiegel, 2003).

Unfortunately, however, the trend in modern living is towards less sleep. Jet lag is a common transient circadian cycle disruption experienced by long-distance travellers rapidly crossing time zones. Similarly, shift work sleep disorder (SWSD) is experienced by people working during normal sleeping hours. Exposure to changed light and dark cycles can produce temporally delayed, advanced or erratic sleep timing (Auger and Morgenthaler, 2009) and suppress melatonin secretion even in conditions of low levels of ambient light (Scheer and Czeisler, 2005). In a review of alertness management strategies for operational contexts, Caldwell et al. (2008) suggested that the circadian cycles of nighttime shift workers can be adjusted by avoiding morning light exposure and modifying the sleep environment by reducing environmental noise and light.

Substance abuse is associated with disturbed sleep and disturbances in circadian rhythm (Hasler et al., 2012). Alcohol abuse affects core body temperature, producing a lower-than-normal temperature during the afternoon and a higher-than-normal temperature in the early morning (Danel et al., 2001). Medication can also affect sleep quality. For example, beta blockers used to

normalise blood pressure and dopamine agonists used to regulate movement and mood in people with Parkinson‘s disease can induce nightmares and deteriorate sleep (Pagel and Helfter, 2003), and patients including war veterans experience additional sleep disruption as a consequence of prescribed pain medication (Zeitzer et al., 2009).

Sleep and circadian rhythm disruption is common in many large patient cohorts, e.g. in people with cancer (Dickerson et al., 2014), and is widely observed in neurodegenerative and psychiatric diseases and in abuse disorders, e.g. in Alzheimer‘s disease with rapid eye movement (REM) sleep behaviour disorder (RBD) characterised by sleepers who act out their dreams. RBD has been reported to cause damage to the sleeping person or partner (Gagnon et al., 2006). RBD is also present in Parkinson‘s disease and has been found to be a risk factor for dementia and hallucinations, besides a detriment to sleep quality (Arnulf and Oudiette, 2008). Huntington‘s disease features frequent awakening and increased activity during the day (Morton et al., 2005). Schizophrenia might show reduced sleep time, sleep efficiency, and difficulty in initiating sleep (Cohrs, 2008). Multiple sclerosis includes problems of insomnia linked to pain, depression and fatigue (Bamer et al., 2008). People with post-traumatic stress disorder (PTSD) can experience frequent and substantial problems with sleep, including frequent problems with sleep initiation, sleep maintenance, and nightmares (Schoenfeld et al., 2012) and episodes of excessive movement (Augedal et al., 2013). People with seasonal affective disorders report poor sleep quality and low energy and mood (Tsuno et al., 2005), and alcoholism shows abnormal REM–NREM sleep cycles, daytime sleepiness, reduced alertness and performance, and exacerbates apnoea (Roehrs and Roth, 2001).

However, despite the fact that the stabilisation of sleep and circadian cycles is known to reduce symptoms in psychiatric and neurodegenerative diseases and improve life quality, little is usually done to support circadian stabilisation in these patient populations (Wulff et al., 2010).

2.3 Assessment and Entrainment of Circadian Rhythms

Circadian rhythms are affected by social and behavioural patterns, medication, sleep environments, and are observed in a number of biological processes. The observations and analysis of these multifactorial elements can help understand and explain the link between these factors and eventually normalise the circadian cycle. Researchers have recommended long-term

recording and analysis of multiple environmental and psychological factors in different cohorts to better isolate and explain circadian rhythms, sleep disturbances, and better management of diseases. For example, in a review of sleep disturbances in children with multiple disabilities, Tietze et al. (2012) recommended the analysis of psychological and environmental factors such as ambient noise, light and temperature in the home environment to develop effective treatments. Similarly, in a review of sleep assessment in children with Down's syndrome, Churchill et al. (2012) recommended the long-term recording of physiological and environmental signals, as well as the sleep patterns of family members. Wright et al. (2013) also recommended the long-term recording of environmental factors so as to understand the disturbance of circadian cycles in shift workers, and Portaluppi et al. (2012) concluded that long-term data recording could help to determine better management of patients with cardiovascular conditions, e.g. selecting the time of medication or altering sleep routines.

Circadian phase assessment can be conducted by measuring levels of melatonin in the saliva and also by analysing physiological signals and activity patterns. However, assessments of melatonin rhythms require the use of laboratory facilities wherein light and calorie intake are controlled. Other less expensive approaches have been developed with the benefit that circadian rhythms are assessed in the real environment of the patient. For example, actigraphy is a low-cost method with minimum invasiveness that uses an accelerometer worn on the wrist to detect episodes of wakefulness and sleep or human rest/activity (De Souza et al., 2003). Bonmati-Carrion et al. (2014) assessed ambulatory circadian phases and patterns by monitoring wrist temperature, ambient light and actigraphy, and the responses to a sleep questionnaire. The results for 13 participants over a 10-day period were consistent with dim light melatonin onset measurements and the authors concluded that their *"results indicate that circadian phase in humans can be reliably assessed by ambulatory circadian monitoring (ACM), while subjects maintain their normal life style"*.

Patterns of core body temperature can be used both for the assessment of rhythmicity of circadian rhythm and to detect sleep disorders. For example, body temperature maxima and minima can be phase-delayed and phase-advanced in people with sleep onset insomnia and early morning awakening insomnia, respectively (Bjorvatn and Pallesen, 2009). Observations of body temperature patterns can be used to guide and select treatment. For example, the use of bright

light is one of the therapies used to adjust the circadian cycle: bright light in the morning for phase-delayed body temperature and bright light at night for phase-advanced core body temperature (Lack et al., 2008) or a combination of bright light therapies with the administration of exogenous melatonin at night (Bijorvatn and Pallesen, 2009). Physical activity and yoga have also been recommended to improve sleep quality. For example, Passos et al. (2011) reported that people with insomnia had improved sleep quality and mood when undergoing regular and moderate exercise. Patra and Telles (2010) studied the effect of yoga on sleep heart rate variability and the breathing rate in 30 healthy participants. The results indicated that yoga improved participants‘ sleep quality, normalised HRV and decreased the breathing rate during sleep.

Improvement of the environmental conditions of sleepers can have a positive effect on sleep and circadian rhythms. Sleep hygiene concerns the set of behaviours and environmental conditions that promote sleep (Irish et al., 2014). Sleep hygiene recommendations include sleeping in a quiet and dark room that is not too hot or cold, as well as avoiding excessive exercise, caffeine, alcohol, stress, and large meals before going to bed (Stepanski, 2003). Improving sleep hygiene has been shown to improve the sleep quality of people with post-traumatic stress disorder (PTSD) (Ruff et al., 2012), which, in turn, can reduce PTSD symptoms (Ruff et al., 2009). Noise in the sleep environment can result in insomnia, delays in sleep onset, early awakenings, poor sleep maintenance, excessive body movement, fragmented rapid eye movement (REM), and variations in the heart rate. However, the influence of noise in the sleep environment depends on a number of factors, e.g. its intermittency, duration, intensity, as well as any background noise which could have a masking effect (Muzet, 2007). To understand how noise characteristics affect sleep, Lee et al. (2010) compared sleep quality during different combinations of traffic, construction and TV noise. Construction noise combined with traffic noise caused the most sleep disturbance and most of the early awakenings were caused by a sudden construction noise. The study, however, was limited to sleep assessment only through questionnaires and had no objective assessment through physiological or environmental data.

In chronobiology the rhythmicity of biological patterns can be observed and modelled by a number of methods. These methods include visual inspection of time plots, cross-correlation, cross-spectral analysis, chronodesms, and other mathematical methods (Refinetti et al., 2007). A

common analysis of physical signals such as core body temperature and pulse rate includes modelling by one or more cosinusoids (–cosinor analysis"). This method models through one or more cosinusoids the patterns capable of extracting amplitude, phases with a good response to noisy data, and sampling rates that are not uniform. On the other hand, other methods requiring a uniform sampling rate are not able to compute phases or amplitude, e.g. spectral analysis of circadian rhythms. Environmental factors, health conditions and temporal alteration of zeitgebers can create transients in the biorhythms of a person. The modelling of these more complex rhythms requires multiple cosinusoids (Senyuk and Yasinkaya, 2006). These approaches model the rhythms and show phase shifts of rhythms but do not explain the multiple factors that can affect circadian cycles or health problems.

2.4 Sleep, Sleep Stages and Sleep Assessment

Timing and duration of the cycles of sleepiness and wakefulness are indicators of the circadian rhythms; therefore, assessment of sleep is of particular interest. Normal sleep comprises four or five cycles of rapid eye movement (REM) and non-REM sleep. During REM sleep most muscles are paralysed and the sleeper is more difficult to rouse than at any other sleep stage. The proportion of REM sleep increases as sleep progresses. Non-REM sleep is classified into several stages. There are two systems of sleep stage classification and recording. Rechtschaffen and Kales (R–K) system (Kales and Rechtschaffen, 1968) classifies sleep into six different stages: awake, REM, and non-REM sleep stages S1–S4 of increasing depth. The American Academy of Sleep Medicine (AASM) system (Moser et al., 2009) classifies sleep into five stages: awake, REM, and non-REM stages N1, N2 and N3 (Novelli et al., 2010).

Disturbances in sleep stages, particularly in REM sleep, are significant in a range of pathologies. Abnormalities in the duration, latency and number of REM sleep episodes occur in schizophrenia, depression and PTSD (Agarwal et al., 2005; Mellman et al., 2002). Schizophrenics have reduced REM latency and density (Cohrs, 2008). Alcoholics predisposed to relapses have shorter REM latency and high REM density. Alcoholics who have normal REM sleep characteristics and sleep well in general are less prone to relapses (Roehrs and Roth, 2001). People with Alzheimer's disease have fewer REM episodes (Gagnon et al., 2006). People with Parkinson's disease have disrupted REM sleep (Arnulf and Oudiette, 2008). Altered REM has

been observed years before the development of neurodegenerative diseases such as Parkinson‘s, dementia and Alzheimer‘s (Arnulf and Oudiette, 2008).

The R–K system classifies non-REM stages according to the characteristics of EEG (electroencephalography) correlated with electrooculography (EOG) and electromyography (EMG). For example, stage S1 occurs when EEG activity moves from 8–13 Hz alpha frequencies (common in waking) to 4–7 Hz theta frequencies. In stage S2, EMG activity decreases and EEG activity concentrates in the theta range. In stages S3 and S4, lower-frequency (delta) EEG activity increases. The duration and amplitude of delta EEG activity are also used to classify NREM, S2, S3 and S4 stages. A scoring system which combines metrics is used to classify stages. Limitations in R–K assessment and scoring (Himanen and Hasan, 2000) led to the development of the AASM system. This defines stages N1 and N2 similarly to R–K‘s S1 and S2, but S3 and S4 are combined in stage N3 (Schulz, 2008).

Polysomnography is the multi-parametric recording of sleep. Figure 2.3 shows an illustrative overview of polysomnographic sensing and also the reality of invasive sensing of a real sleep study participant, which, together with the unusual sleep environment, makes sleep more difficult for the subject. Polysomnography typically comprises electroencephalography (EEG) to evaluate electrical brainwaves, electrooculography (EOG) to detect REM sleep, electromyography (EMG) for muscle activity detection, and electrocardiography (ECG) for heart rhythms, pulse oximetry, respiratory rate and respiratory effort. Recorded data is analysed and interpreted by a sleep expert, who can then diagnose sleep disorders and detect the sleep stages. The complexity of the process, the cost, and the quantity of apparatus required by polysomnography have meant that it has traditionally been confined to clinical sleep laboratory environments to which there has been necessarily limited access (Komatsu et al., 2006).

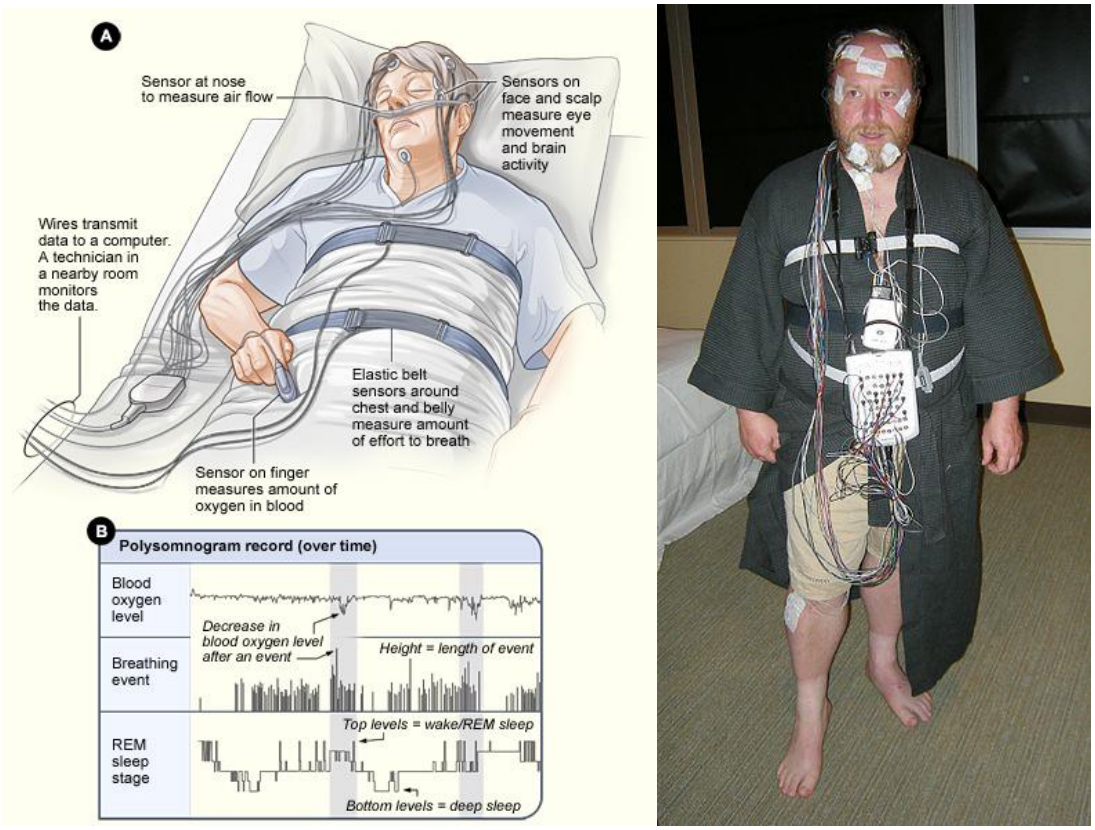


Figure 2.3 Left: An overview of polysomnography assessment; Right: A real sleep study participant (Left: Public domain, National Heart Lung and Blood Institute (NIH); Right: Wikimedia Commons, Joe Mabel)

2.4.1 **Indirect Methods of Sleep Assessment**

Lower-cost, less invasive and more accessible objective alternatives (or supplements) to sleep laboratory polysomnographic sleep assessment are understandably desirable. Automated algorithms using different recorded variables for sleep stage detection and sleep quality assessment have been the ambition of active research in recent years. For example, amplitudes of heart rate variability and actigraphy were used by Kurihara and Watanabe (2012) to distinguish between REM and non-REM episodes. While this approach performed well compared to other non-invasive approaches, the sleep stage agreements with conventional R–K assessment were only 51.6%, 56.2% and 77.5% for stages six, five and three, respectively. Respiratory patterns of effort and ECG signals have also been used to distinguish between REM and non-REM sleep, achieving an accuracy of up to 87.6% in a study with 14 well subjects (Long et al., 2013). However, the accuracy in detecting sleep stages of indirect methods is adversely affected by

sleeper movement (Long et al., 2013) and characteristics of the patient, such as age, if presenting a sleep disorder and excessive movement during sleep.

In addition to recording the heart rate and movement via sensing under a mattress topper, Paalasmaa et al. (2012) also recorded ambient noise, ambient luminosity and ambient temperature and collected participants‘ reports of alcohol intake, stress, and exercise. The authors observed that alcohol consumption during the evening affected the heart rate at sleep onset. Authors reported that the lack of daytime actigraphy limited the assessment of participant activity and limited characterisation of the circadian patterns, which requires long-term measurements.

In a review of actigraphy in the assessment of sleep and sleep disorders, Chesson et al. (2007) concluded that actigraphy can benefit objective sleep assessment criteria in healthy populations as well as those with certain sleep disorders. However, the review also concluded that actigraphy assessment has limitations; in particular, it significantly overestimates episodes of sleep when, in fact, subjects are awake but not moving. However, actigraphy was recommended for populations in which polysomnography cannot be easily achieved, e.g. for children. In a review of the validity of actigraphy in sleep medicine, Sadeh (2011) reported that actigraphy has ~~"re~~asonable" accuracy in assessing sleep quality in healthy people, but in people with sleep-related disorders the validity is not good enough to draw conclusions. The author recommended more objective and subjective assessments and also the inclusion of environmental assessments of, for example, light and temperature to investigate their influence on sleep quality.

Recent literature accounts various proposals for alternative and simplified detection of REM episodes. Agarwal et al. (2005) detected REM sleep via time domain analysis of data from two EOG channels. The slope of EOG signals of five subjects was calculated and used to discriminate REM from NREM with a sensitivity of 67.5% and a specificity of 77.5%. Merica and Fortune (2005) observed in 18 healthy subjects that during REM sleep the RMS power of EEG frequencies higher than 18 Hz increased significantly. Virkkala et al. (2007) calculated the RMS power of EOG frequencies in the range of 18–30 Hz of 235 participants and observed an increase of RMS power in REM sleep. Further work by Virkkala et al. (2008) reported REM and S1 and S2 detection by means of actigraphy and frequency analysis of RMS power of 18–30 Hz

from a single-channel EOG with a specificity of 72% and a sensitivity of 96%. Virkkala et al. (2009) reported that REM, S1 and S2 detection is possible through the analysis of RMS power in the band 18–45 Hz.

2.5 Health Monitoring in the Real-World

Assessment, disruption and stabilisation of circadian rhythms and deterioration of health can be observed in behavioural, social, activity and physiological patterns. This section covers technological approaches that could be applied to observe circadian rhythms and the deterioration of health conditions of patients. These technologies include smart home sensing with an emphasis on activity patterns, on-body sensing for ambulatory physiological measurements relevant to circadian patterns with no restriction of time and location so as to increase both its coverage and quality, and commercial wearable devices.

2.5.1 Smart Homes

Sensing technology has many healthcare applications. For example, ―smart homes" with embedded sensing technology can monitor activity patterns of elderly people and people with dementia in order to detect changes in their well-being (Bharucha et al., 2009; Suryadevara et al., 2012). Much of the work on smart homes has focused on motivating the elderly to follow diets, comply with medical treatments and exercise (Coughlin et al., 2007) for cheaper treatments as a result of population ageing and the high costs and availability of hospitals and nursing homes (Deen, 2015). Changes in lifestyle and routine can be inferred from sensed activities and the use of appliances, and can act as indicators of well-being changes (Brownsell et al., 2011). However, these approaches are limited to sensing in the home environment and it takes time to establish patterns; furthermore, interpreting results can be complex for carers and clinicians (Noury et al., 2011) and there is little understanding of how to relate this data with the detriment to health and how to filter out the influence of seasonal variations on behaviour (Brownsell et al., 2011). Nikamalfard et al. (2012) reported a system designed to identify patterns of appliance usage in people with early dementia as possible signs to carers of deterioration of cognitive functions. Sleep quality was also evaluated with pressure and passive infrared sensing (PIR) of bed occupancy. While unobtrusive, this indirect sensing fails to distinguish episodes of wakefulness from episodes of sleep, overestimating sleep quality and duration. In the review of smart home

technologies for health and social care support, Martin et al. (2008) concluded that the papers reviewed presented little evidence of smart homes for effective interventions for health support and a poor description of the methodology followed so as to generalise the findings. According to Deen (2015), smart homes have the potential of reducing healthcare costs of the elderly population, developing early treatments and automated detection of the deterioration of health; however, the collaboration between clinical experts and gathering medical requirements of physiotherapists, kinesiologists and orthopaedic clinicians are necessary.

2.5.2 **On-Body Sensing**

In the last decade or so, a number of wearable sensing systems, designed to record physiological signals in the real world, have been reported in literature (Pantelopoulos and Bourbakis, 2010). For example, Pandian et al. (2008) reported a vest with sensors with which to record ECG, electrodermal activity (EDA) and skin temperature. Data recorded was sent wirelessly to a remote monitoring system. A similar project was developed by Tay et al. (2009), who, in addition to data recorded by ECG sensors embedded in a T-shirt, recorded temperature and capillary oxygen saturation (SPO2) on the earlobe. Furthermore, researchers included alarms for the user and clinician when critical values of the heart rate were detected. Authors focused on decreasing power consumption and reducing the weight of the system for a comfortable unobtrusive monitoring system. Lopez et al. (2010) developed a shirt with embedded sensors to acquire physiological signals of both patients in bed in hospital and patients with medium mobility. Signals included ECG, pulse rate and body temperature, as well as wireless networks to determine the location of the patient in the hospital. This data was sent in real time to cardiologists. These systems were limited to the display of unprocessed data with simple thresholds used to trigger alarms. The sensor positions could not be adjusted and data was not recorded during sleep. Validation was performed based on the quality and representation of the ECG signal on the display interface with five healthy and five cardiac patients.

Issues of comfortability, data privacy, interference of medical devices, and usability have been discussed in wearable health technology and it seems that they have been the main premises for the design of wearable devices. For example, Chen et al. (2016) in their project entitled –Smart Clothing" collected data of six ECG channels and body temperature by means of a wired dry sensor to reduce interference with other devices, facilitate washing clothing and increase

comfortability. Chronic disease management has become important in recent years due to the increase of population ageing and modern lifestyles, which are factors linked to problems of diabetes, hypertension and obesity — the monitoring and management of these conditions have been the target of technological approaches. Kakria et al. (2015) used a mobile phone wirelessly connected to a temperature sensor, a blood pressure sensor and an ECG Holter to monitor and detect heart events, targeted towards cardiac patients and chronic diseases. The authors identified in their literature review concerns that can affect the performance of wearable health technology. These issues concerned gathering requirements of medical professionals at each step of the development and clinical validation; again, the discussion surrounded issues of comfortability and data privacy.

Despite new technological efforts to create new wearable systems for medical applications, including chronic disease management and their monitoring, there is still a lack of clinical involvement in the process. For example, Bellos et al. (2013) conducted clinical validation of a wearable system for patient management in chronic obstructive pulmonary disease (COPD) and chronic kidney disease (CKD). Clinicians remotely monitored parameters and automated system reports. However, their role was limited to evaluating the system assessment via a usability scale questionnaire. Triantafyllidis et al. (2013) also reported the design of a multisensor system for disease management for hypertensive patients. The system wirelessly sent heart rate, activity, posture, respiration rate and skin temperature data recorded in waking hours from a chest band to a smartphone. The system assessment was based on open questions in respect of the attitude of users towards the system, its use, and general feedback.

2.5.3 **Commercial Monitoring Devices**

In recent years, there has been very significant application of technology in health, rehabilitation and well-being. This includes the use of various monitoring and sensing technologies and the development of adapted and assistive technology.

There has been a recent surge in the availability and popularity of commercial fitness-monitoring devices and apps. For example, Fitbit produces a popular range of activity-monitoring wristbands and clip-ons from approximately £50 to £200. The Fitbit One clip-on costs around £65 and is described as a wireless *"activity and sleep tracker"*, though sleep estimation is

limited to actigraphy detection. The Polar sports watch (£40) can sense the heart rate via a chest band; additional functionality is provided by the higher-end watch, which costs approximately £350. Jawbone Up (£40) is a wristband device that assesses activity and attempts to categorise sleep into light and deep sleep using accelerometry (Chen et al., 2013); like some similar devices, it has mixed user reviews, with many users disappointed with its accuracy. Commercial activity monitors have been used in some clinical studies to complement collected patient data. For this reason, device validation is desirable. For example, validation of Fitbit One has been reported for treadmill walking (Takacs et al., 2014). However, validation is problematic for newer devices, given that the firmware and software are frequently updated by manufacturers. Moreover, commercial devices are aimed mainly at activity tracking for healthy adults, and usually fail to detect very slow walking and low activity levels. This is not a problem in fitness sensing for healthy adults, but it is significant in many patient cohorts. Sasaki et al. (2015) assessed the accuracy of Fitbit Classic with 20 participants. However, energy expenditure was underestimated and problematic in respect of its use in weight control or making intervention decisions. The major problem with commercial devices is that the software and algorithms are proprietary and not accessible to researchers who do not know how parameters are calculated, how algorithms work, and it is not possible to make changes. Alharbi et al. (2016) tested Fitbit Flex with cardiac and healthy participants. The study recommended being cautious when using Fitbit Flex for research purposes, because even though it is accurate for step counting, it overestimates energy expenditure in cardiac patients. The Polar S810 heart rate monitor was assessed with healthy participants and reported as providing inaccurate measurements of HRV in periods of 10 minutes or longer (Nunan et al., 2009). According to Zambotti et al. (2015) and Jeon and Finkelstein (2015), the poor clinical and research utility of consumer electronics for sleep relies on inadequate metrics of data, such as ―light sleep" and ―deep sleep", not compatible with scientific and clinical outcomes, inaccessible raw data, and unknown and proprietary algorithms produced by manufacturers. According to Piwek et al. (2016), evidence of consumer wearables as a diagnostic tool for chronic diseases and comorbidity is insufficient to draw conclusions due to the few clinical studies and results being mainly in the academic research world.

2.6 Issues of Wearable Technology for Health Monitoring

One major concern is the limited information provided for WHMSs and the observations of data for short periods of time. Circadian rhythms and behaviour of diseases are observed in a number of biological processes, such as body temperature, blood pressure, heart rate variability, and other physiological signals. However, they also are observed in sleep patterns, with hormone secretions synchronised mainly with light and dark cycles, behavioural and activity-related patterns such as social and feeding cues. Changes in these diverse patterns might be indicators of circadian rhythm problems and health deterioration. More and diverse objective physiological, environmental and behavioural information could benefit diagnosis and treatment management. Missing information on the patient does not enable a correlation in the variables that could adversely affect the disease (Dieffenderfer et al., 2016). Sarabia et al. (2008) proposed wrist temperature for circadian cycle assessment along with sleep–wake diaries. Wrist temperature changes during periods of activity and rest and although affected by ambient temperature, food intake, and naps, it can estimate patterns of activity and inactivity. However, authors concluded that assessments of circadian rhythms with a single-marker circadian can fail, as they can be affected by exogenous factors such as ambient temperature, activity, and feeding. However, much of the work has focused on comparing phase shifts of circadian cycles and explaining them with limited behavioural, social and activity-related information. For example, Lin et al. (2012) assessed the circadian cycle using two accelerometers — one worn on the wrist and one on the ankle — to estimate physical activity and detect cycles of sleeping and waking. Users also completed diaries to record social interaction on weekdays and at weekends in order to assess the influence on sleep and wake patterns. Virone (2009) assessed circadian rhythms of the elderly from patterns of activity and from their presence in different areas of their homes, using sensors in electrical appliances and PIR sensors for estimating activity and mobility in their homes. However, as reported by Brownsell et al. (2011), there are seasonal factors that affect the behaviour of people and are not necessarily an indicator of an abnormality. Furthermore, although changes in behavioural patterns could be signs of cognitive deterioration (Nikamalfard et al., 2012), it is complicated for medical staff to achieve the analysis (Noury et al., 2011).

According to Chiauzzi et al. (2015), the advances in wearable health technology have led to the miniaturisation of systems, extended battery life, and low-cost products; however, key challenges are still data privacy, data validation, and clinical integration. Moreover, there is a

lack of how wearable health-monitoring devices could impact upon the treatment effectiveness and disease management of chronic diseases, as the evidence has been in short-term clinical trials. According to Wieringa et al. (2017), in addition to improvements in ergonomics, miniaturisation, and systems that are easy to use, it is necessary to have applications that fit clinical needs for a wider adoption of wearable health technology. These include extended risk assessment for products in different scenarios, comply with safety standards, and recorded data providing useful, reliable information for nurses and doctors, and when the wearable device is intended to detect abnormal medical conditions such as heart problems, there should be meaningful events so as to avoid unnecessary medical visits.

In a review of smart health-monitoring systems, Baig and Gholamhosseini (2013) reported that systems can be unsuitable for use over long periods, as sensors can restrict movement and irritate the skin. The authors also observed that the quality of data can be poor and not clinically relevant, and that sensing is often limited to activity or restricted to the home environment. Furthermore, aesthetic and wearability issues have been reported as significant for patients (Dias et al., 2012). There is much literature in the field of wearable computing published to improve issues of comfort, physical appearance, mobility, personal privacy, and improving users‘ acceptance (Buenaflor and Kim, 2013). According to Spagnolli et al. (2014), the importance of these aspects depends on the personal attributes of gender, age, and experience with gadgets, the field and the scenario. For example, privacy might not be so important for young users, as they are used to share information on social media. In the context of medical devices, privacy and perceived usefulness are good predictors of acceptance. Although medical information is sensitive, Li et al. (2016) suggest that if the perceived benefit of the user is higher than the perceived privacy risk, it is more likely that the user will adopt wearable healthcare technology. According to Fang et al. (2016), those users who need to carry out hospital visits show higher acceptance towards the use of wearable technology.

Investigation into issues of usability and their effects on skin contact for long periods of time has been recommended by Lymberis and Paradiso (2008) for smart textile and Rodrigues Filho et al. (2013) for wearable technology. Paying attention to possible problems of disinfection, and complying with safety regulations when this technology could be in contact with wounds and blood. Lymberis and Paradiso (2008) have pointed out the lack of penetration of medical devices

due to the immaturity of technology, including testing and certification of products. According to Fajingbesi et al. (2017), despite the effort of research into wearable computing for cardiac-related diseases that could be extended to monitoring chronic diseases, there is not adequate research that includes participation of multidisciplinary groups; there is limited evidence of implementation in the medical field and poor evidence of reliability, accuracy, data privacy, and algorithms for multi-parameter management.

The objective assessment of patient sleep has been recommended for inclusion in patient-sensing systems for neurodegenerative diseases (Wulff et al., 2010), PTSD, and to extend the studies to other groups such as adolescents and children in order to develop effective behavioural and pharmacological interventions for sleep restoration (Germain, 2013). Bamer et al. (2008) theorised that the restoration of sleep of patients with multiple sclerosis, in return, can improve functioning problems such as those of fatigue, pain and depression, which are linked to sleep problems. In a review of body-worn sensor design entitled *"What do patients and clinicians want?"*, Bergmann and McGregor (2011) concluded that in order to have wearable technology adopted, clinicians need to be included in the process of design and testing. Moreover, McAdams et al. (2011) claimed that the poor clinical viability of wearable technology of academic research has been the product of the lack of validation of technology in real scenarios for extended periods of time during which identification of issues can be observed. The lack of clinical opinions and feedback of medical staff in research projects is another issue which needs to be tackled (Rodrigues Filho et al., 2013). In the review entitled Wearable Sensors for Remote Health by Majumber et al. (2017), the challenges, issues and concerns regarding wider adoption of wearable health systems included the privacy and security of medical data recorded, the integration of data among different platforms, low-power systems for long-term monitoring, and for low-cost and easy-to-use devices to be accepted by users.

2.7 Evaluating Healthcare Interventions Vs. Health Technology

Medical care has evolved over time from physicians visiting patients in their own homes to a centralised model wherein clinicians and medical resources are concentrated in hospitals and clinics (Arnrich et al., 2010). This centralised model faces significant challenges from the increasing cost of care and the demands made by populations that are ageing and affected by increasingly prevalent, longer-term chronic conditions such as diabetes, arthritis and

cardiovascular diseases (Dall et al., 2013; Lehnert et al., 2011). Pervasive healthcare has been proposed as a way in which to move away from the centralised model towards a more sustainable model, supporting patients in managing their health in their own homes (Arnrich et al., 2010). Various benefits of decentralised monitoring of patients have been reported in literature. These benefits include the elimination of restrictions of time and place with the application of short-term monitoring and long-term monitoring, healthcare maintenance, and check-ups (Varshney, 2015), healthcare professionals remotely monitoring individuals with applications for predicting and monitoring seasonal and epidemic diseases (Albayrak and Turhan, 2017), and cost reduction, availability and accessibility in respect of other medical experts and the efficient administration of healthcare resources. However, visions of pervasive healthcare present technological, methodological and administrative challenges (Arnrich et al., 2010). The technological challenges include the development of devices that are intuitive and easy to use, the development of reliable infrastructure and interoperable systems with which to support communication between different devices, networks and systems, and the development of security technologies and mechanisms with which to protect confidential data (Varshney, 2007). Issues of diversity of patients, medical requirements, and the representation of medical information (including processing and storage) need to be tackled (Varshney, 2015).

Methodological challenges include the development of procedures with which to provide standardised, reliable and comparable results in controlled and uncontrolled environments (Bardram, 2008). Administrative challenges include the ethical and regulatory challenges involved in developing, evaluating and certifying solutions (Varshney, 2007).

In clinical studies the evaluation of a medicine or intervention is typically carried out in staged clinical trial phases (NHS, 2013).

- Phase zero trials assess the effects of interventions on a small number of healthy human subjects.
- Phase one trials involve a small number of people, who may be healthy participants, to determine safe dosages and identify side effects.
- Phase two trials are short-term studies which test the effectiveness of a new treatment (usually compared with a placebo) in larger groups.

- Phase three trials involve longer-term evaluations, with large groups of patients receiving the treatment and controls receiving an existing treatment or placebo.
- Phase four trials continue to investigate safety, side effects and effectiveness of the treatment while it is being used in practice.

Clinical trials are expensive, long-term endeavours that require substantial commitment to legal and regulatory processes. Before a clinical trial can begin a research protocol must be submitted for ethical approval, funding must be secured, liability insurance must be obtained, a hospital or research institute must agree to provide a home base for the study, and researchers must obtain certification. For studies involving medical device technologies which may be commercial progenitors, Medicines and Healthcare products Regulatory Agency (MHRA) processes must also be followed. This long-term investment in formal testing contrasts with the rapid advances in mobile technology and also in user expectation. Years invested in formal testing might well provide important clinical evaluation, but the technology might be out of date and users might not want to use it. If the tested system were updated to a more current platform, and possibly improved with functionality provided by such a platform, then the old evaluation may be invalid.

Much of the early research in pervasive healthcare has involved the production of technological proof-of-concept systems that have provided useful evidence of technological feasibility but have not progressed the clinical application. The creation of a new academic journal, the IEEE Journal of Translational Engineering in Health and Medicine, with a focus on the ―intersection of engineering and clinical translation" evidences the need to help health technology across this difficult divide.

In pervasive healthcare research a methodology involving a ―Clinical Proof of Concept" (CPoC) has been recommended as a compromise between the two extremes: clinical trials and laboratory proofs of concept (Bardram, 2008; 2010). The recommendation is that the CPoC is a working, usable prototype that is evaluated by real users for an appropriate amount of time. Of course, however, access to ―real users", i.e. to patients, involves obtaining clinical permissions similar to those involved in clinical trials. In the UK, testing new technology with real patients is unlikely to be approved without good evidence, e.g. from testing with healthy participants.

Iterative prototyping and user participation are central to ISO recommendations for Human-Centred Design (ISO 9241-210, 2010), which recommends the following:

- ~~"~~The design is based upon an explicit understanding of users, tasks and environments.
- Users are involved throughout design and development.
- The design is driven and refined by user-centred evaluation.
- The process is iterative.
- The design addresses the whole user experience.
- The design team includes multidisciplinary skills and perspectives."

Participatory design, i.e. design with the participation of users, stakeholders and designers (Muller, Wildman and White, 1993), can substantially benefit the design of working prototypes and improve the quality of the proposed solution (Muller, 1991) and of user satisfaction (Kujala, 2003). Usability and accessibility of eHealth systems have to be considered from the early stages of the design with the patients and general practitioners to meet expected requirements with user-centred approaches such as the iterative ISO 9241-210 standard (Goldberg et al., 2011). The concept of usability has been misunderstood as making products that are easy to use; however, 9241-210 considers usability to be a concept with multidimensional properties. According to Viitanen et al. (2011), *"~~t~~he aim for designing for the whole user experience involves considerations of organisational impacts, user documentation, support and maintenance, training, and long-term use. Seeing that the definitions for usability emphasise various viewpoints and cover issues ranging from emotional and temporal dimensions to user's goals, one can realise that usability is not only a characteristic of a user interface."* The standards are a set of guidelines but do not specify how to follow them; however, in the ISO 9241-210 guidelines and recommendations, human factors are the main components that need to be taken into account in the design process (Villa and Cabezas, 2014), where the iterative design process provides constant end-user feedback (Schreuder et al., 2013).

2.8 Assessment Criteria for Wearable Sensing Health Systems

The ultimate goal of research in healthcare using either consumer wearables or research prototypes is the acceptance of users and the application of these devices in real scenarios to provide useful and meaningful information to medical staff. However, it is necessary to include the opinions and assessments of all users of the wearable health technology. Much of the work discussed in previous sections shows that the efforts for wearable health-monitoring devices have been towards improving appearance of the devices, comfortability, miniaturisation, improving data privacy and accuracy and, more importantly, little participation of medical experts in the stages of the design. According to Gao et al. (2015), factors of appearance, comfortability, data privacy, and cost are important for fitness wearables, but for medical devices, factors of usefulness and perceived efficacy of the device are more important characteristics for the users.

The maturity questionnaire shown in Table 1.1 was proposed by Pantelopoulos and Bourbakis 2010) for surveying wearable sensing systems for health application. This questionnaire is assessed by the user (who may be a patient or wearer), clinicians, and device designers or manufacturers. These three parties give a weighting and ranking of features (F1–F16). The questionnaire provides a useful starting point for generic system assessment but neglects some features that literature in the field considers to be important, particularly clinical hygiene and disinfection (Rodrigues Filho et al., 2013) and associated requirements, such as one-time-use systems and disposable electrodes, the integration of data with actual medical platforms (Majumber et al., 2017), metrics of data not compatible with clinical standards, and a lack of knowledge regarding how algorithms calculate variables (Jeon and Finkelstein, 2015). Of the features, interference robustness (F13) assesses wireless communication robustness rather than communication robustness *per se*, and computational & storage requirements (F8) have an unclear contribution.

Table 2.1 The wearable sensing health system maturity questionnaire proposed by Pantelopoulos and Bourbakis (2010)

Feature	**Description**	**Weight**	**Maturity/ Development**
Wearability (F1)	The system must have low weight and size.		
Appropriate placement on the body (F2)	The system has to be unobtrusive and comfortable, in order not to interfere with the user‘s movements and daily activity.		
Aesthetic issues (F3)	The system should not severely affect the user‘s appearance.		
Data encryption and security (F4)	Encrypted transmission of measured signal and authentication requirement for private data access.		
Operational lifetime (F5)	Ultra low power consumption for long-term, maintenance-free health monitoring.		
Real application (F6)	The developed system is applicable (and useful) to real-life scenarios/health conditions.		
Real-time application (F7)	The wearable system produces results, e.g. display of measurements, alerts, diagnosis, etc., in (or near) real time.		
Computational & storage requirements (F8)	The computational and storage resources required or utilised by the system to achieve desirable results.		
Ease of use (F9)	The system incorporates a friendly, easy-to-use and easy-to-learn user interface.		
Performance and test in real cases (F10)	Sufficient results and performance statistics are provided to verify the system‘s functionality in real cases.		
Reliability (F11)	The system produces reliable and accurate results.		
Cost (F12)	The amount of money required to produce and purchase the proposed wearable system.		
Interference robustness (F13)	Availability and reliability of wirelessly transmitted physiological measurements.		
Fault tolerance (F14)	The system produces reliable results under any circumstances, such as various kinds of patient movements.		
Scalability (F15)	Potentiality of upgrading, enhancing and easily incorporating additional components into the developed system.		
Decision support (F16)	The implemented system includes some type of diagnosis/decision mechanism or an algorithm/pattern recognition system for context-aware sensing of parameters.		

According to Rodrigues Filho et al. (2013), this questionnaire can help in focusing on relevant aspects of the research project if it is intended to be used in a clinical scenario, and can assess the maturity before deploying in real conditions. However, this maturity questionnaire has some limitations that could lead to wrong conclusions. For example, the weight is the perspective of the three parties. A high score for a feature, which is the result of the perspectives of the user, clinician and manufacturer, it can be concluded that it is important from the three perspectives. However, a low score cannot be understood as being an unimportant characteristic, as it can be the result of low importance from two perspectives but high importance for the other party. For example, this could be crucial if the high value comes from the user or clinician but the low value derives from the manufacturer, as they will be the users. Another limitation is that this is a generic maturity questionnaire whose results of the assessment of maturity of different technological solutions cannot be compared. For example, the operational lifetime (F5) of a wearable device that is intended to collect data in a short period of time but with high consumption of energy could have a low score when it is not relevant to its use or application, or a wearable device that is recording only raw data without any automatic diagnosis could lead to a low maturity score for decision support (F16). Moreover, not all features are equally important or relevant to the wearable health solution. Important features with low scores can lead to preventing the adoption of technology, despite high scores on other less important features.

Pantelopoulos and Bourbakis (2010) evaluated the maturity of 19 research projects. Some characteristics that the researchers chose to select these projects included the citation number of other projects and the information available in published projects. However, this does not imply that the documentation would be enough to assess the 16 features of the maturity questionnaire. In general, the scores of the 19 projects assessed ranged from 2 (medium-low maturity) to 4 (high maturity), with a maximum of 5 (maximum maturity). For example, the project entitled Personal Health Monitor by Leijdekkers and Gay (2005) received a score of 4 (high maturity); however, it is not clear how it received a score of 4, as the paper does not provide enough information on data encryption (F4), operational lifetime (F5) and fault tolerance (F14), and the authors stated that the algorithm is very basic and that more tests are necessary to reduce false alarms. Therefore, this limited information would impact upon the assessment of some features, such as interference robustness (F13), performance and test in real cases (F10) and decision support (F16). Similar problems were encountered with the project entitled MagIC System by Di

Rienzo (2005), which also received a score of 4 (high maturity). This short paper of three pages does not provide enough information to determine a number of features, including data encryption and security (F4) and operational lifetime (F5). Again, the author was improving the project to use it in clinical settings and daily life conditions. This lack of testing and clinical validation does not enable assessing decision support (F16), fault tolerance (F14), reliability (F11) and performance and test in real cases (F10). On the contrary, the project entitled LiveNet by Sung et al. (2005) described promising results in pilot studies in the detection and classification of movements in Parkinson‘s disease, receiving a score of 2. The smart vest, a general health-monitoring system by Pandien et al. (2008), received a score of 4. This device was validated by comparing short-term trials of healthy participants with commercial ECG and blood pressure (BP) monitoring devices. In dynamic conditions the system showed errors in ECG, photoplethysmography (PPG) and blood pressure measurements. A fully charged battery lasted only 4.5 hours, with no clinical algorithm decision support or real-time process.

Comparisons of the maturity of research projects with unclear methodology and limited information would be irrelevant and lead to wrong conclusions. However, this maturity questionnaire can be useful in taking into account features that have been reported to be important in the literature. However, some of these features could not be relevant to the application developed. A combination of the maturity questionnaire and discussions with clinical experts have been recommended by both Rodrigues Filho et al. (2013) and Pantelopoulos and Bourbakis (2010) in the design stages of the device. Focus groups and interviews give the possibility of discussions with clinicians so as to improve and find issues in all stages of a clinical prototype with the possibility of being used.

Table 2.2 shows that in the first approaches of wearable health-monitoring devices to monitoring health conditions, personal digital assistants (PDA) were used as a processing unit. Data from on-body sensors was connected to the PDAs and combined with in-built sensors of devices such as the global positioning system (GPS) and accelerometers (Sung et al., 2005; Tay et al., 2009). Advances in the processing power of mobile phones enabled real-time processing and decision support for applications in the presence of a heart attack (Leijdekkers and Gay, 2008), real-time assessment of the health status of people with chronic obstructive pulmonary disease (Bellos et al., 2014), self-management of hypertension, and sharing data with doctors (Triantafyllidis et al.,

2013). There are several approaches in which sensors are embedded in clothes such as vests for monitoring of cardiac patients (Di Rienzo et al., 2005), with multiple sensors in a T-shirt for vital signal monitoring (Lopez et al., 2010) wherein data is wirelessly sent to a computer for processing and displaying. Collection of physiological and environmental data has been carried out by both commercial wearable monitors connected to mobile phones, such as ECG Holter monitors for cardiac patients (Leijdekkers and Gay, 2008; Kakria et al., 2015) and multi-physiology wearable monitors for body temperature and heart and respiratory rates (Triantafyllidis et al., 2013), and commercial wearable data loggers of temperature, actigraphy and light (Bonmati-Carrion et al., 2014). However, according to Jeon and Finkelstein (2015), commercial devices have the limitations of inaccessible raw data and unknown and proprietary algorithms produced by manufacturers. The role of a microcontroller in these research projects has been to collect data from sensors and send it to a mobile phone or computer, wherein problems of complex processing and displaying can be easily solved. These research devices show little participation of clinicians, as shown in Table 2.2, or clinicians‘ opinions have been limited for visualisation assessment or decision support validation. Validation of the built devices has been achieved by comparing data with commercial device results and has been omitted when the solution has a commercial wearable device. Despite the recommendation of the inclusion of behavioural information on patients, a few projects include reports of this information.

Table 2.2 Summary of projects reviewed

Project title or project description	Hardware	Signals measured	Medical applications	Validation, evaluation or assessment of the device	Clinical participation
LiveNet (Sung et al., 2005)	PDA connected to on-body sensors, sensors in objects and appliances	Body temperature, heart rate, actigraphy, location, ambience and interaction with objects or appliances	Detection of movement of people with Parkinson‘s. Depression episodes based on usage of appliances and possible applications for epilepsy seizure detection	Two pilot studies with seven Parkinson‘s cases to detect movement disorders One pilot study with patients with depression	Classification of movement disorders provided by the system and compared with clinicians‘ opinions No information available
MagiIc (Di Rienzo et al., 2005)	Fabric sensors embedded in a vest connected to a board. Data wirelessly sent to a computer	ECG, motion and respiration signals	Monitoring of cardiac patients	Cardiac rhythms of people performing physical activity	No information
Personal Health Monitor (Leijdekkers and Gay, 2008)	Mobile phone wirelessly connected to a commercial wearable heart rate monitor	ECG	Heart attack detection	Trials with patients in a hospital	No information
Smart Vest (Pandian et al., 2008)	Vest with embedded sensors connected to a dsPIC30F6014 microcontroller	ECG, temperature, PPG, EDR, blood pressure calculated from PPG and ECG signals	General health monitoring	30-minute data of 25 healthy participants. Data was compared with commercial BP, ECG monitors	No information
MEMSWear-biomonitoring system (Tay et al., 2009)	PDA with on-body sensors connected by Bluetooth with a Texas Instruments MSP microcontroller	ECG, SpO2, temperature and blood pressure	Remote vital sign monitoring	No information	No information

LOBIN (Lopez et al., 2010)	Shirt with embedded sensor and a microcontroller sending data to a computer	ECG, heart rate, movement, body temperature and location	Remote vital sign monitoring and location of patients	Pilot studies with users wearing the shirt to detect issues of comfortability, accuracy of data and usability of interface	Clinicians providing feedback on usability and representation of data sent to a monitor
Sleep classification (Paalasmaa et al., 2012)	Sensors collecting data sent wirelessly to a computer	Heart rate and respiration rate measured indirectly with a piezo electric sensor, ambient temperature and ambient light, complemented with patient‘s lifestyle data	Sleep disorder patients	40 patients of a sleep clinic	No information
Self-management of chronic patients (Triantafyllidis et al., 2013)	Commercial monitoring device connected by Bluetooth to a mobile phone	Heart rate, respiratory rate, skin temperature, and activity, information related to the disease provided by patient	Monitoring of chronic diseases, i.e. hypertensive patients	16 hypertensive patients to assess user acceptance and perceived usefulness	No information
CHRONIOUS (Bellos et al., 2014)	Mobile phone connected to wearable sensors on a jacket and data from external commercial devices	ECG, respiration rate, actigraphy, ambient humidity, body and environment. External data from blood pressure, blood glucose, and clinical data of patient and patient‘s lifestyle	Health status of people with chronic obstructive pulmonary disease (COPD)	30 participants with COPD who wore the system in their home and hospital	Clinicians provided rules programmed in the classification algorithm to detect critical conditions of the patient
Circadian assessment (Bonmati-Carrion et al., 2014)	Three commercial data loggers. An iButton DS1921H for wrist temperature and Pendant G Acceleration Data Logger for actigraphy and for	Wrist temperature and actigraphy, complemented with sleep log and light exposure	General assessment of circadian cycles for sleep medicine	13 healthy subjects. Data of participants was compared with melatonin patterns	No description

	light measurement				
Remote monitoring of cardiac patients with a mobile phone (Kakria et al., 2015)	Commercial wearable health monitors connected by Bluetooth to a mobile phone	Heart rate, blood pressure and temperature	Monitoring of cardiac patients and chronic disease management	Tested with 40 healthy users with no description of protocol	No information
Smart Clothing (Chen et al., 2016)	Embedded sensors in a T-shirt collected by a microcontroller. Data sent data to a mobile phone or computer	ECG, EEG, body temperature, SpO2	Possible uses of monitoring health of the elderly and sportsmen‘s performance	No information	No information
Sleep problems in the elderly (Merilahti et al., 2016)	A commercial wearable wrist device	Wrist temperature complemented with test results of pain, cognitive and mental functioning, physical activity	Sleep problems in the elderly and people with dementia	Comparisons of cycle rhythms of 16 nursing home residents over a period of months	No description

2.9 Summary

Literature reveals the importance of long-term recordings of physiological, environmental and behavioural information of patients for managing and monitoring chronic diseases and circadian rhythms. A wearable health-monitoring system recording this information would provide several benefits. These include reducing the cost of treatments, fewer hospital resources, and better diagnosis and assessment efficacy of treatments. As diseases have multifactorial causes, what information to record and how to deliver such information to clinicians are themes of discussion. Despite the amount of literature on wearable health-monitoring devices, smart homes for activity recognition, and the availability of commercial fitness devices, there are issues that need to be addressed and discussed with clinicians and users. Issues relate to what physiological and environmental variables are to be recorded and what behavioural data is to be reported and registered by patients. Some desirable features of wearable health-monitoring devices have been reported in the literature concerned with comfortability, easy-to-use devices, data privacy, accuracy, and validation of devices. However, the recommendation has been to work alongside clinicians from early stages to the detection of features that would make a clinically relevant device. The maturity questionnaire presented in this chapter has many features that are important for wearable health-monitoring devices.However, not all features are equally important — some features might not be part of the solution regarding the intended use of the device. The inclusion of clinicians in interviews and focus groups would enable exploring the importance of the features, including more features and discussing issues to produce a clinically relevant device.

2.10 Research Questions

The first research question emerged as a result of the lack of long-term observations of objective and subjective data provided to the clinician by patients, both revealed in the literature review and discussed with clinical participants in interviews and focus groups. There are a number of different solutions for monitoring health conditions. They can be real-time approaches, observations of one or a few physiological variables or for short periods of time. The solution proposed is that of long-term monitoring of physiological, environmental and behavioural data with offline processing for a simple interface for users. The wearable health-monitoring system will identify, along with clinicians, variables of interest and data collection, analysis and

presentation for general monitoring of chronic diseases and circadian rhythm. In this scenario the question that emerged is as follows:

1) How can we design, prototype and develop a real-world, multimodal and long-term patient-monitoring system?

The literature review identified features of interest of wearable health-monitoring devices, with some of these features having been widely discussed, such as comfortability, usability, appearance, easy-to-use devices, and accuracy. Other features of wearable health devices have been reported to be important but with little discussion in the literature, such as hygiene, disinfection, and data presented in medical data standards. Further discussions with clinicians showed that more features and issues need to be addressed and, again, they depend on the wearable health-monitoring solution proposed.

2) What features and issues need to be considered in a long-term wearable health-monitoring system to produce a clinically relevant device?

Clinicians are familiar with short-term measurements of vital signals typically taken in their office and sometimes the results of laboratory tests handed in at the time of the appointment. The lack of information provided by the patient can limit the resources of the clinician in diagnosing or assessing the condition. Multimodal and multirate variables recorded pose the problem of how to deliver information to clinicians so as to extract patterns or draw conclusions from data presented. Discussions with clinicians in the interviews and focus groups suggested visualisations to observe trends and compare data over long periods of time in order to assess and monitor the disease.

3) How can complex multimodal patient data be analysed, presented and visualised to provide trends, summaries and assessment of diseases?

CHAPTER 3

CIRCADIANSENSE SYSTEM DESIGN

3.1 Introduction

The literature review presented in Chapter 2 shows that accounts of physiological, environmental and behavioural data can provide useful information with which to understand and explain circadian cycle abnormalities, sleep disturbances, and for monitoring and managing chronic diseases. This chapter presents an overview of the prototype, system requirements, sensor specifications, and hardware design to record physiological and environmental variables related to sleep hygiene. The stages of the design were discussed with clinicians and informed by the literature review for continuous improvements to CircadianSense.

3.2 CircadianSense Origin and Motivation

As presented in Chapter 1 and shown in Figure 1.1, the origin of CircadianSense is rooted in initial meetings with a clinical collaborator who expressed problems in respect of the lack of objective and subjective information of patients at the moment of meeting. As reported in the literature and by clinicians, more information on patients, including behavioural and environmental conditions, can help to understand their influence on the prognosis and explain the symptoms of diseases. Furthermore, the literature review shows that a system for long-term objective recordings relevant to the circadian cycle in the daily life activities of a patient can provide information with which to explain and design treatments to stabilise the circadian cycle and sleep quality (Tietze et al., 2012; Churchill et al., 2012). Observation of the long-term behaviour and patterns of physiological signals can help to assess treatments and modify medication (Wright et al., 2013).

It has been reported that a comfortable sleep environment with recommended levels of noise, temperature and light promotes sleep and adjusts the circadian cycle (Caldwell et al., 2008). In addition to psychological treatment, improving sleep hygiene has been shown to be effective in reducing nightmares in people with PTSD (Augedal et al., 2013). Although objective measurement of sleep quality is more accurate than the patient‘s report, the use of objective and subjective sleep assessment has been recommended to compare both results (Sadeh, 2011). It is of particular interest to include clinicians in the design stages of CircadianSense so as to identify issues in early stages of a clinically relevant wearable monitoring system, as recommended by Bergmann and McGregor (2011) and Baig and Gholamhosseini (2013).

The motivation, as mentioned earlier, is that there is an increase of interest in long-term health-monitoring systems for a number of patient cohorts in the environment wherein they perform their activities and the problems are more evident than in the office of a clinician. A wearable health-monitoring system designed with clinicians can detect issues surrounding how to deliver clinically relevant information so as to improve life quality, diagnosis and treatment, with additional benefits such as reduced health cost, fewer hospital resources, and patients not attending scheduled hospital visits. Figure 1.1 shows activities relevant to the design of CircadianSense, as well as ethical approval granted to test the system with the research team and clinicians.

3.3 CircadianSense System Requirements

The general ambition for CircadianSense was to prototype a sufficiently wearable and lightweight system for real-world patient use during typical activities of everyday life and for monitoring during both the day and night. The requirements of the CircadianSense system in order to achieve observation of sleep, circadian cycle patterns, and behaviour of physiological signals were as follows:

- An ambulatory, comfortable, unobtrusive and low-cost sensing system during typical real-world activities of everyday life.
- Minimal user interaction to start and stop data recordings.
- Continuous recording of variables without user or researcher intervention.

- Provision of objective insights into patients‘ sleep, well-being and lifestyle at selected intervals in the duration of their care without the need for sleep laboratory evaluation.
- Recordings of physiological and environmental variables.
- Collection of behavioural patterns and zeitgebers that affect the circadian cycle, sleep quality, and diseases.
- Data security and privacy of data collected.
- System being easy to clean and disinfect.
- Device being suitable for use in a hospital environment and at home.

3.3.1 Usability Requirements

CircadianSense is a self-managed system that will be worn for a minimum of 24 hours to collect both daytime and nighttime data. In real clinical application, however, longer periods of time are necessary to observe the circadian rhythms, sleep patterns, trends and monitoring of chronic diseases. Given the nature of the long-term use of CircadianSense, it is relevant that users do not feel frustrated when using the system and that its use be abandoned. The usability requirements of CircadianSense are as follows:

- The system must be as unobtrusive as possible.
- The system must not interfere with the activities of the person.
- The battery life must last long enough to collect data for at least 72 hours.
- The user interface of the device must be easy to use with minimal user manipulation.
- The system must be easy to wear and remove.
- The system must fit people with different physical characteristics in respect of height and weight.
- Continuous recordings of variables without researcher intervention and minimal user intervention.

3.3.2 Hardware and Software Requirements

The CircadianSense system is a data logger with further offline processing of data recorded. A data logger enables a simple interface to eliminate the need for displays and controls to show

information which could increase the size of the system and the complexity of the user interface. Data processing will be conducted on a computer. The hardware requirements are as follows:

- The system must have a small microcontroller board.
- The sensors with which to record data must be small and comfortable.
- The system must have low power consumption.
- The memory unit must be capable of storing all data collected for several days in a single unit.
- The software used to design the system and analyse data to be used will preferably have low cost or free use with sufficient libraries for rapid development of the prototype.
- Data visualisation must be through software of common use to allow users the manipulation of data processed if desired.

3.4 Data Storage

A battery-powered ambulatory solution was dictated by the real-world continuous sensing requirement with an equivalent system for sleeping. The lifestyle requirement rendered the recording of activity and ambient variables important. The low-cost and easy-to-use requirements made a simple, sealed single-unit microcontroller solution desirable with only one switch for the user to start and stop recordings. The ambition was to power the system with rechargeable batteries for up to 3 days and 3 nights of continuous use without the need to recharge, although longer periods of time would have been preferable for less intervention between the user and the researcher.

The choice between wired and wireless sensing was significant; each removes problems associated with the other while introducing its own set of issues. There are a number of wearable and remote health systems with wireless communication; however, wireless data transmission presents concerns and issues not fully addressed in respect of data security, privacy, and compliance with medical and ethical standards (Baig and Gholamhosseini, 2013).

The advantages and disadvantages of three alternative approaches were analysed before constructing the system. In these approaches the recording unit is a processor, a piece of hardware, dedicated to recorded data from sensors. The alternatives were as follows:

a) Recording unit with wired sensors: The processor has an external memory unit storing data collected from all sensors connected by wires to the processor.
b) Recording unit with wireless sensors: All sensors would require a processor to send data recorded to the recording unit, a battery, and a wireless communication module. This approach would require more processors, more energy consumption and more interaction with the user to turn them on and off.
c) Independent sensors: Each sensor has an independent recording unit and an independent memory unit to store sampled data. This option would require a processor, a memory unit and a battery for each sensor. Users would be required to turn on and off all of the sensor units individually.

The approach of a recording unit with wireless sensors was dismissed because the risk assessment conducted with the technician of the School of Electronic, Electrical and Computer Engineering of the University of Birmingham (UoB) identified possible issues of compliance for hospital use and possible interference of wireless communication with medical devices in the hospital. Moreover, it requires more interaction from the user with regard to turning on and off the sensors. On the other hand, a recording unit with wired sensors has the following advantages: the user controls only one recording unit to start and stop data recording, and there is no risk of interference with medical devices in the hospital. Indeed, wired sensors between sensors and the recording unit present technical and user operability advantages, but increased discomfort due to wires on the chest and arms.

3.5 Methodology for Selection of Variables

A review of the literature was conducted which encompassed health technology, sleep medicine, chronobiology and rehabilitation literature. Circadian variables were first selected in the literature review based on recommendations of researchers for monitoring different health conditions. These included environmental and physiological signals in both waking hours and sleeping hours, as shown in Table 3.1. These variables were presented first to the main clinical

collaborator for preliminary discussions surrounding their feasibility and relevance. In further one-on-one interviews with the other three clinicians these were discussed again.

In the literature review, long-term recordings of physiological signals have been recommended, e.g. circadian rhythms of the heart rate to prevent cardiovascular diseases and perform early preventative interventions (Stein and Pu, 2012; Portaluppi et al., 2012). Long-term recordings of core body temperature have also been recommended, as it is an objective assessment of the circadian cycle that can guide in respect of making changes to treatments of sleep problems (Bjorvatn and Pallesen, 2009; Lack et al., 2008). A number of studies have recommended recording environmental variables to determine how they affect sleep, circadian cycle and health conditions; for example, Churchill et al. (2012) recommended registering environmental conditions to determine how they affect children with Down‘s syndrome, Caldwell et al. (2008) to determine the effects on health and occupational performance, Wright et al. (2013) to understand the health risks of shift work due to sleep disruption, Tietze et al. (2012) to help adjust treatments for children with disabilities based on their symptoms and sleep problems, and Ruff et al. (2012) to improve sleep quality and reduce symptoms of people with PTSD by means of better sleep hygiene.

The circadian cycle is synchronised by zeitgebers. The use of diaries to register behavioural activities such as food, exercise, and social interaction has been recommended. Information to be registered in the daily log, as informed by literature and discussed with clinicians, is presented in the next chapter. Table 3.1 shows recommended variables that were found in the literature review. Variables were considered in further interviews with clinical participants. In these interviews, pulse oximetry and respiration rate were recommended for sleep apnoea evaluation. Rapid eye movement (REM) was recommended by the main clinical collaborator because its duration and frequency during nighttime might be altered by medication deteriorating sleep quality; moreover, the literature review shows that abnormal characteristics of REM, such as latency, amount and density, are present in a number of psychological and neurological conditions. Ambient variables were recommended by clinicians because of the poor environmental conditions in the hospital that do not promote good sleep quality; literature also recommends good sleep hygiene conditions.

Table 3.1 Variable recorded (R) or suggested (S) for sleep and circadian cycle disruption in the literature review

Source	Possible sensors R: recorded, S: suggested																				
	Energy expenditure	sleep afficiency	Pulse rate		Breathing rate		EOG	Pulse oximeter	Stress		Body temperature		Ambient temperature		Ambient light		Ambient noise		Behavioural data	Blood pressure	Blood sugar
Day (D), Night (N)	D	N	D	N	D	N	N	N	D	N	D	N	D	N	D	N	D	N	D	D	D
Churchill et al. (2012)	S	S	S	S				S					S	S	S	S	S	S			
Portaluppi et al. (2012)			S	S															S		
Stein and Pu (2012)			S	S																	
Bjorvatn and Pallesen (2009)											S	S			S	S					
Lack et al. (2008)											S	S			S	S					
Caldwell et al. (2008)	S												S	S	S	S	S	S	S		
Wright et al. (2013)	S												S	S	S	S	S	S	S		
Tietze et al. (2012)											S	S		S		S		S	S		
Ruff et al. (2012)														S		S		S			
Interview with clinicians	S	S	S	S		S	S	S	S		S	S	S	S	S	S	S	S	S	S	S
Focus groups with general practitioner	S	S	S	S		S		S	S		S		S	S		S		S	S	S	S
Proposed system	R	R	R	R			R		R	R	R	R	R	R	R	R		R	R		

As shown in Table 3.1, there are variables that do not produce reliable measurements in ambulatory conditions. For example, pulse oximetry is measured on the finger of a hand and interferes with activities performed. Blood pressure requires a protocol in which the patient is asked to sit still and have his or her blood pressure taken at around the same hour because food intake and activity affect measurements. Blood sugar is also a variable that needs a protocol to allow measurement. However, these variables can be supplied with data of commercial devices prescribed by clinicians and annotated in a daily log. These would not produce continuous data but would enable observing trends in those variables as suggested by clinicians.

Variables monitored using polysomnography, assessed in sleep hygiene and recommended in the literature for real-world circadian and sleep assessment are listed in Table 3.2. Table 3.2 also includes the variables that clinicians recommended in the interviews. Ideally, all variables should have been used in the design for broad application in healthcare monitoring of different patient cohorts. However, the variables were selected because of their application to the circadian cycle, sleep quality, general physiological signal monitoring, their feasibility of being implemented, reliability in daily life activities, and because of being easy to interpret without the need of an expert.

The analysis of EOG, EEG and EMG signals has been used for sleep stage classification. However, sleep stage classification requires a sleep expert to score the signals and classify the stages. REM sleep sensing was pursued because of its significance in sleep disorders in different patient populations as presented in the literature review (Agarwal et al., 2005; Gagnon et al., 2006; Arnulf and Oudiette, 2008). EEG and EMG are signals that were not recorded because of their increased invasiveness and the difficulty of acquisition and interpretation of the signals. Furthermore, although sleep assessment was an ambition, the detection and analysis of all sleep stages were not. Instead, EOG estimation of REM episodes and sleep quality were pursued.

Pulse oximetry was a variable recommended by clinicians; however, the relevance of this variable is to specific application of sleep problems such as sleep apnoea. The respiration rate for sleep disordered breathing. With the analysis of the pulse rate, body temperature, EOG and actigraphy, a number of sleep problems can be observed, such as insomnia, delayed sleep–wake phase disorder, advanced and delayed sleep–wake phase disorder, and irregular sleep–wake

rhythm and general circadian rhythm sleep–wake disorders. However, both blood pressure and pulse oximetry information can be taken in regular periods of time and annotated in the daily log.

Table 3.2 Collated Variables

Recommended variables for sleep monitoring	Recommended in waking hours	Recommended in sleeping hours	Feasibility (for real-world monitoring)	Included in CircadianSense
Electrodermal activity (EDA)	Yes		Good	Yes
Actigraphy		Yes	Good	Yes
Energy expenditure	Yes			Yes
Pulse rate	Yes	Yes	Good	Yes
Body temperature		Yes	Good	Yes
Pulse oximetry	Yes	Yes	Not possible for ambulatory with limited relevance	No
Respiration rate	Yes	Yes	Poor	No
EOG		Yes	Possible	Yes
EEG		Yes	Poor	No
EMG		Yes	Possible, but limited use without EEG	No
Blood pressure	Yes	Yes	Not possible for ambulatory	No
Blood sugar	Yes		Not possible for ambulatory	No
Ambient noise		Yes	Good	Yes
Ambient light		Yes	Good	Yes
Ambient temperature		Yes	Good	Yes

3.6 CircadianSense System Overview

The CircadianSense prototype which evolved from this process comprises a sensing system and a set of behavioural assessments of sleep hygiene, a sleep questionnaire and the collection of users‘ data annotated in a daily log. It is a proof-of-concept prototype developed to record physiological and environmental signals for an improved understanding of patients‘ well-being, lifestyle and sleep.

CircadianSense Sensing System: Three subsystems, as shown in Figure 3.1, form the CircadianSense sensing system. Each subsystem has a processor that reads data from wired sensors and records data onto a Secure Digital (SD) card. The processor board used was the Arduino Pro Mini. There are advantages of Arduino boards over other microcontrollers: Arduino boards are programmed by a USB cable connected to the computer; they are low-cost boards; and Arduino has a free integrated development environment (IDE) and well-supported C++ libraries freely available for analogue signal acquisition and for interfacing with an SD card for data storage. These characteristics make Arduino suitable for the rapid development of programs.

The Arduino board version selected was dictated by the hardware requirement established for CircadianSense. The 8MHz Arduino Pro Mini was chosen for the following reasons: it has a small form factor of 18 mm x 33 mm; it is desirable for a compact wearable system; this Arduino version operates at 3.3 volts, which is suitable for direct interfacing with SD cards and sensors that run at 3.3 volts; and the power consumption of the processor at 8 MHz is lower than 10 mW, which is important for preserving battery life, compared to Arduino boards at 16 MHz with a power consumption of 45 mW of the processor alone and digital voltages higher than 3.3 volts.

Figure 3.1 shows the three subsystems that compose CircadianSense and the changes of the systems based on recommendations from clinicians and users after the initial short-term testing. These are capable of recording physiological and environmental signals during both the waking hours and the sleeping hours.

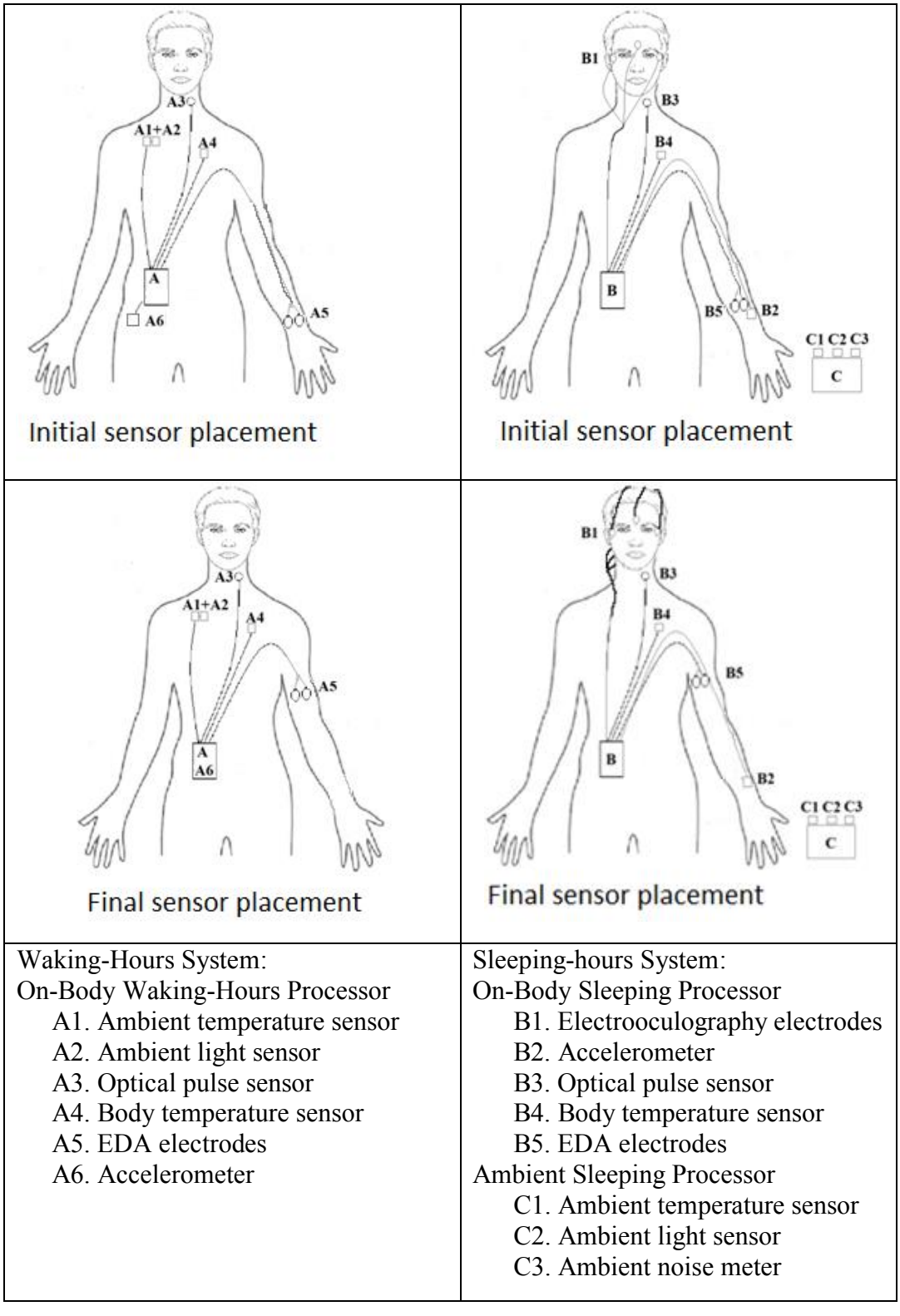
A stress estimator was achieved by means of measurements of EDA. The typical placement of EDA electrodes on the hands, wrist or feet are invasive and problematic in work and other

environments (Muller et al., 1993). In the first prototype, measurements of EDA were carried out with Ag/AgCl electrodes placed on the wrist, but these were found to be obtrusive because of the cables running from the wrist to the processor over the arm and chest. Moreover, the risk assessment with the main clinical collaborator found that it could interfere with manual activities and the movement of the EDA electrodes to a position under scrubs was required. The upper arm was suggested. The literature review showed that the placement of electrodes on the upper arm is less sensitive than on the palm, wrist or feet (Liden et al., 2002) but can provide useful EDA activity information. For example, Perala and Sterling (2007) showed that EDA electrodes in armbands worn by soldiers produced good correspondence with salivary amylase activity in assessing stress in training exercises.

The energy expeniditure in metabolic equivalent (MET) measured during daytime by an accelerometer was initially external to the processor box and connected with a cable. A reduction of cables was achieved by putting the accelerometer inside of the processor box with the limitation of using the processor box on the waist for a more accurate measurement of energy expenditure, as it is the mass centre of the body.

EOG cable placement was adjusted on the advice of an academic with sleep expertise at the University of Birmingham. Electrode placement was assessed as being correct but it was recommended adjusting the cable placement of EOG electrodes on the back of the head to increase comfortability.

Another recommendation in the risk assessment by the main clinical collaborator was to change the flat cables of the processor box connected to the sensors to other cables that were easier to disinfect and clean. Sleeved round cables were used.



Waking-Hours System: On-Body Waking-Hours Processor A1. Ambient temperature sensor A2. Ambient light sensor A3. Optical pulse sensor A4. Body temperature sensor A5. EDA electrodes A6. Accelerometer	Sleeping-hours System: On-Body Sleeping Processor B1. Electrooculography electrodes B2. Accelerometer B3. Optical pulse sensor B4. Body temperature sensor B5. EDA electrodes Ambient Sleeping Processor C1. Ambient temperature sensor C2. Ambient light sensor C3. Ambient noise meter

Figure 3.1 The CircadianSense sensing subsystems

3.7 CircadianSense Sensing Summary

The CircadianSense sensors and the associated variable ranges are listed in Table 3.3. Up to three types of ranges were identified for each variable with the help of the clinical collaborator:

i) A normal or healthy range depending, for example, on the patient‘s sex and age,
ii) A physiologically possible range, and
iii) The range measurable by CircadianSense.

The normal range comprises values that are normally expected for a patient given, for example, their gender and age. The physically possible range extends beyond the normal values, including values that can exist in extreme conditions. Values in iii), which are beyond those physiologically possible, could be caused by, for example, a faulty or detached sensor.

Table 3.3 CircadianSense sensors and variable ranges

Variable	Minimum detected by CircadianSense	Minimum physiologically expected	Normal healthy/comfortable minimum	Normal healthy/comfortable maximum	Maximum physiologically expected	Maximum detectable by CircadianSense
Waking hours variables						
Accelerometer	0 g	0 g	N/A	N/A	6 g	6 g
Energy expenditure	1 MET	1 MET	N/A	N/A	12 MET	8 MET
EDA	~200 Ω	N/A	N/A	N/A	N/A	~50 MΩ
Pulse rate	0	30 BPM	Typically ~60 beats per minute but defined by activity, age and fitness	Typically ~100 beats per minute but defined by activity, age and fitness	300	1200
Body temperature	-9°C	28°C	35°C	38°C	41°C	50°C
Ambient temperature	-9°C	N/A	N/A	N/A	N/A	100°C
Ambient light	Complete darkness	N/A	N/A	N/A	N/A	Bright light
Sleeping hours variables						
REM	Episode not detected	N/A	N/A	N/A	N/A	Episode detected
Accelerometer	0 g	0 g	N/A	N/A	N/A	6 g
EDA	~200 Ω	N/A	N/A	N/A	N/A	~50 MΩ
Pulse rate	0	30	Typically ~40 beats per minute but defined by activity, age and fitness	Typically ~50 beats per minute but defined by activity, age and fitness	300	1200
Body temperature	-9°C	28°C	35°C	38°C	41°C (6)	50°C
Ambient variables						

Variable	Minimum detected by CircadianSense	Recommended minimum	Recommended maximum	Maximum detected by CircadianSense
Sound	25 dB	N/A	≤40 dB	72 dB
Ambient temperature	-9°C	~18°C (<12°C is disruptive)	~23°C (>24°C is disruptive)	109°C
Ambient light	Complete darkness	Dark room	Dark room	Bright light

3.8 Multistage Clinical Prototyping Methodology

The multistage prototyping methodology followed recommendations of the iterative, user-centred approach recommended in Human-Centred Design (ISO 9241-210, 2010) and was also informed by the "Clinical Proof of Concept (CPoC)" methodology recommended by Bardram (2008) in his paper entitled "Pervasive Healthcare as a Scientific Discipline".

The main aspects that were considered in the clinical prototyping were discussions of clinicians to identify how to deliver clinically relevant data of a patient. These included the selection of physiological, environmental and behavioural data to be collected by means of one-on-one interviews with clinicians and a larger group of general practitioners who participated in four focus groups in Mexico and a final session for the assessment of the prototype evolved.

The initial technological proof-of-concept prototyping was conducted by the research team and in short-term testing, as it is recommended by Bardram (2008), to provide evidence of reliable and comparable results in controlled and uncontrolled environments. Such testing was first in short-term trial episodes, building up to days and nights of use. Thereafter, testing continued with participants from the University of Birmingham and then with clinical participants from QEHB. Refining of the system was iterative by following a waterfall design model in which initial issues detected in the testing by researchers and participants were modified before CircadianSense was worn by more participants. Collection of data required multidisciplinary skills and perspectives. An academic sleep expert of the UoB was visited, who provided feedback on the collection of data using EOG electrodes and made recommendations to increase comfortability. The limited number of clinical participants of QEHB who helped in refining and assessing CircadianSense work in a hospital environment with a perspective of problems and issues present in patients confined to a hospital. A larger number of clinical participants were recruited in Mexico to discuss a wearable health-monitoring system for monitoring and managing patients' conditions. This group of general practitioners complemented with different perspectives on features for a WHMS and on data to be collected, summarised and visualised, as presented in Chapters 6 and 7. Ethical and data privacy issues arise when data is collected from participants. A discussion with the secretary of the Committee of Medical Research was carried out surrounding how these issues should be treated and informed to people involved in the study.

As reported in the literature, visualisation of medical data is an important task with which to provide relevant and meaningful data so as to extract conclusions. Clinicians provided feedback on visualisations to summarise data, observe trends and make data comparisons as discussed in interviews and focus groups.

The involvement of clinicians with the actual testing and use of the CircadianSense prototype system went beyond the participation typically involved in participatory design. We believe that this closer clinical collaboration very significantly informs and improves upon the design process and could help to take technologies across the difficult divide and transition them from engineering prototypes to clinical practice. New technologies would need to evolve and be tested and demonstrably safe before permissions would be granted in patient cohorts.

The permissions and procedures for the testing and clinical study are summarised below.

Real-World Testing I and II. With approved risk assessments, University of Birmingham ethical approval was sought from the Science, Technology, Engineering and Mathematics Ethical Review Committee. Approval was granted i) for initial testing on the research team (PhD researcher, collaborating and supervising academics) and, subsequently, ii) for testing on recruited participants.

Clinical Study. NHS and hospital permissions for testing were sought for recruited clinical participants. A protocol evolved and, again, a risk assessment made and approved.

The clinical study was entitled *"CircadianSense – Unobtrusive multi-sensing of circadian parameters in real environments"* and was formally approved by the hospital host, Queen Elizabeth Hospital Birmingham (QEHB). The University of Birmingham acted as an insuring sponsor and all of the necessary NHS approvals were obtained via the IRAS system. The relevant documents for this study are in Appendix A.

The approvals required risk assessments that, when were assessed and achieved, dictated modification of CircadianSense. Non-clinical users also provided feedback issues related to

comfortability, aesthetic issues, and discussions surrounding features which need to be considered for CircadianSense.

3.9 On-Body Variables Recorded

The complete diagrams of the waking hours and sleeping hours subsystems are shown in Figure 3.2 and Figure 3.3, respectively. Descriptions of the design, filters and calibration are explained in detail in further sections. Integrated circuits chosen were suitable because of low cost, low power consumption and low offset voltage suitable for medical instrumentation. Operational amplifier MCP6024 used in the amplification stages of CircadianSense offers these characteristics. Circuits for EOG, A-weighted filter and amplification stages were simulated in TINA® TI, free software from Texas Instruments® with SPICE models of circuits. Design and simulations of filters used were using FilterLab®, a free software tool from Microchip® for filter design.

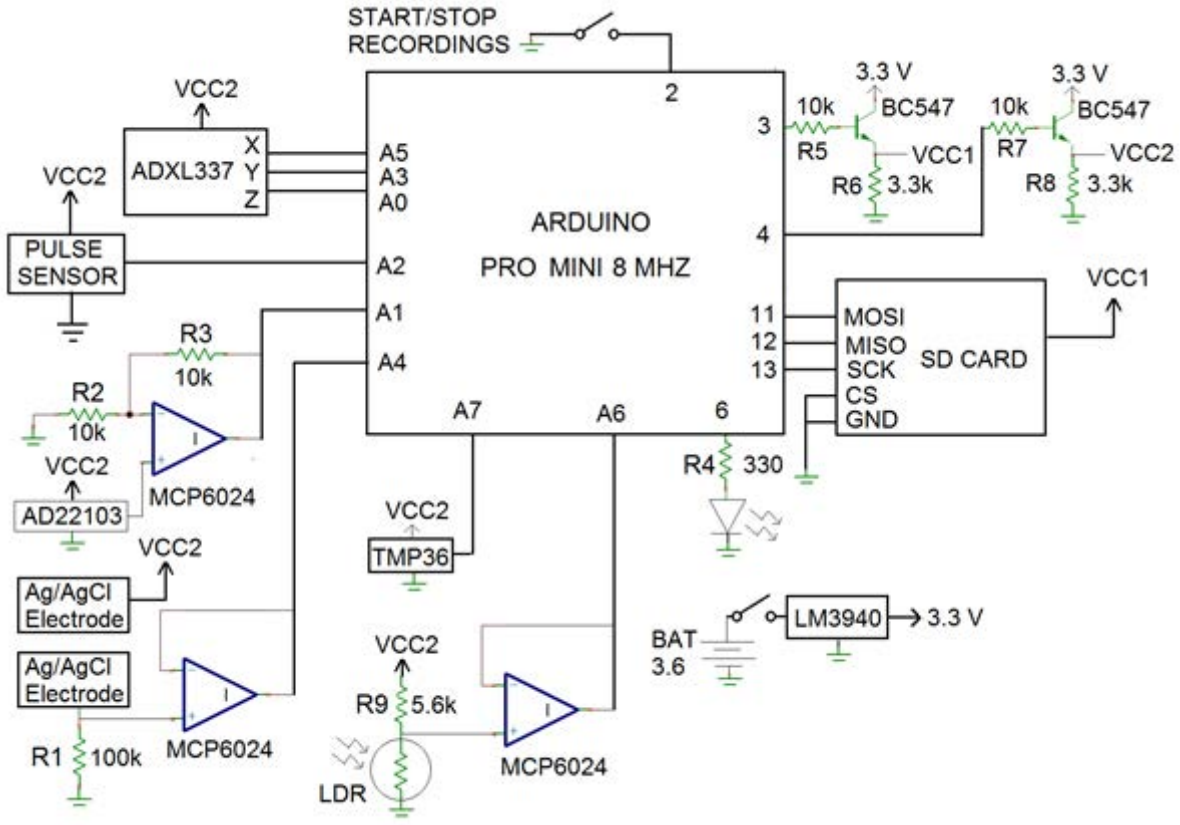


Figure 3.2 Schematic diagram of the CircadianSense waking hours subsystem

The complete diagram of the CircadianSense subsystem for sleeping hours is shown in Figure 3.3.

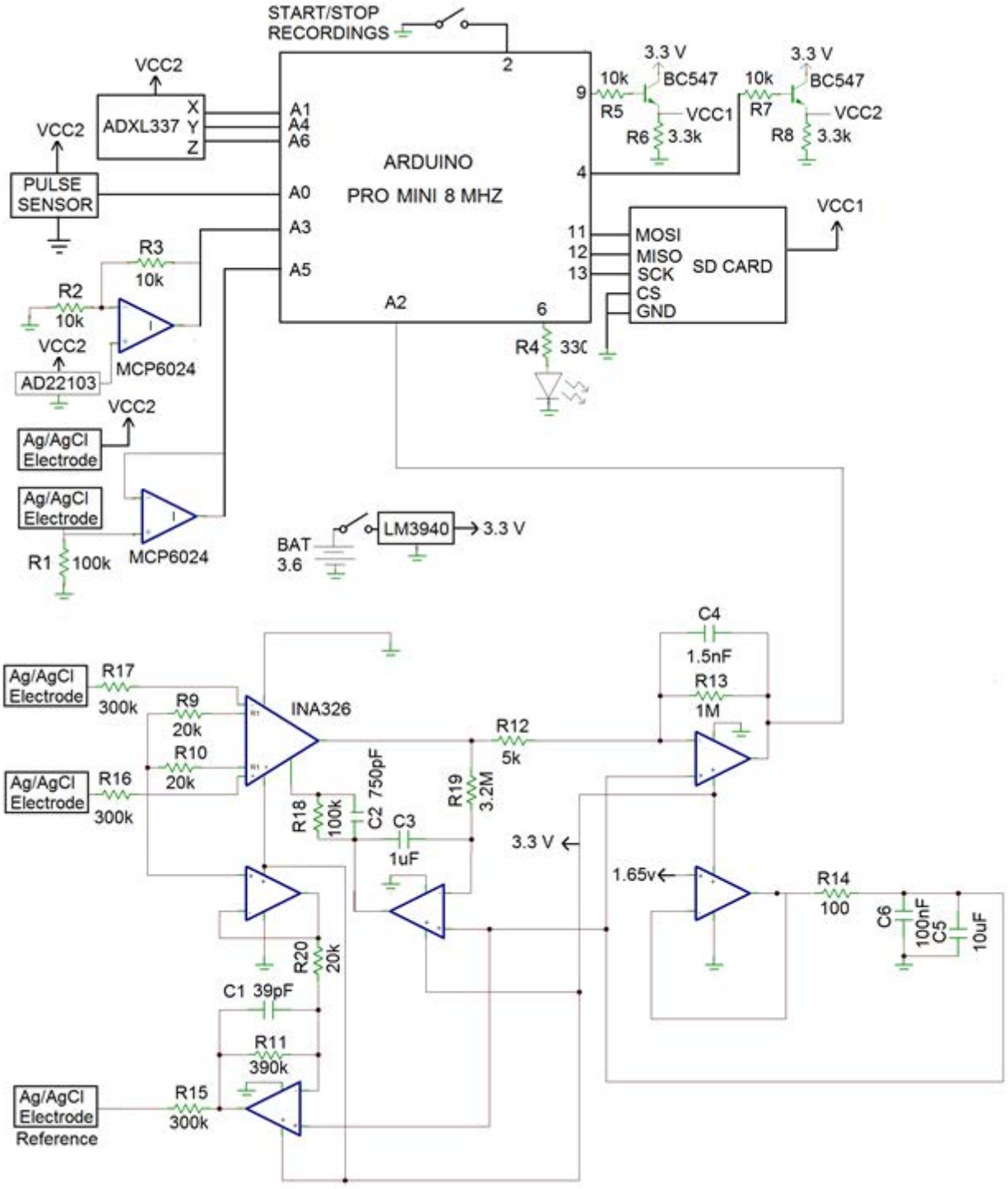


Figure 3.3 Schematic diagram of the CircadianSense sleeping hours subsystem

The Arduino C++ program flowchart with which to read and store data from sensors of the sleeping hours subsystem is shown in Figure 3.4. In the timer interrupt subroutine called every 2 ms a variable called *Counter2ms* is increased and tested to read sensors at different sampling rates. Pulse was sampled every 2 ms (500 Hz). The three axes of the accelerometer and EDA were sampled every 24 ms (41.6 Hz) and EOG was sampled every 8 ms (125 Hz). The Arduino C++ program flowchart and firmware of the three CircadianSense subsystems are included in appendix B.

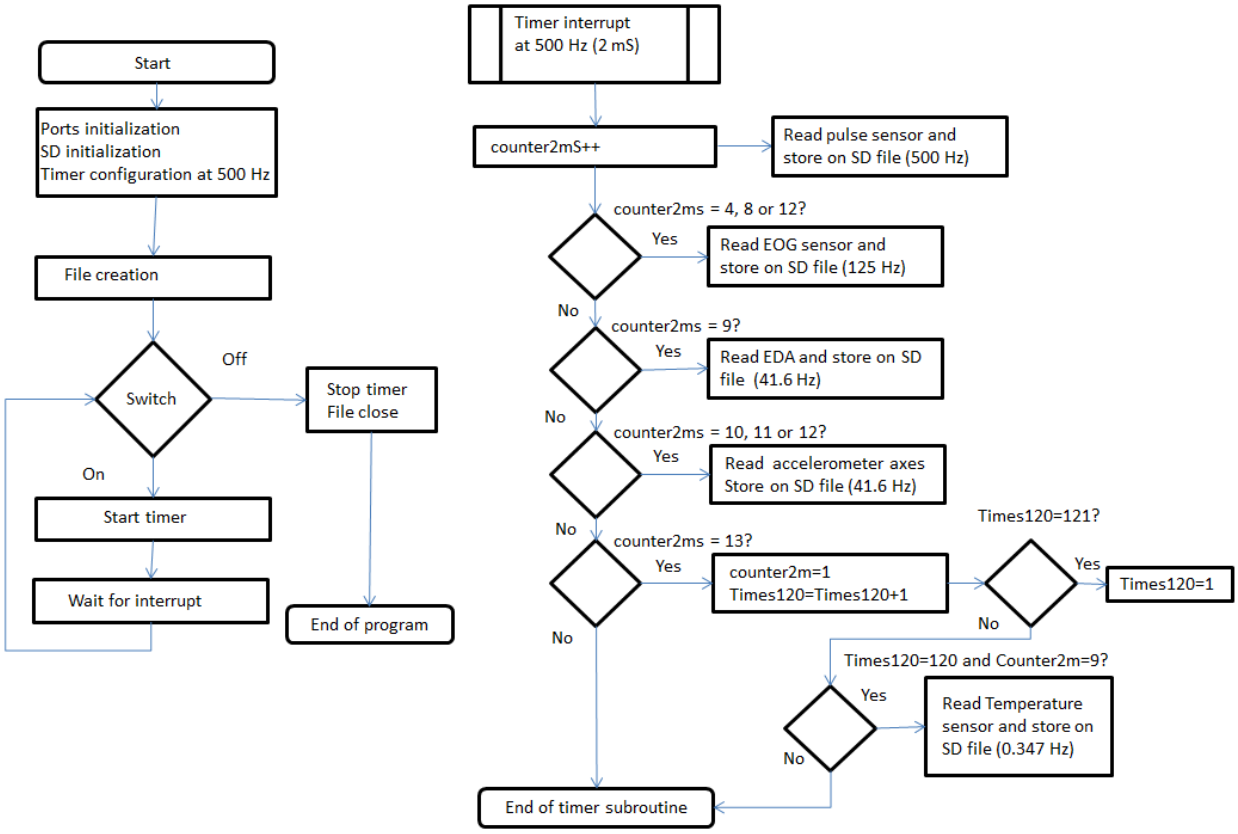


Figure 3.4 Arduino C++ program flowchart of the sleeping hours subsystem

Table 3.4 shows the sampling rate for each variable recorded and the amount of data created in one hour by each CircadianSense subsystem. Arduino recorded raw data of all sensors and the processing was performed offline in Scilab.

Table 3.4 Bytes stored on the SD card per hour by each CircadianSense subsystem

Waking hours variable	Sampling rate	Bytes per hour
Ambient temperature	0.3472 Hz	1250
Ambient light	0.3472 Hz	1250
Pulse	500 Hz	1,800,000
Body temperature	0.3472 Hz	1250
EDA	41.6 Hz	149,760
Accelerometer for MET	41.6 Hz per axis	449,280
Total bytes stored on the SD card in one hour		2,402,790
Sleeping hours variable	Sampling rate	Bytes per hour
EOG	125 Hz	450,000
Accelerometer for actigraphy	41.6 Hz per axis	149,760
Pulse	500 Hz	1,800,000
Body temperature	0.3472 Hz	1250
EDA	41.6 Hz	449,280
Total bytes stored in one hour		2,850,290
Ambient sleeping hours variable	Sampling rate	Bytes per hour
Ambient temperature	1 Hz	3600
Ambient light	1 Hz	3600
Ambient noise	100 Hz	360,000
Total bytes stored on the SD card in one hour		367,200

3.9.1 **Electrodermal Activity (EDA)**

Measurements of electrodermal activity (EDA), also known as electrodermal response (EDR) or galvanic skin response (GSR), are widely used as objective estimates of arousal, including when subjects are active and performing tasks (Sudheesh and Joseph, 2000). Poh et al. (2010) demonstrated the feasibility of the assessment of arousal by EDA in long-term recordings in

daily life activities with Ag/AgCl electrodes on the wrist. EDA changed with cognitive, emotional and physical stressors. In the physical task the participant bicycled for 5 minutes and remained seated afterwards. In the cognitive task the participant performed mental arithmetic operations and a Stroop word–color matching test. In the emotional task the participant watched clips of 5 minutes with scenes of violence and chaos. The experiments by Poh et al. (2010) showed that these stressors increased skin conductance through a greater sympathetic activity that elevated sweating. Once stressors stopped, skin conductance decreased until reaching a baseline.

In the report entitled "Recommendations for electrodermal response", Boucsein et al. (2012) recommended silver/silver chloride (Ag/AgCl) electrodes when a DC voltage source is used. CircadianSense measures skin resistance using the voltage divider circuit shown in Figure 3.2 and Figure 3.3. Direct current from a regulated 3.3V supply passes through the skin via a pair of Ag/AgCl electrodes on the wrist and R1, a 100kΩ series resistor. The voltage across resistor R1 is calculated with a voltage divider formula:

$$V_{R1}=3.3*R1/(R1+Rs) \quad (3.1)$$

Where R1 is a resistor of 100 kΩ and Rs is the skin resistance between the two Ag/AgCl electrodes. V_{R1} is measured using channel 5 of the analogue-to-digital converter of Arduino Pro Mini at a sample rate of 41.6 Hz for an 8-bit conversion.

The magnitude of the current density through the skin must be kept lower than 10 μA/cm^2. Higher current densities can damage the sweat glands (Poh et al., 2010). Maximum current flows when the skin resistance (Rs) is 0 Ω and the current is only limited by R1. In this case the maximum current is 3.3 V / 100 kΩ = 33 μA. This current is distributed by two circular Ag/AgCl electrodes with a diameter of 2 cm. The total area of the two electrodes distributes the 33 μA in 6.28 cm^2 for a current density of 5.25 μA/cm^2.

EDA contains two components. Tonic EDA is the baseline of skin resistance. The tonic component varies from person to person and changes slowly over time. Phasic EDA is affected

by changes in emotional state and by physical activity because of an increase in the activity of sweat glands, which produce a reduction in superficial skin resistance.

The offline calculation of skin resistance (Rs) is performed in Scilab using:

$$Rs=R1(3.3-V_{R1})/V_{R1} \quad (3.2)$$

EDA readings were tested with external resistors in the extremes of the cables of the Ag/AgCl electrodes. Tested resistors comprised 10 KΩ, 100 KΩ and 1 MΩ, and the values of the calculation of the resistance in Scilab comprised 10.39 KΩ, 100.70 KΩ and 100.88 MΩ. The difference in the values measured is due to the discretisation of the 8-bit conversion of the voltage divider, as expected.

To obtain the phasic component and eliminate motion artifacts, Rs is bandpass-filtered in Scilab by a 6th order digital Butterworth filter. The upper and lower cut-off frequencies of the bandpass filter were 0.2 and 3 Hz to filter out the tonic component and the motion artifacts, respectively, as shown in Figure 3.5. Finally, the absolute value of conductance of the phasic EDA envelope is taken and displayed, as shown in Figure 3.6.

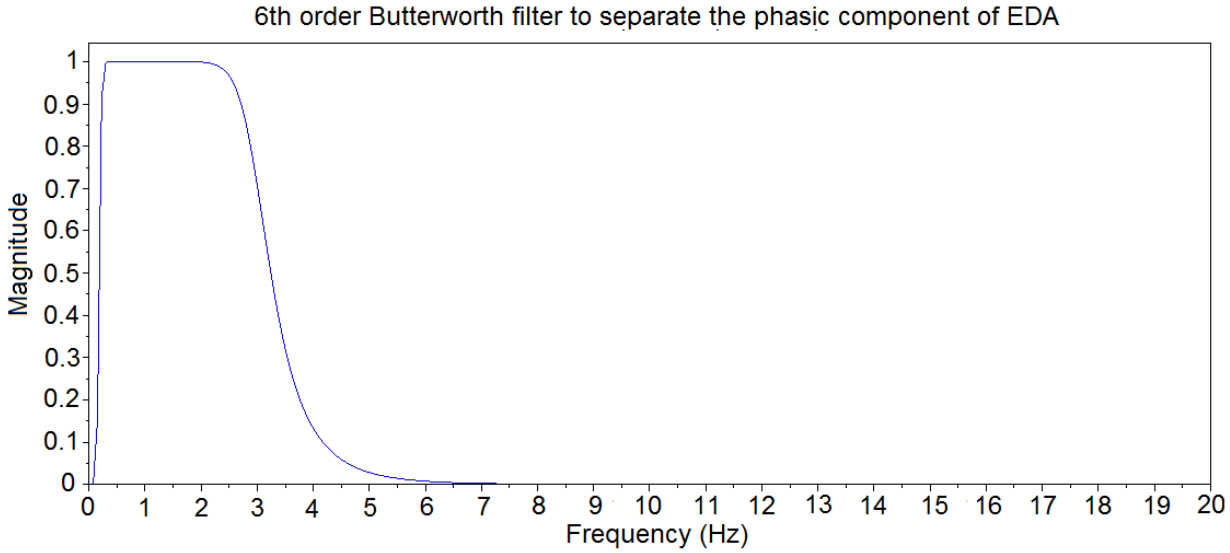


Figure 3.5 Butterworth filter implemented on Scilab to separate the phasic component of EDA

Increases of the skin conductance in Siemens are a result of both physical activity and psychological arousal.

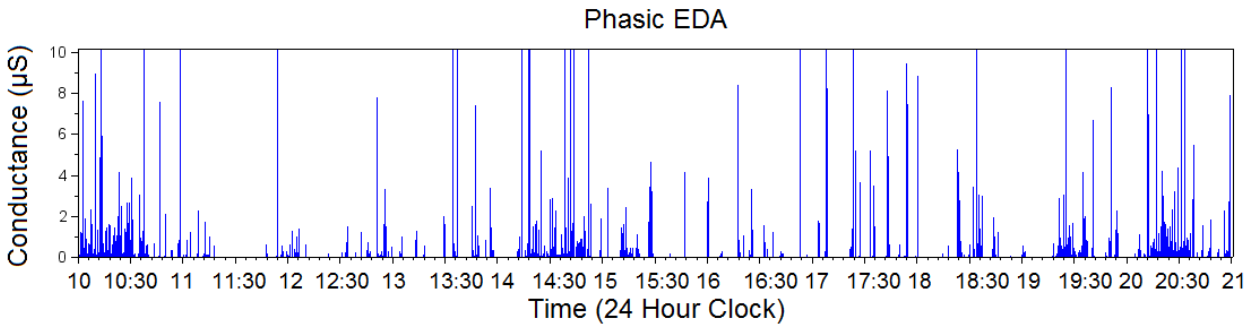


Figure 3.6 Phasic EDA conductance by means of two Ag/AgCl electrodes

3.9.2 **Energy Expenditure**

Single tri-axial accelerometers have been used to estimate energy expenditure using a regression method with which to establish the relationship between energy expenditure and oxygen consumption (Park et al., 2011). Bouten et al. (1994) developed the linear regression method for three accelerometer axes correlated with energy expenditure. The model can estimate energy expenditure in sedentary activities and while walking at different speeds. The analysis showed that a linear relationship exists between the integral of the accelerometric magnitudes and energy expenditure for sensor placement on the anterior superior iliac spine or right iliac crest of the waist. This point on the body is close to the centre of mass and is affected by acceleration of body movement (Wang et al., 2010).

Algorithms used to calculate energy expenditure by means of tri-axial accelerometers have the limitation that they underestimate energy expenditure when the person is performing activities on inclined terrains or carrying heavy weights (Shany et al., 2012). To improve the accuracy of energy expenditure, additional sensors have been used, e.g. a barometric sensor to detect whether the person is climbing stairs (Anastasopoulou, 2012) or video cameras for filming activities. However, these additional sensors increase the size and limit the area of activity by adding cameras.

CircadianSense uses a single analogue tri-axial accelerometer to estimate energy expenditure. An Analog Devices ADXL337 accelerometer was used with each of its analogue outputs (x, y and z acceleration) connected to a separate ADC input channel on Arduino. The range of this sensor is between -6 and +6 g in each direction.

Both the sensitivity and the offset for zero acceleration of ADXL337 have to be characterised. The zero g-offset or offset is calculated for each axis by placing the accelerometer in a vertical position. The two axes that are perpendicular to the direction of gravity have zero acceleration and the zero g-offset voltage is measured. This procedure is repeated in order to determine the offset for the other axes. The sensitivity of the axes is measured using the known acceleration of gravity of 1 g = 9.81 m/s^2. The accelerometer is again placed in a vertical position. The axis in the direction of gravity has a force of 1 g = 9.81 m/s^2. Sensitivity is calculated as follows:

$$\text{sensitivity}=(\text{Output\_Voltage}-\text{offset})/1\text{g} \tag{3.3}$$

Where Output_Voltage is the voltage of the axis aligned in the direction of gravity and offset is the voltage at 0 g, as shown in Figure 3.7. For example, one of the four accelerometers used has an offset of x = 1.636 V, y = 1.618 V and z = 1.645 V and a sensitivity of x = 311 mV/g, y = 322 mV/g and z = 324 mV/g. These calibration values are used in the Scilab code along with the algorithm for MET calculation.

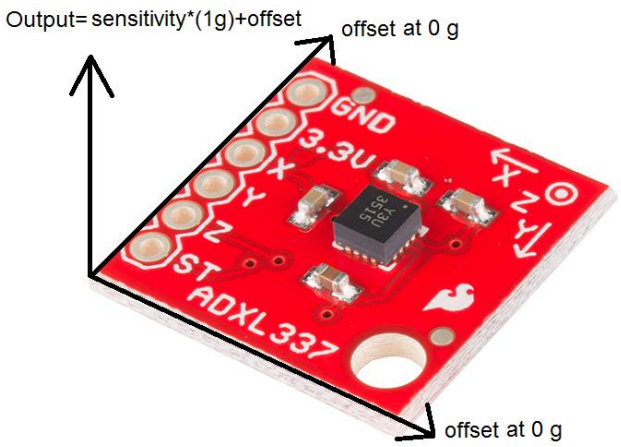


Figure 3.7 Characterisation of zero g-offset and sensitivity of accelerometer

Amplitudes and frequencies of acceleration vary depending on body placement. On the waist, whereon the CircadianSense accelerometer was positioned, an acceleration range of -6 to 6 g is sufficient. Frequencies present in normal daily life activities are lower than 20 Hz (Bouten et al., 1997). The sampling rate was 41.6 Hz with an 8-bit-resolution digital conversion. Data was passed through a 5th order high-pass Butterworth digital infinite impulse response (IIR) filter to

eliminate the effect of gravity. Gravity is a constant that was removed using a high-pass filter with a cut-off frequency of 0.1 Hz. The calculation of energy expenditure in MET per minute was performed in Scilab using the following equations:

Velocity of each axis was calculated:

$$\text{Vx}=\int_0^t ax(t)dt \tag{3.4}$$

$$\text{Vy}=\int_0^t ay(t)dt \tag{3.5}$$

$$\text{Vz}=\int_0^t az(t)dt \tag{3.6}$$

MET per minute was calculated using:

$$\text{MET}=1.68\int_0^t \frac{|vx*ax+vy*ay+vz*az|dt/2}{60}+1.06 \tag{3.7}$$

If there is no acceleration of the body the MET result of equation (3.7) is 1.06 close to 1 MET for a person resting or sleeping. Scilab code for MET calculation is found in Appendix C.

Figure 3.8 shows the raw data of two axes recorded with Arduino and the MET values calculated with Scilab after processing. The MET values are in the range of 2 to 4 MET for different walking speeds.

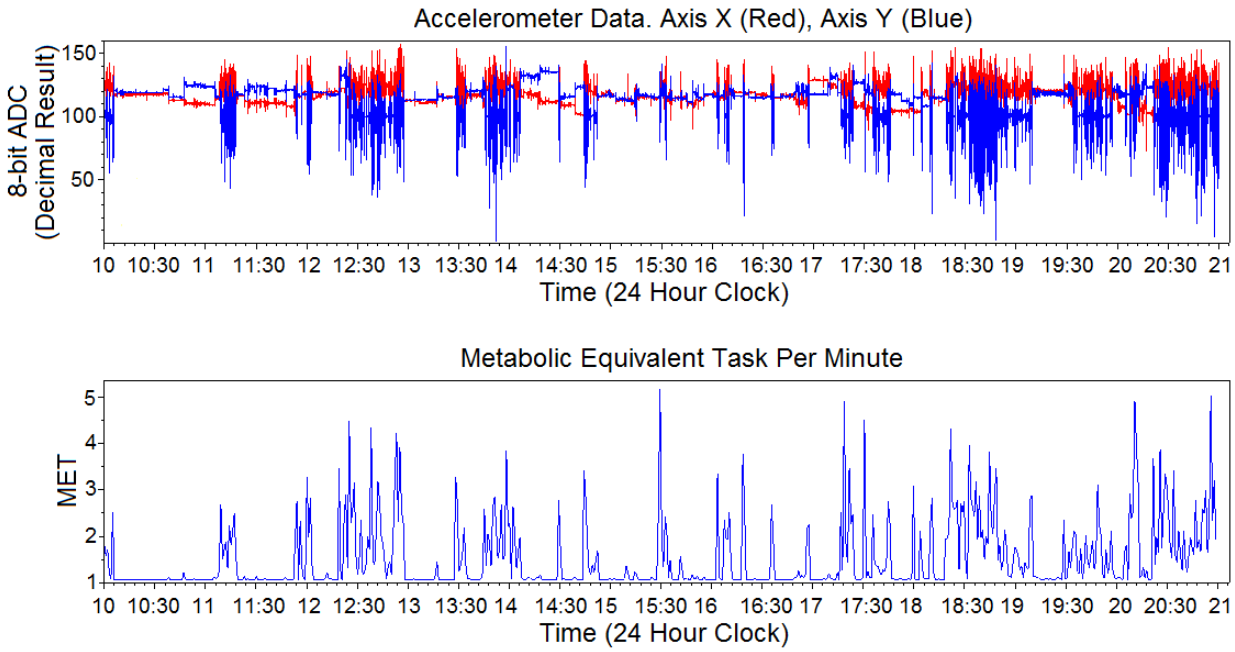


Figure 3.8 Raw data of accelerometer of two axes and the MET averaged per minute after processing the three axes

3.9.3 **Actigraphy**

Actigraphy is a method used to monitor and collect data generated by movement in order to assess sleep–wake patterns. The measurement unit of amplitude and frequency of movement for actigraphy is given in *counts* (Rothney et al., 2008). Actigraphy uses an accelerometer that can be placed on the legs when periodic limb movement disorder (PLMD) is suspected. Placement on the wrist is carried out to assess sleep quality, circadian rhythm disorders, and other sleep problems such as insomnia and excessive sleepiness (Ancoli-Israel et al., 2003). There are three common approaches to sleep actigraphy using an accelerometer worn on the dominant hand. The threshold used to count activity is commonly set between 0.1 and 0.2 g (Ancoli-Israel et al., 2003). The zero-crossing method counts the number of times that an activity is higher than a threshold set to zero or very close to zero. The time-above threshold computes the duration of activity above a threshold. The third method, called digital integration or proportional integration, calculates the area under the curve of actigraphy. However, literature does not report a superior algorithm and the decision as to which algorithm is going to be used depends on the researcher (Sadeh, 2011). CircadianSense senses the dominant hand and uses the zero-crossing method, i.e. counting the number of times that the activity of the hand is higher than a threshold set to 0.1 g. Sampling is conducted at 41.6 Hz with an 8-bit-resolution ADC conversion. A 5th

order high-pass filter with a cut-off frequency of 0.1 Hz eliminates the effect of gravity on the three axes. It has been reported in the literature that relying on only actigraphic data can lead to erroneous discrimination of sleeping from waking because the person might be awake while lying still in bed. Additional variables recorded by CircadianSense help to discriminate sleeping from waking, e.g. pulse rate, body temperature, and frequency analysis of EOG signals. When the sleeper wakes there is an increase in body temperature and pulse rate, as shown in Figure 4.11, in contrast to normal patterns of body temperature, pulse rate and actigraphy, as shown in Figure 4.12. Figure 3.9 shows the counts per minute of actigraphy for participant 5, who reported waking twice (at around 02:30 and 06:00).

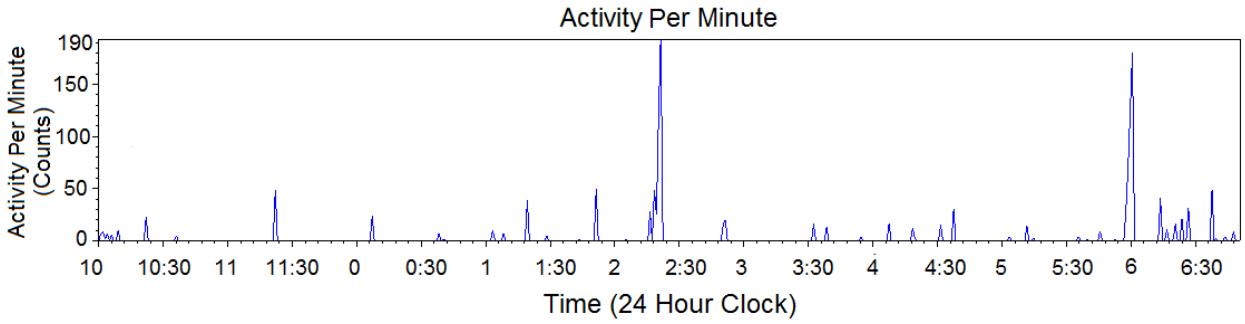


Figure 3.9 Actigraphy of participant 5, who woke and slept twice a night

The actigraphic counts in Figure 3.9 can be contrasted with those in Figure 3.10 for participant 1, who slept all night. This graph shows lower activity for participant 1 than for participant 5.

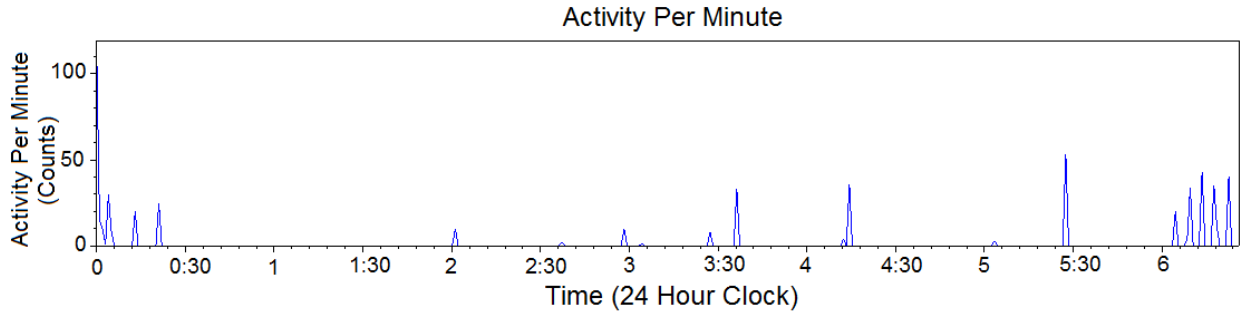


Figure 3.10 Actigraphy of participant 1, who slept all night

3.9.4 **Electrooculography (EOG)**

Normal sleep comprises four or five cycles of REM. The proportion of REM sleep increases as sleep progresses. The main clinical participant showed an interest in REM recordings. This collaborator reported in the initial meetings that inpatients are heavily affected by medication and conditions of the hospital; in particular, REM sleep episodes can be removed by medication. Furthermore, in interview I another anaesthesiologist recommended the assessment of sleep quality of inpatients to improve hospital conditions so as to promote sleep. The identification of abnormalities in the amount, duration and latency of REM are also reported in the literature, as abnormal REM characteristics are associated with several neurodegenerative and psychological problems. For example, people with Alzheimer‘s disease have fewer REM episodes (Gagnon et al., 2006). People with Parkinson‘s disease have disrupted REM sleep (Arnulf and Oudiette, 2008). Schizophrenics have reduced REM latency and density (Cohrs, 2008). Alcoholics who have normal REM sleep characteristics and sleep well are less prone to relapses (Roehrs and Roth, 2001). Abnormal REM has been observed in people before they develop Parkinson‘s, dementia, and Alzheimer‘s disease (Arnulf and Oudiette, 2008).

REM episodes were detected through a frequency analysis of data from the differential EOG channel (Virkkala et al., 2009). A differential amplifier circuit, as shown in Figure 3.11, was used to detect changes of electric potential generated by eye movements.

The circuit used is an instrumentation amplifier (INA326) from Texas Instruments, with a gain of 5 (14 dB) set by R9, R10 and R18 using the following formula:

$$\text{Gain}=2*\text{R18}/(\text{R9}+\text{R10}) \tag{3.8}$$

The feedback network by capacitors C2, C3 and R19 creates a two-pole high-pass filter with a cut-off frequency of 0.05 Hz to eliminate the DC offset created by the difference in electrode potential between the two Ag/AgCl electrodes on the skin. The signal amplified by 5 and high-pass-filtered at 0.05 Hz from INA326 is connected to a low-pass filter formed by operational amplifier U3 with a gain of 200 (R5/R4) and a cut-off frequency of 100 Hz. The cut-off frequency is given by:

$$\text{fc} = 1/(2*\pi*\text{C4}*\text{R13}) \tag{3.9}$$

Operational amplifier U6 is configured as a voltage follower of 1.65 volts to offset 1.5 volts of the signals of EOG so that left and right directions of eye movement can be observed with a single voltage source. Operational amplifiers U2 and U4 form the reference electrode.

Three attachable and disposable Ag/AgCl electrodes were used. The reference was placed on the forehead, the second electrode was placed 1 cm from the outer cantus of the left eye, and the third electrode was placed 1 cm from the outer cantus of the right eye.

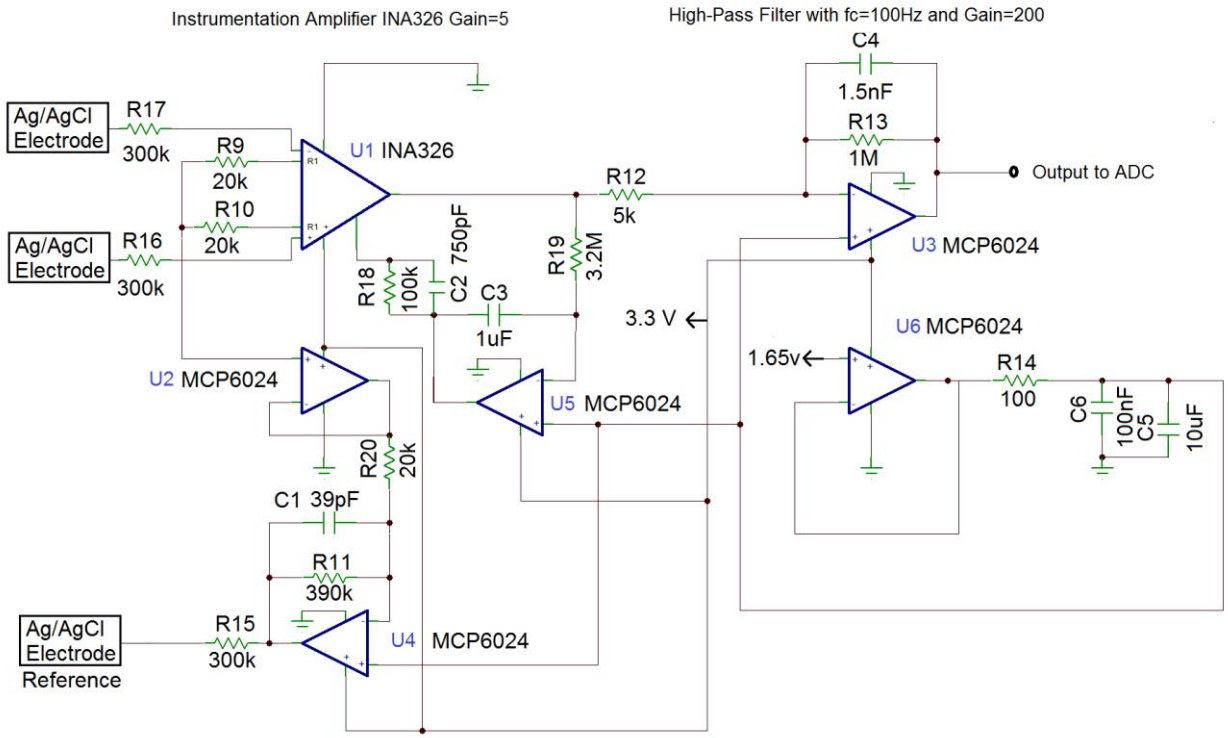


Figure 3.11 Schematic diagram of the EOG amplifier

The total gain of the circuit is 1000 (60 dB) with a bandpass filter with a low cut-off frequency of 0.05 Hz to remove the DC offset produced by the electrodes on the skin and a high cut-off frequency of 100 Hz to limit the bandwidth of EOG, as shown in Figure 3.12.

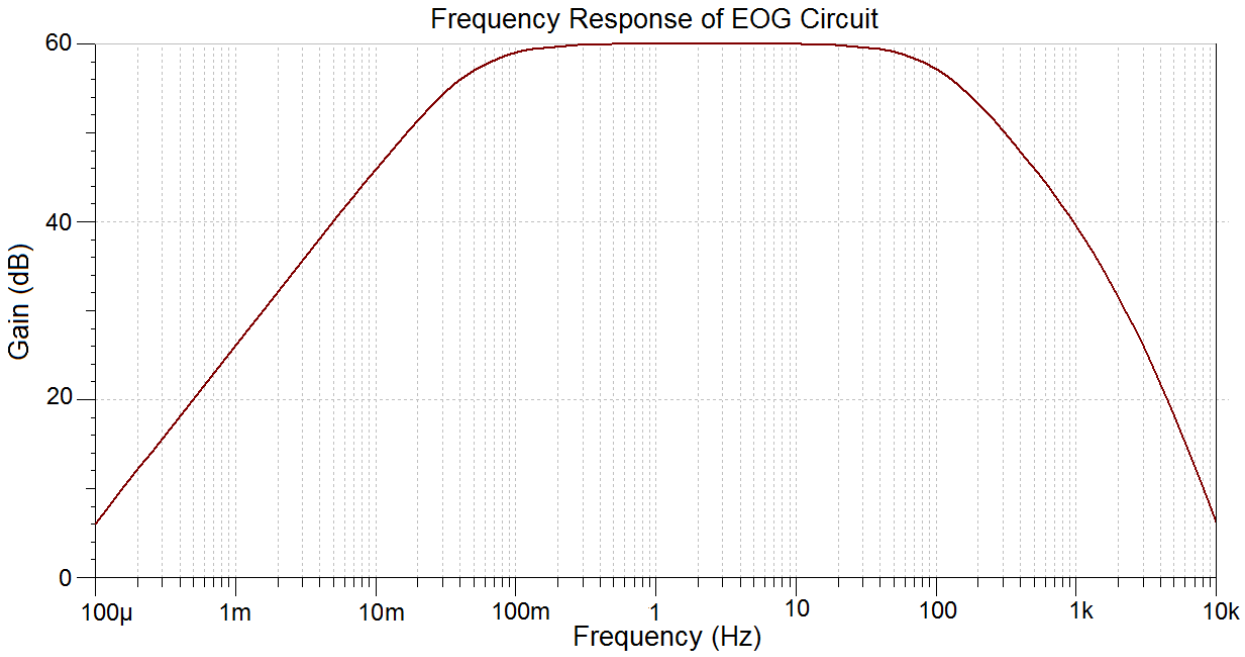


Figure 3.12 Frequency response of EOG circuit

Root mean squared (RMS) values were calculated for data from these electrodes in the range of 18 to 30 Hz and 8 to 12 Hz. An REM episode is characterised by an RMS power reduction of the 8–12Hz band and an increase of the 18–30 Hz band, as described by Merica and Fortune (2005). EOG raw data was bandpass-filtered using a 10^{th} order Butterworth IIR filter in Scilab to separate signals in the frequency of 8 to 12 Hz and 18 to 30 Hz. The frequency response of the filters used is shown in Figure 3.13.

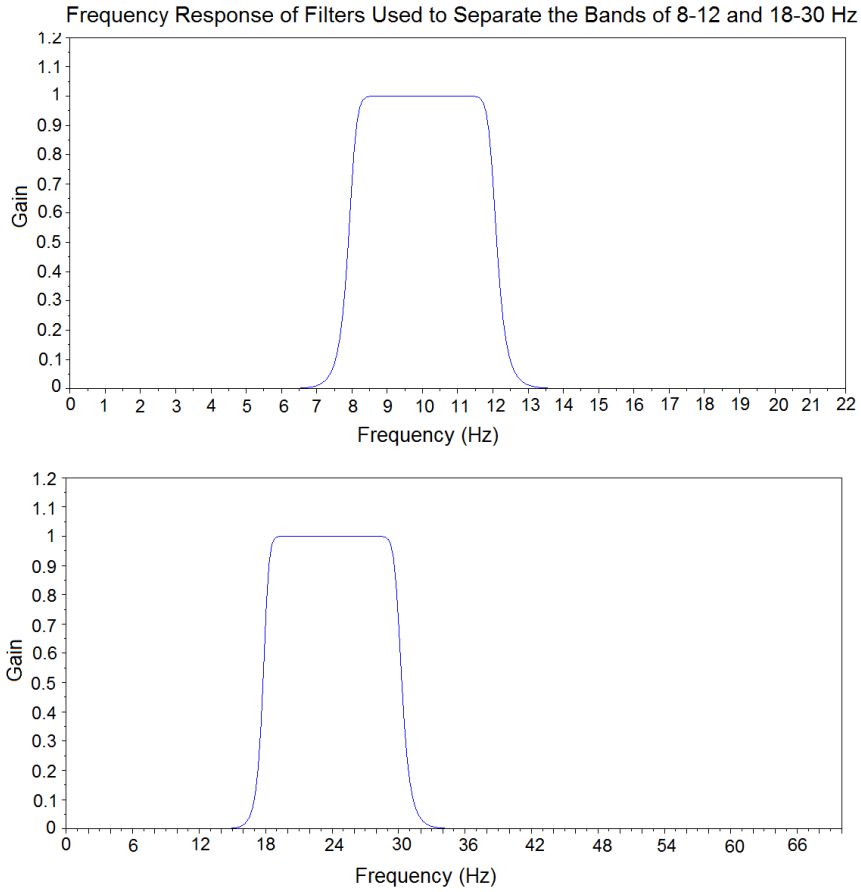


Figure 3.13 Filter response of the filters used to separate signals in the bands of 8–12 and 18–30 Hz

The RMS power of the filtered output signal s(n) for each filter was calculated using equation (3.10).

$$\text{RMS Power} = \sqrt{\sum_0^n s(n)^2/n} \tag{3.10}$$

Figure 3.14 shows the changes of RMS power in both bands in an REM episode marked with a solid brown line for participant 1.

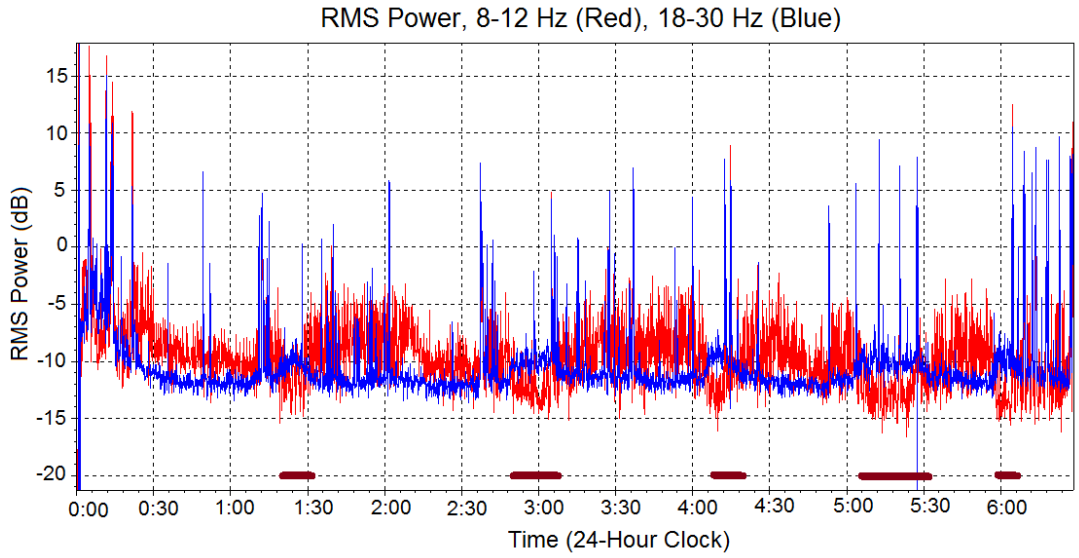


Figure 3.14 REM episode detection through frequency analysis of the bands 8–12 and 18–30 Hz. (Signals from participant 1) solid brown lines show the REM episodes characterised by an increase of 18–30Hz RMS power and decrease of 8–12Hz RMS power.

3.9.5 **Pulse Rate**

The pulse rate was measured with an optical pulse sensor: „Pulse Sensor Amped", an open-source, analogue, reflective optical blood-flow sensor. It consists of a super-bright LED and an ambient-light sensor with built-in signal conditioning circuitry. This sensor consists of three cables: two cables to power the circuitry in the range of 3 to 5 volts and one cable for the output. The blood-flow sensor output was sampled at 500 Hz by one of the 8-bit ADC channels.

Optical pulse detection can be used on the parts of the body where veins transporting blood are close to the surface of the skin. The amount of light reflected to the emitter of the sensor varies depending on the blood flow that absorbs more or less light. The sensor can be placed on fingers, the lobe of the ear, or another superficial vein. Sensor placement on the finger was invasive and the reliability of the data was poor because of the movement. The position on the earlobe had poor data reliability and was very visible. Carotid veins were chosen as the site for data collection, being the most reliable and least invasive. The sensor was attached to the neck with medical-grade tape. Figure 3.15 shows a plot of raw data of the pulse sensor.

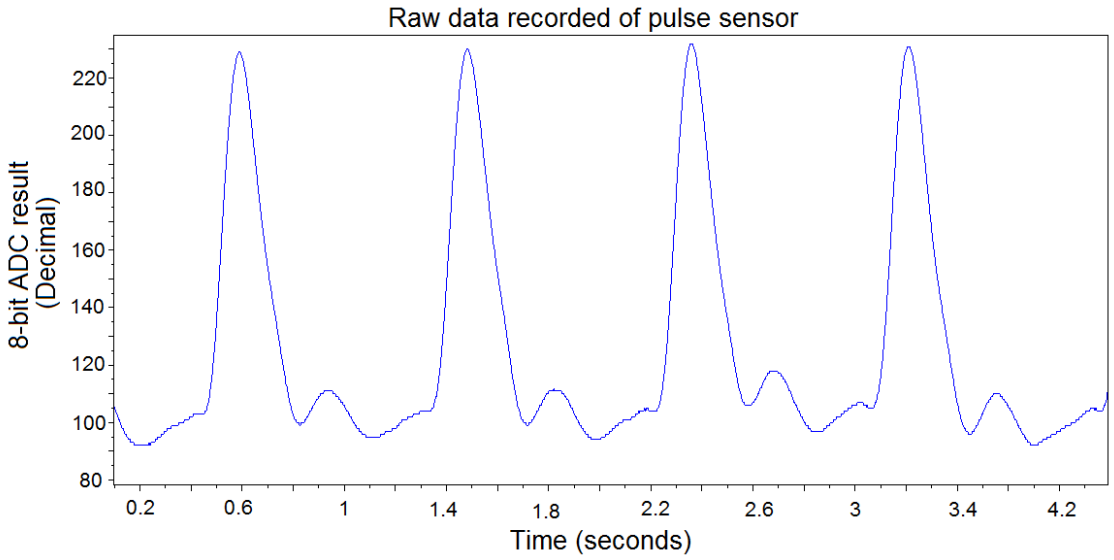


Figure 3.15 Raw data of pulse sensor stored on the SD card

A bandpass filter was used to limit the bandwidth of the signal in the range of 0.5 to 20 Hz for a pulse rate of 30 and 1200 beats per minute (BPM), respectively. The pulse rate would not be expected to be lower than 30 or higher than 300 beats per minute. Clinical recommendation for the calculation of BPM is based on counting the beats in 15, 20 or 30 seconds and multiplying the count by a factor to obtain the number of beats per minute. Even calculation can be on the frequency of a single beat. Analysis of the pulse rate was performed on eight periods of 7.5 seconds to calculate the BPM. The median of the eight periods was taken to produce the result of the BPM. The decision was made to produce at least 1 minute of valid data because the dataset included maximum and minimum values of 1 minute. Validation of pulse rate calculation was conducted by comparing the results with a commercial pulse oximeter that shows readings of the pulse rate. In ambulatory conditions, pulse oximeter produced unreliable data, with testing being on conditions of sitting after an activity was performed to increase the pulse rate. Pulse readings of pulse oximeter at different time intervals were annotated and compared with data stored on the SD card after processing, as shown in Table 3.5. The pulse rate measurements of CircadianSense are of periods of 1 minute. Pulse oximeter produces measurements between beats. The comparison shows that the pulse rate calculated in 1 minute is within the range of the pulse rate displayed by the minimum and maximum BPM with the commercial pulse oximeter.

Table 3.5 Comparison of pulse rate with CircadianSense vs. a commercial pulse oximetry

Condition	Pulse measured	Pulse rate by pulse oximetry
Resting	84	81–85
Walking	91	89–94
Walking faster	109	103–114
Climbing upstairs	146	139–148

3.9.6 **Body Temperature**

Core body temperature reaches a maximum value at sleep onset, decreases during sleep and increases again at the end of sleep. Early morning awakening insomniacs and sleep onset insomniacs show phase-advanced and phase-delayed core body temperature (Bjorvatn and Pallesen, 2009). Skin temperature has been used as a reliable way in which to assess ambulatory circadian monitoring (Bonmati-Carrion et al., 2014).

Body temperature was recorded by an Analog Devices AD22103 analogue temperature sensor to measure in the range of -40 to 53°C. The sensor was connected to another of the 8-bit ADC inputs and sampled at a rate of 0.32 Hz (19 samples per minute). The transfer function of AD22103 at 3.3 volts is:

$$Vout=0.25V+(28mV/°C)*T \quad (3.11)$$

Where T is the temperature in degrees Celsius. The minimum and maximum expected skin temperature range is between 28 and 41°C. According to equation (3.11), a temperature of T=0°C and T=50°C produces an output voltage (Vout) of 0.25 and 1.65 volts, respectively. A simple non-inverting amplifier of 2 was used to have an output voltage of 0.5 and 3.3 volts for a temperature range of between 0 and 50°C. The temperature range is much wider than the expected skin temperature. However, amplifying the output voltage from 0 to 3.3V so as to match a temperature expected for the skin of 28 and 41°C would require adding an offset voltage and more operational amplifiers, increasing the size and power consumption. The chosen amplification of 2 produces a resolution of 0.2304°C, which is enough to detect small changes in skin temperature. The 8-bit analogue-to-digital conversion provides a decimal result of 38 for 0.5 volts (0°C) and 255 for 3.3 volts (50°C). With these results the resolution in °C is (50°C-

0°C)/(255-38)=0.2304°C. Sensor AD22103, which is connected to the non-inverter amplifier and Arduino, is shown in Figures 3.2 and 3.3.

The sensor was attached to the chest with medical-grade tape. Initial readings of skin temperature are close to those of ambient temperature. Some minutes later the sensor reaches the body temperature as shown in Figure 3.16. Initial readings of skin temperature were discarded. The body temperature graph shows the average of 1-minute data of waking hours. In waking hours, body temperature is masked by the influence of environmental temperature. Body temperature in sleeping hours, as shown in 4.10, is less affected by the ambient temperature and follows the expected circadian temperature pattern.

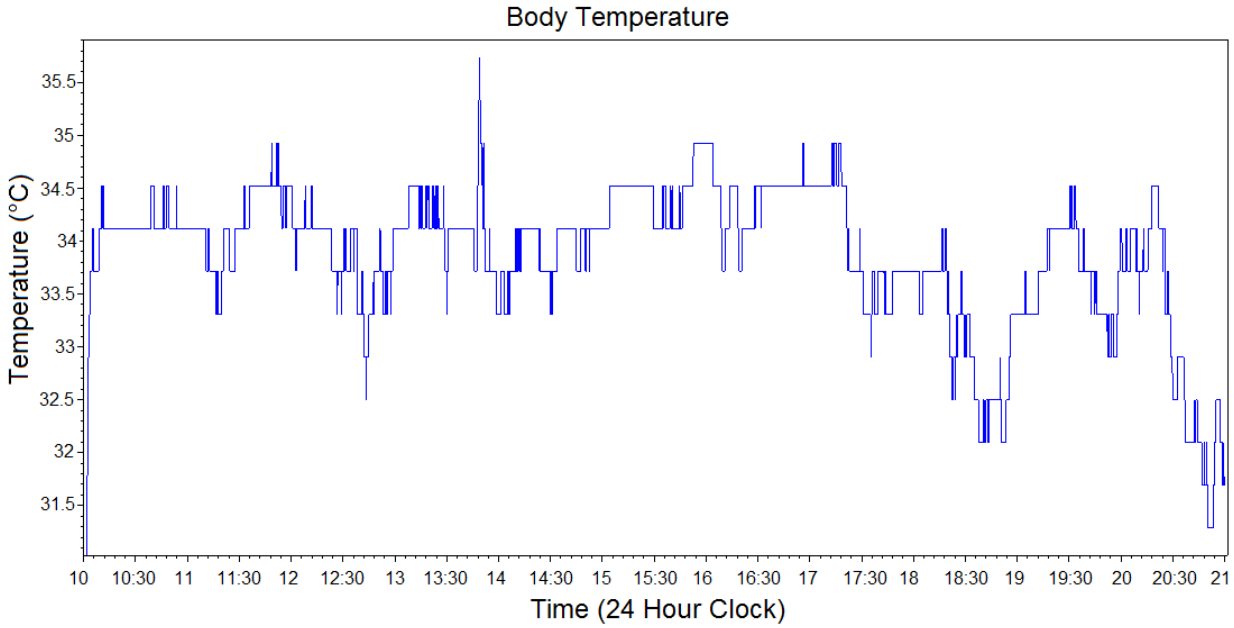


Figure 3.16 1-minute average of body temperature

3.10 Ambient Variables

The subsystem with which to record ambient variables is shown in Figure 3.17. This subsystem records ambient temperature, ambient light and ambient noise as recommended by literature and clinicians to assess objectively the conditions of the environment wherein the person sleeps. The firmware and flowchart of Arduino of the ambient variable subsystem are shown in Appendix B and the Scilab code with which to process raw data recorded by Arduino is shown in Appendix C.

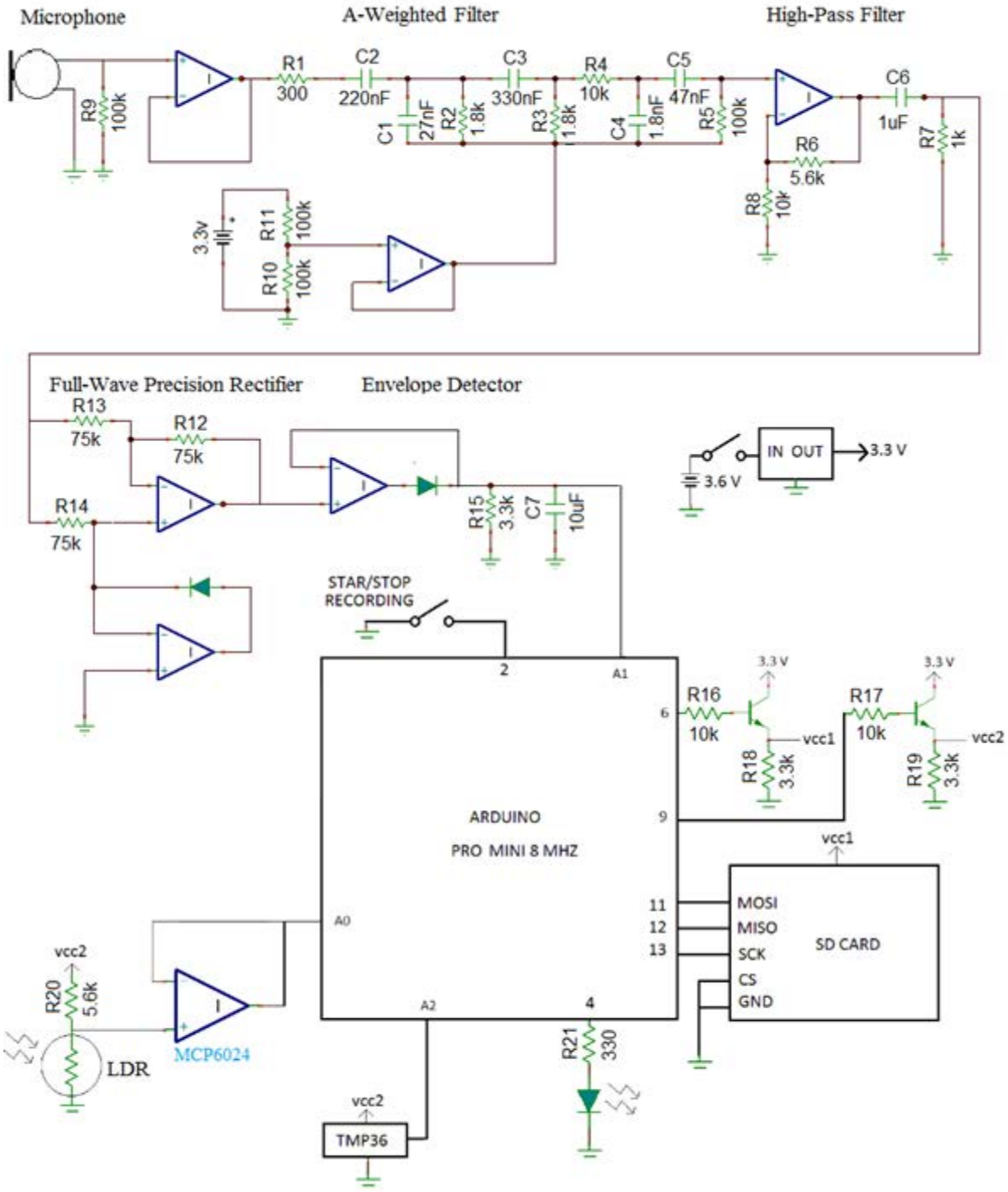


Figure 3.17 Schematic diagram of the environmental CircadianSense subsystem

3.10.1 **Ambient Temperature**

Ambient temperature in waking hours was measured by means of an analogue temperature sensor worn over the clothes and attached by a clip. In the sleep system the ambient temperature sensor was mounted on the bedside box. The transfer function of TMP36 is as follows:

$$Vout=0.25V+(28mV/^{\circ}C)*T \qquad (3.12)$$

The output of this sensor was not amplified. The resolution of the measurement can be calculated from two points of temperature. T = 25° C and 50° C produces an output of 0.95 and 1.65 V respectively. These two voltages are converted by the 8-bit ADC to the decimal values of 73 and 128. The resolution is (50° C - 25° C)/(128-73)=0.45° C. Figure 3.18 shows an example of ambient temperature in averages of 1 minute recorded in waking hours.

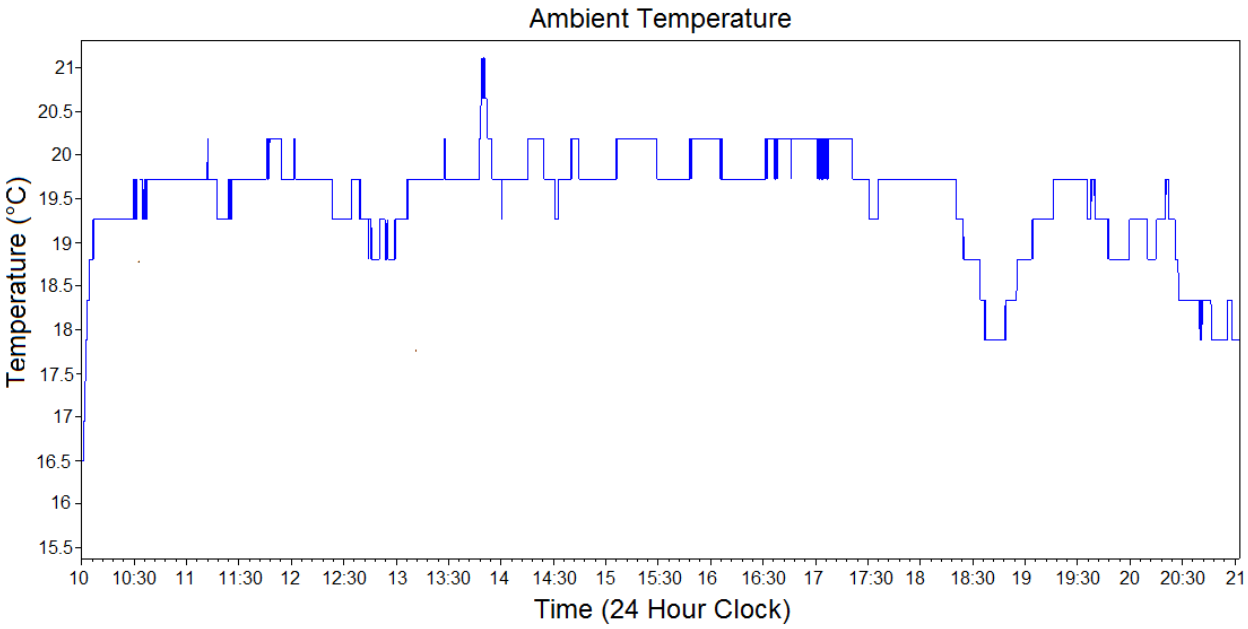


Figure 3.18 Ambient temperature recorded with CircadianSense

3.10.2 **Ambient Light**

Ambient light was measured by a light-dependent resistor (LDR) connected to a voltage divider. One of the 8-bit ADC channels was used to sample the voltage of the LDR.

This sensor was worn over the clothes and attached with a clip. In the sleep system the ambient light sensor was mounted on the bedside box. Figure 3.19 shows an example of ambient light recorded by CircadianSense. There were no comments from the clinicians in the interviews on this simple and cheap approach to subjectively assessing light with labels of bright and dark. However, literature recommended providing scientific and standard measurements of data recorded. In the study with general practitioners in Mexico it was also recommended to provide standardised values of data recorded. A discussion with the secretary of the Committee of Medical Research also recommended providing scientific metric data. If the system that is measuring light conditions is intended to be used in sleep problems, scientific outcomes are expected to make comparisons with other studies. Changes to the circuit for light measurement were made and are presented in Chapter 7.

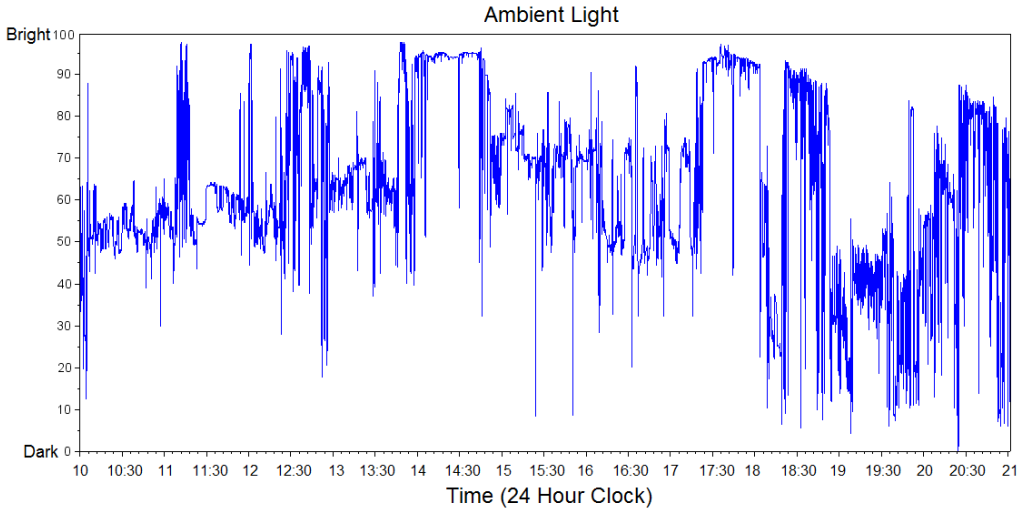


Figure 3.19 Ambient light recorded with CircadianSense

3.10.3 **Ambient Noise**

The range of human hearing is from approximately 20 to 20 kHz with a non-uniform response in the range. An A-weighted filter emulates the response of the human ear (Kjellberg et al., 1997). Commercial A-weighted sound meters estimate sound pressure levels as they would be perceived by the human ear. A-weighted sound meters are used to measure the annoyance of

noise in sleep studies (Muzet, 2007) and the condition of work environments. CircadianSense can measure from 25 to 72 dB. These levels of noise are equivalent to quiet conversation and busy road noise, respectively. The signal from the microphone was filtered with an A-weighted filter, rectified, and low-pass-filtered. The output voltage was connected to channel 0 of the ADC, as shown in Figure 3.17, for an 8-bit conversion and sampled at a rate of 100 Hz. The response of the A-weighted filter circuit is shown in Figure 3.20, as simulated in Tina TI® software.

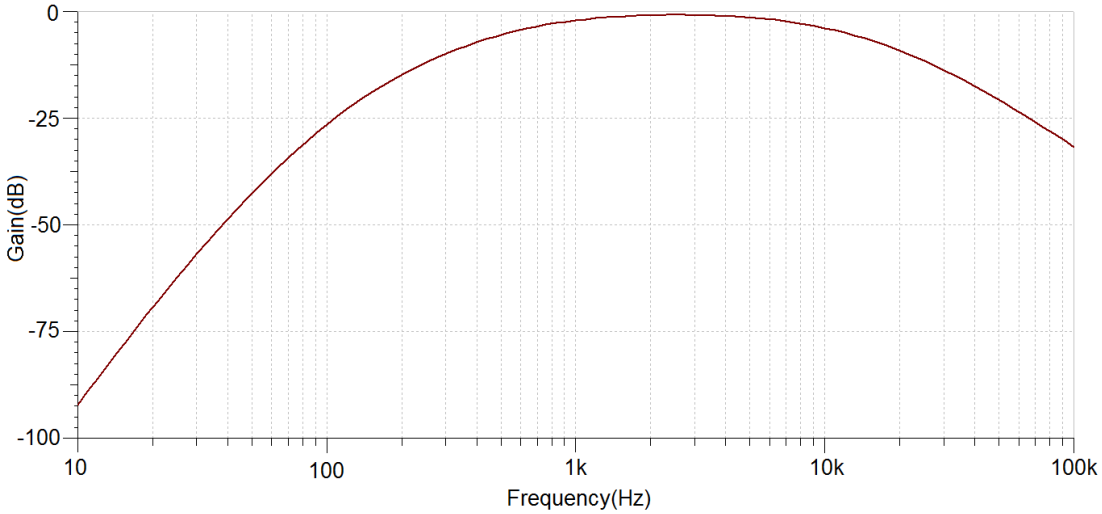


Figure 3.20 Response of the A-weighted filter

Calibration was conducted with a commercial sound level meter using white and pink noise sources at A-weighted sound pressure levels of 10, 20, 30, 40 and 50 decibels. A 1st order linear approximation was applied to the data recorded with Arduino to convert it into decibels. Data stored on the SD card was processed offline in Scilab and displayed in a 15-minute average of noise levels, as shown in Figure 3.21. Louder sound levels between 23:00 and 3:00 am were because participant lived near a bar, after the bar closes the sound levels decrease and increase again around 6:30 am because of traffic noises.

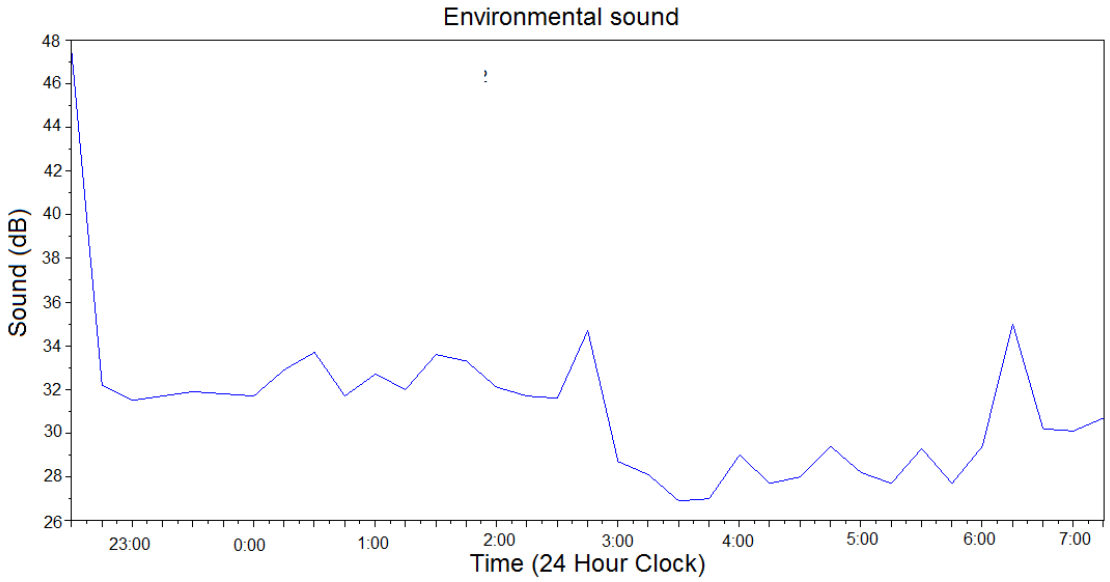


Figure 3.21 15-minute average of environmental noise

3.11 CircadianSense Risk Assessments and Actions Taken

Risk assessments were conducted for the ethical approvals of the UoB and the R&D department of QEHB for testing CircadianSense with the recruited participants. Examples of risks identified and actions taken are shown in Table 3.6.

Table 3.6 Risk assessment evaluation

Identified risks	Actions taken	Identified by
Skin irritation due to the electrodes or tape	Conduct a patch test of the electrodes and sticking plasters Advise changing the position of sensors and tape to avoid accumulation of irritation	Research team after short-term testing
Disturbed sleep due to the EOG electrodes and cables on the outer cantus of the eyes and forehead	Wear the system for the first time away from normal working hours to ensure that it does not impede function or sleep Advise discontinuing use if detrimental to sleep	Research team
EOG electrode cables could tangle or be uncomfortable	Advise running EOG cables from the face to the back of the head and then to the processor box	Sleep expert of the UoB
Long EDA electrodes could tangle and clinicians could not wear them	EDA electrodes were moved up to the upper arm	Main clinical collaborator, and was observed after testing the system in the hospital simulation suite with a resuscitation manikin
Possible security concerns over wearing electronics at airports, etc.	Avoid wearing the system when going to airports, train stations, etc.	Research team
Interference with medical devices	No wireless communication	Technician of the UoB
Cables not easy to clean and disinfect	Changed by round sleeved cables	Main clinical collaborator

3.12 Testing with Participants

Two duplicate CircadianSense systems were made for participant use. In total, 10 people wore the system. The participants and their use of the system are summarised in Table 3.7. All participants were healthy volunteers. The main clinical collaborator recruited three participants who work in the intensive care unit of QEHB. These two male and two female clinical participants have specialisation in anaesthesiology. Four members of the research team wore the system in short-term trials and for 3 days. These were the first in testing CircadianSense to identify areas of improvement before it was worn by the recruited participants. Two undergraduate male students of the UoB also wore the system, but one stopped testing CircadianSense after one day due to skin irritation of the EOG electrodes. One female non-student with disturbed sleep was recruited and wore the system for three days. Skin irritation caused by medical-grade tape and Ag/AgCl electrodes was discussed with anaesthesiologists. Via e-mail, one clinician recommended using materials used in plastic surgery because their use is suitable for long periods of time.

Table 3.7 Participants

Participant (ID)	**Participant and recruitment**	**Data collected**	**Notes**
Researcher 1 (Participant 1)	Male research team member	3 days and nights + 3 days and nights	
Researcher 2 (Participant 2)	Female research team member	3 days and nights + 3 days and nights	
Researcher 3 (Participant 3)	Male research member	Short-term trials + 3 days and nights + 9 days and nights	2 weeks of use was attempted but stopped after 9 days due to skin irritation from sensor adhesion
Clinician 2 (Participant 4)	QEHB (female clinical collaborator)	3 days and nights	Used CircadianSense in real environments, including at work in the hospital. Data for 1 day was lost due to SD card problems
Participant 5	Female non-student	3 days and nights	
Participant 6	UoB (male UG student)	Short-term trials + 1 night	Stopped due to skin irritation from sensor adhesion and EOG electrodes
Participant 7	UoB (male UG student)	Short-term trials	

Clinician 1 (Participant 8)	QEHB (female clinical collaborator)	Short-term trial + testing in hospital simulation	Tested CircadianSense in the hospital simulation suite with a resuscitation manikin
Clinician 3 (Participant 9)	QEHB (male clinical collaborator)	3 days and nights	Used CircadianSense in real environments, including at work in the hospital. SD card failure caused data losses
Participant 11	Male research team member	Short-term trials on 2 days	

3.13 Summary

This chapter presented the sources that inspired the CircadianSense system, the physiological and environmental variables selected according to their feasibility selection, and recommendations by both clinicians and literature. More variables were listed such as blood pressure, pulse oximetry, and glucose levels. However, they are not suitable for ambulatory collection. The design of firmware, hardware, data validation and calibration was presented. Changes to CircadianSense were made through feedback from participants and risk assessments. In the next chapter, visualisations of the data recorded of participants are discussed and modified, again, through clinical participation.

CHAPTER 4

DATA PREPARATION AND VISUALISATION

4.1 Introduction

Diseases have multifactorial causes in which diverse behavioural and environmental factors might affect the condition of the patient and circadian rhythms, and deteriorate sleep quality. One important task is the visualisation so as to deliver meaningful and useful visualisations to find associations between variables, explain phenomena and deliver and summarise information to clinicians. This chapter presents different visualisations of the data recorded with CircadianSense. These visualisations (scatterplots, histograms, heat maps, and dynamic visualisations) were presented to clinicians, who were asked to provide feedback and suggestions.

4.2 Data Preparation of CircadianSense Data and Datasets

Some of the challenges of big data in medicine as reported by Wang and Krishna (2014) in producing informative results included preprocessing raw data, handling inaccurate data and missing values, data interpretation, and data selection. Another starting point for the data preparation was the recommendation of Shneiderman (1996): overview first, zoom and filter, and then details on demand. Data processing, analysis, data preparation and its visualisation were conducted under these premises.

4.2.1 Data from sensors

Data was collected from the participants listed in Table 3.7 in Chapter 3. All CircadianSense sensor recordings were stored on an SD card in files containing the 8-bit conversion of raw data. The data was processed offline in Scilab, an open-source application for engineering and numerical computation. Scilab offers a number of toolboxes for signal processing, image

processing, artificial intelligence, and other mathematical and scientific libraries well documented and widely used in the academic world.

Different time averages or time granularities were computed for data visualisation for their discussion with clinicians in order to explore general overviews and detailed data presentations. Data was averaged over periods of 15 minutes, 1 hour, and portions of the day. Averages of data shorter than 15 minutes are necessary in conditions wherein rapid changes of physiological signals are indicators of pathologies such as cardiac problems. However, the goal of CircadianSense was to present to clinicians observations of long-term recordings of physiological and environmental variables and behavioural data. Furthermore, interviews with clinicians and focus groups with GPs, as described in Chapters 5 and 6, showed that they are interested in observing trends and making comparisons of signals by looking at big blocks of data and then examining data averaged in shorter periods of time if abnormalities were detected.

Physiological and environmental signal values were averaged per intervals of 15 minutes. However, averaging data in blocks of 15 minutes can lead to a loss of important event data. For example, the pulse rate and EDR change quickly due to physical activity or changes in emotional states. Significant changes in these parameters can last for much shorter than 15 minutes and can be lost through the averaging process. For this reason, the maximum and minimum were also included and the values imported into Excel. Behavioural and activity-related variables included in the daily log were stress, sleep, and food and stimulants taken by users because of their influence on circadian rhythms and effects on disease. The dataset contained the set of mean, maximum and minimum values listed in Table 4.1.

Table 4.1 Waking hours and sleep variable summaries

Physiological waking hours variables included in the dataset	Physiological sleeping hours variables included in the dataset
Mean pulse rate Maximum pulse rate Minimum pulse rate	Mean pulse rate Maximum pulse rate Minimum pulse rate
Mean body temperature Maximum body temperature Minimum body temperature	Mean body temperature Maximum body temperature Minimum body temperature
Mean phasic EDA Maximum phasic EDA	Mean phasic EDA Maximum phasic EDA

Minimum phasic EDA	Minimum phasic EDA
Mean energy expenditure Maximum energy expenditure Minimum energy expenditure	Mean actigraphy Maximum actigraphy Minimum actigraphy
	REM episode detection
Environmental waking hours variables included in the dataset	Environmental sleeping hours variables included in the dataset
Mean ambient light Maximum ambient light Minimum ambient light	Mean ambient light Maximum ambient light Minimum ambient light
Mean ambient temperature Maximum ambient temperature Minimum ambient temperature	Mean ambient temperature Maximum ambient temperature Minimum ambient temperature
	Mean ambient sound Maximum ambient sound Minimum ambient sound
Behavioural waking hours variables included in the dataset	
Meals/snacks	
Stimulants	
Mood	

4.2.1.1 Handling Missing Data

Missing values can be a result of a faulty sensor, a sensor not being properly worn by a user or movements. Handling of missing values is part of data preprocessing. Techniques of imputation can be used in order to cope with and fill gaps due to missing values. Imputation methods range from averaging adjacent valid data to fill gaps of data through the creation of logic rules to estimating the missing value. After the first technical trial, in which CircadianSense was worn by the research team, it was discussed with clinical collaborators how to handle missing data. The multifactorial causes that modify the behaviour of physiological signals can render the use of an imputation technique a complex and time-consuming task. Some variables change quickly, such as pulse rate and EDA signals, but others, e.g. body temperature, are modified slowly over time. Mean imputation methods could wrongly estimate fast-changing signals, although logic rules could be used to impute data with possible little success. If logic rules are going to be used by an expert, several signals should be observed to estimate the values of missing data. For example, gaps of data of the pulse rate could be completed by analysing MET values and skin temperature. Again, however, false imputation could be due to an increased pulse rate being a result of stress or medication, rather than physical activity. Mean imputation methods could be applied to low-

speed change variables such as body temperature. The recommendation was not to impute values, because of possible inaccurate imputation and the time-consuming process when performed by a medical expert. Moreover, the interest of clinicians was in observing trends of physiological data and finding associations with environmental and user information. Clinicians also reported that observations of very short time averages of data would be prescribed for very specific pathologies such as cardiac problems, to which a suitable solution could be a Holter monitor.

4.2.2 **Daily Log and Icons**

As reported in the literature, stress, stimulants, medicine, naps, and physical activity are important factors to assess, due to the influence that they have on the management and behaviour of chronic diseases and circadian rhythms. The proposed daily log to be completed by participants is shown in Figure 4.1 in periods of 15 minutes. Vanroy (2014) reported that recording activities of a very short duration can lead to failures in maintaining a diary; however, a minimum of 15-minute durations is recommended and these intervals have been useful and shown feasibility for self-monitoring activity diaries in hospitalised patients. There were no changes suggested in the format of the daily log.

Daily Log

Participant:_____ Date:_____

Time	Activity Intensity (light, medium, high),	Meals, snack (light, medium, large)	Stimulants /Medicine	Stress (Light/Medium / High)	Sleep/ naps	Any changes in behaviour due to wearing the system	System comments. (E..g., Sensors removed for shower, sensor detachment, etc)
6:00 AM							
6:15							
6:30							
6:45							
7:00							
7:15							
7:30							
7:45							
8:00							
8:15							
8:30							
8:45							
9:00							
9:15							
9:30							
9:45							
10:00							
10:15							
10:30							
10:45							
11:00							
11:15							
11:30							
11:45							
12:00 PM							

Figure 4.1 Daily log proposed to be completed by participant

Information to be registered in the daily log was discussed with clinicians and evolved over time. Data annotated in the daily log by participants was presented in the dataset and heat maps as icons, as shown in Figures 4.16 and 4.17 in waking hours and sleeping hours, respectively. The icons and information were discussed with clinicians and evolved over time, as shown in Figure 4.2. In a) the original icons proposed are shown. In b) the main clinical collaborator recommended an icon for being awake in bed, because if a person is still in bed the accelerometer will not detect any activity and this should be reported in the daily log. An icon for drowsiness was added because some medicine can have such an effect on the patient. Emotional states of happiness and unhappiness were also recommended to be reported and represented as icons. Indoor activity and outdoor activity icons were also recommended. Simplification of the icons for alcoholic beverages and stress levels was recommended. In c) the other three anaesthesiologists found icons for watching TV and browsing the Internet to be a relaxing activity with no physical activity, which could be represented only as an icon for relaxing. It was also suggested to include in one icon alcohol, beer or a glass of wine so as to keep the list of icons short. The icons representing stress were recommended to be only one icon.

Icons for different levels of physical activity were also recommended. These were icons in respect of light, moderate and intense activity. Including icons for mood was also asked, as emotional states are of medical interest due to the effect that they have on diseases. Icons of awake in bed and getting up were also suggested. The final set of icons and information to be registered in the daily log was complemented by general practitioners in the focus group 3 is shown in d). In the assessment of clinicians in interview II, as shown in Chapter 5, adding information on sugary food was recommended, and GPs who participated in focus group 3 also recommended information related to sugary food, cigarettes, and water drunk, and suggested simplifying the icons for activity by eliminating housework and outdoor activities. GPs also recommended explaining to patients what activities fall into the category of light, moderate or intense, as they would depend on conditions of age, weight or physical impairment of the patient.

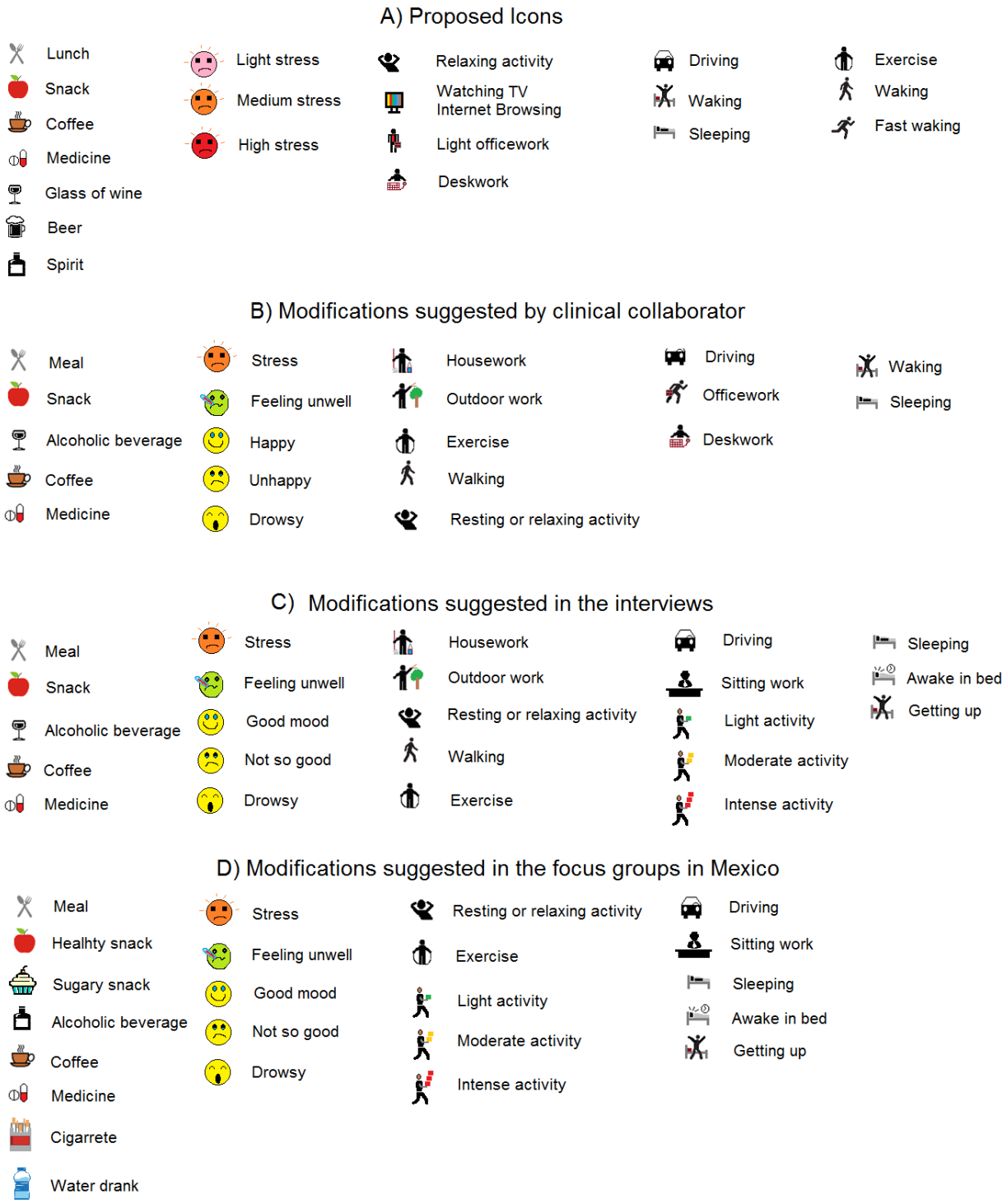


Figure 4.2 Evolved set of icons of the daily log

4.2.3 **Subjective Assessment of Sleep Hygiene and Sleep Quality**

Clinical assessment of patients‘ sleep normally incorporates a patient report of sleep hygiene, an assessment of sleep and a daily log of activities and factors influencing sleep. Subjective reports selected for CircadianSense include a sleep hygiene questionnaire and a commonly used sleep assessment questionnaire (Richards–Campbell Sleep Questionnaire). Comparisons of subjective assessments of sleep hygiene and sleep quality with objective data are recommended in the literature in order to explain the possible causes of the deterioration of sleep. The sleep hygiene questionnaire used is shown in Figure 4.3.

Sleep Hygiene Questionnaire

Participant:_____

Date:_____

Question	Yes/No
1. Take naps during the day	
2. Wake up at approximately the same time	
3. Go to bed at approximately the same time	
4. Drink caffeinated beverages such as coffee or tea or soft drinks from 5 to 10 hours before bedtime	
5. Drink caffeinated beverages such as coffee or tea or soft drinks within 5 hours of bedtime	
6. Drink alcohol within 3 hours of bedtime	
7. Smoke a cigarette or chew tobacco within 2 hours of bedtime or in the middle of the night	
8. Engage in exciting or emotionally upsetting activities near bedtime	
9. Perform activities demanding high levels of concentration near bedtime	
10. Exercise within 4 hours of bedtime	
11. Worry, plan or think about important matters at bedtime	
12. Read in bed	
13. Watch television in bed	
14. Lounge around in bed	
15. Worry, plan or think about important matters in bed	
16. Sleep on an uncomfortable mattress	
17. Sleep in a room with an uncomfortable nighttime temperature	
18. Sleep in a noisy environment	
19. Sleep in a room that is too bright	
Describe activities performed before going to bed	
Are the activities performed the usual ones performed before going to bed?	

Figure 4.3 Sleep hygiene questionnaire

The Richards–Campbell Sleep Questionnaire, as shown in Figure 4.4, is a simple and popular questionnaire for patients‘ subjective assessment of sleep quality on a scale of 0–100. It is a

validated, short and easy questionnaire that has been used with good reliability in the intensive care unit (ICU). The Richards–Campbell Sleep Questionnaire provides self-reported scores on five items: ease of falling asleep, number of awakenings, ease of returning to sleep, depth of sleep, and overall sleep quality. The higher the score of the questionnaire, the better the perception of sleep quality (Richards et al., 2000).

Richards–Campbell Sleep Questionnaire
Participant:_____
Date:_____
Please mark the length on the line that better describes the answer to the question.
My sleep last night was:

_____
Light Sleep Deep Sleep
Last night, the first time I got to sleep, I:

_____
Just never could fall asleep Fell asleep almost immediately
Last night, I was:

_____
Awake all night Awake very little
Last night, when I woke up or was awakened, I:

_____
Couldn‘t get back to sleep Got back to sleep immediately

I would describe my sleep last night as:

_____
A bad night‘s sleep A good night‘s sleep
I would describe the noise levels last night as

_____
Very noisy Very quiet

Figure 4.4 Richards–Campbell Sleep Questionnaire

4.2.4 **Dataset Information**

Data processed with Scilab was exported as a comma-separated values (CSV) file readable by Excel. As shown in Figure 4.5, participants‘ Richards–Campbell Sleep Questionnaire (RCSQ) results and patients‘ information were included in the Excel datasets. The objective of adding the results of the RCSQ is to include a subjective report of sleep quality which could be contrasted with physiological, environmental and behavioural data that could explain the changes in sleep quality as reported by the patient.

Participant Number		5
Data recorded	Sunday 16th March, Monday 17th March, and Tuesday 18th March 2014	
Description	Participant 5 -non-clinician female participant of 37 years. Data recordings are for Friday, Saturday and Sunday. Participant reported disturbed sleep.	
Richard Campbell's Sleep Questionnaire result	Sunday	88.4
	Monday	51.8
	Tuesday	89.6

Figure 4.5 Information of the patient

As shown in Figure 4.6, the mean, maximum and minimum values for each variable were included in the dataset. Colours in the first column identify morning, afternoon and night. This table was created for each participant. Data was arranged in columns and rows of 15-minute average, minimum and maximum variables. Cells were marked in grey to indicate unreliable data or missing data. This representation shows detailed information to the clinician on where values of variables versus time can be observed.

Actual Time	Body Temp Mean			Body Temp Max			Body Temp Min			Pulse Rate Mean		
10:45			32.9			33.3			31.9			98.9
11:00	34.1		32.4	34.5		32.9	33.7		31.8	73.0		99.6
11:15	34.6		32.4	34.9		32.8	34.1		32.1	69.4		89.7
11:30	34.9	32.8	33.4	35.2	32.9	33.9	34.5	32.5	32.9	72.3	90.8	68.0
11:45	35.3	33.1	34.2	35.3	33.3	34.5	34.9	32.9	34.0	67.8	92.5	65.0
12:00	35.5	33.6	34.8	35.7	34.1	34.9	35.3	33.3	34.5	68.5	104.5	63.7
12:15	35.4	32.2	34.1	35.7	33.5	34.9	35.3	30.7	33.3	68.4	113.4	68.2
12:30	35.4	28.2	33.5	35.7	30.1	33.7	35.3	27.0	33.3	67.7	130.3	73.6
12:45	35.2	30.6	33.6	35.3	31.6	33.7	34.9	29.2	32.9	74.2	113.0	76.0
13:00	34.9	30.9	33.3	35.3	31.5	33.4	34.5	29.6	33.1	84.6	123.0	80.7
13:15	34.3	31.8	33.7	34.9	32.5	33.7	33.3	31.0	33.4	71.9	93.9	82.8
13:30	34.9	32.6	33.9	34.9	33.2	34.5	34.9	32.1	33.7	72.7	98.2	88.8
13:45	34.9	33.3	34.0	34.9	33.4	34.4	34.9	33.1	33.7	88.7	85.3	88.3
14:00	34.6	33.7	34.0	35.2	34.1	34.1	33.7	33.3	33.7	101.0	82.6	96.0
14:15	34.9	34.0	33.8	35.3	34.1	34.1	34.6	33.7	33.4	96.9	79.8	81.9
14:30	34.7	33.7	33.0	34.9	33.8	33.7	33.6	33.4	32.7	100.3	84.4	90.7
14:45	32.6	33.7	33.1	33.3	34.1	33.6	31.8	33.7	32.6	103.0	80.7	99.0
15:00	33.1	34.1	33.8	33.7	34.1	34.1	32.5	33.7	33.3	95.2	82.4	89.4
15:15	33.5	30.9	34.5	33.9	33.8	34.9	32.9	27.0	34.1	92.4	97.7	75.2
15:30	33.0	27.3	34.5	33.3	28.4	34.9	32.9	26.2	33.7	101.5		82.5
15:45	34.0	29.5	33.4	34.4	31.5	33.7	33.4	26.7	33.3	87.5	92.7	88.9
16:00	34.3	32.1	33.2	34.5	32.5	33.3	34.0	31.7	32.9	80.8	79.1	90.5
16:15	34.3	32.7	33.5	34.5	32.9	33.7	34.1	32.5	33.3	82.4	79.8	97.2
16:30	34.3	32.9	33.2	34.9	33.3	33.3	33.7	32.9	32.9	80.1	78.2	87.3
16:45	34.5	32.9	33.7	34.5	33.3	33.7	34.1	32.1	33.6	85.8	83.1	65.7
17:00	34.5	28.8	33.7	34.6	32.5	33.7	34.2	26.8	33.7	86.8	106.6	62.9
17:15	34.5	27.2	33.8	34.7	29.2	34.5	34.0	24.4	33.2	87.3	108.3	69.0
17:30	34.5	30.5	34.0	34.9	31.7	34.5	34.1	29.5	33.3	84.8	93.7	75.8
17:45	34.2	32.5	33.7	34.6	32.9	33.9	34.1	31.7	33.4	76.6	77.4	84.0
18:00	34.3	33.1	34.2	34.5	33.3	34.5	34.1	32.9	34.1	79.5	86.6	90.9
18:15	34.2	33.7	34.5	34.5	34.1	34.5	34.1	33.0	34.2	87.9	83.0	94.0

Figure 4.6 Part of dataset created with the 15-minute average, minimum and maximum variables

4.3 Plots of Data Recorded

Examples of scatterplots are provided with three levels of time granularity (15-minute average, 1-hour average, and portions of the day and night). Computation of the averages of portions of the day included the recordings for the morning from the time recordings started up until 12:00, the average of data from 12:00 to 18:00 for the afternoon, and from 18:00 until the system stopped recordings. Periods with missing data were not computed in the averages. Figure 4.7 shows the three different time granularities for participant 1. In **(**A**)**, energy expenditure of MET is averaged in intervals of 15 minutes. This figure shows that this participant was more active on Sunday with activities in the range of light (lower than 2.9) to moderate activities (from 3 to 6 MET). On Monday, all activities performed fell in the range of light intense (lower than 2.9). In **(**B**)**, MET is averaged in intervals of 1 hour. **(**C**)** shows the MET in three portions of the day: from the moment the system was worn until 12:00, from 12:00 to 18:00, and from 18:00 until the user turned the system off. The averages were computed in independent intervals of time.

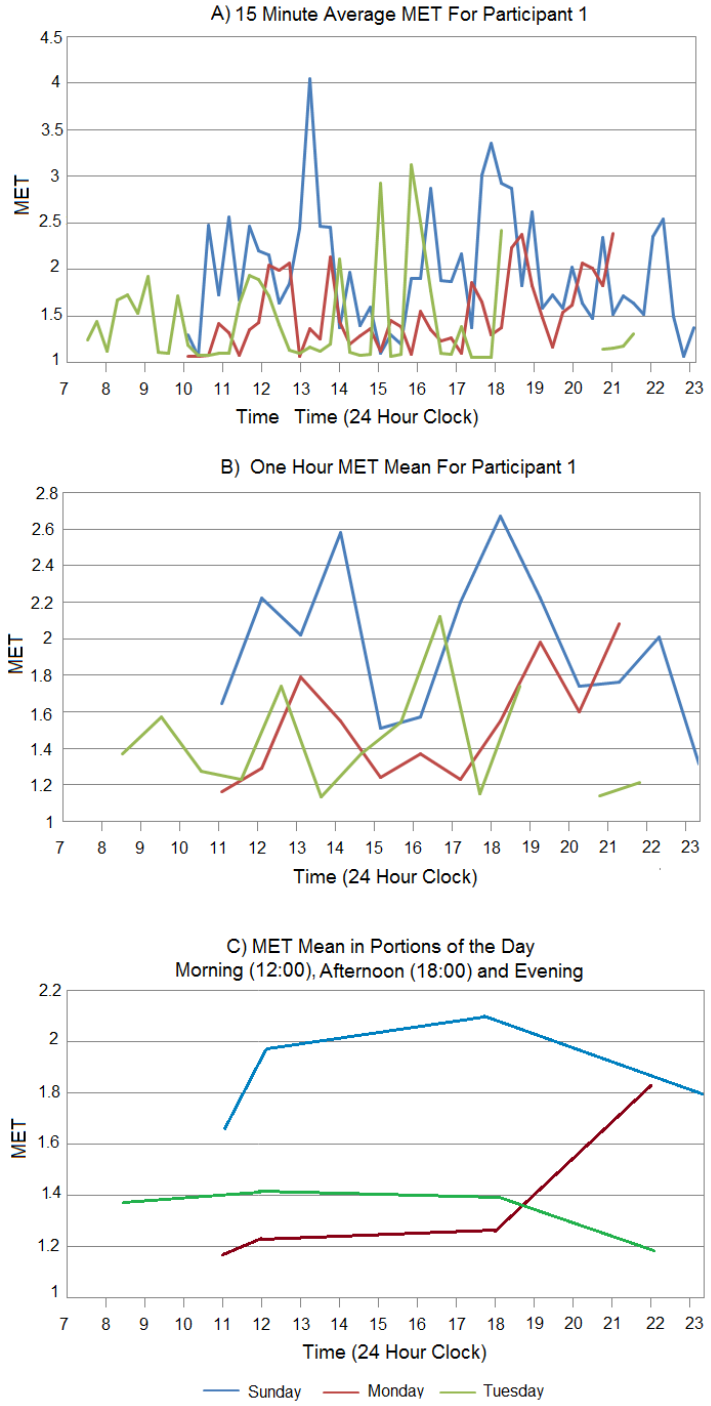


Figure 4.7 MET granularities for participant 1. **(A)** 15-minute average of MET with user more active on Sunday (blue line) and much deskwork on weekdays. In **(B)** 1-hour average of MET and **(C)** portions of the day also show that Sunday was the most active day

Figure 4.8 shows the MET mean for participant 5, who is a housewife. The 15-minute mean MET values are similar on the 3 days with values that fall in the category of light intense

activities (lower than 2.9). The light intense activities performed are explained because the participant lives in a small flat with activities within the house.

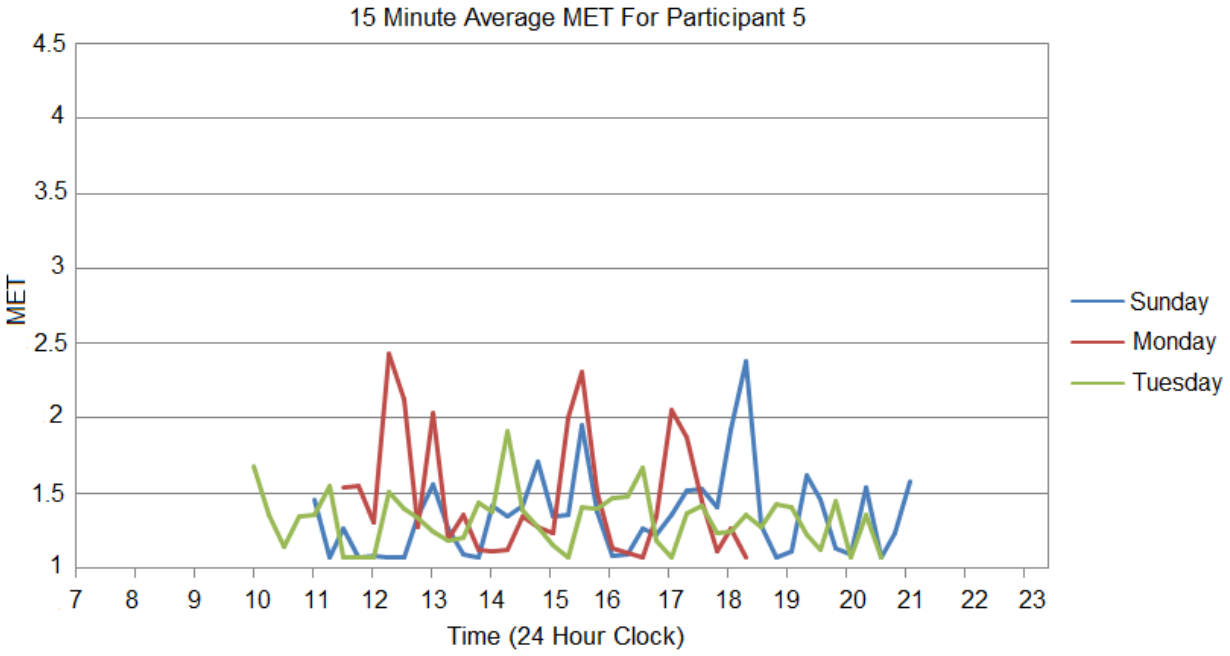


Figure 4.8 15-minute mean MET for participant 5, who is a housewife

Body Temperature. Figure 4.9 shows the pattern of healthy core body temperature over 24 hours as taken from Lack et al. (2008). For example, core temperature reaches the maximum value at the onset of sleep and the minimum core temperature is reached around 2 hours before waking. Sleep problems such as sleep onset insomniacs show delayed temperature rhythms; in contrast, early morning awakening insomniacs show advanced temperature rhythms.

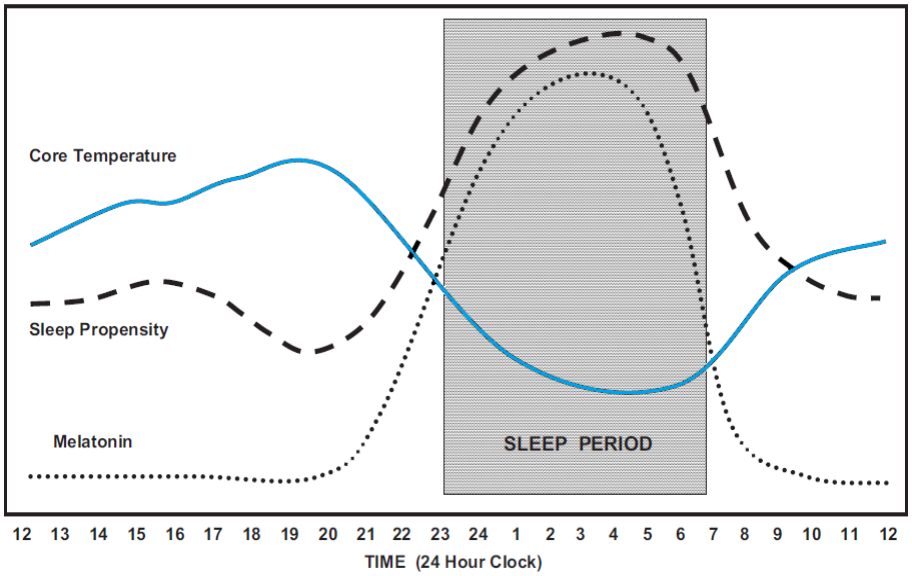


Figure 4.9 Pattern of core body temperature taken from Lack et al. (2008)

CircadianSense temperatures for participant 1 are shown in Figure 4.10. On Sunday there is a delay in the maximum and the minimum skin temperature because the participant slept later than on weekdays. On Monday and Tuesday the participant slept and woke at approximately the same time. The participant reported sleeping at around 00:00 and waking at 06:00 on Monday and Tuesday. On Sunday they slept at around 01:30 and woke at 07:00.

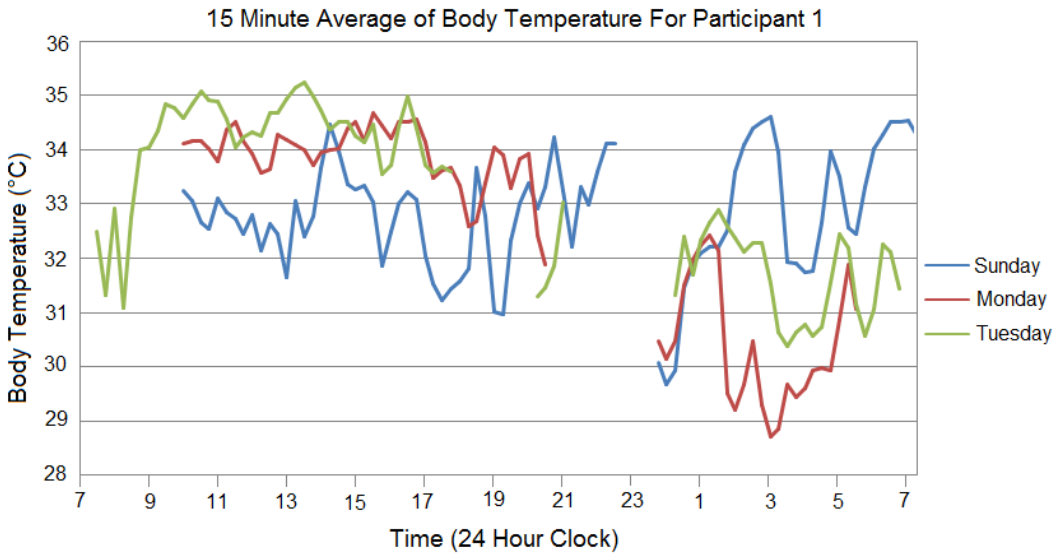


Figure 4.10 15-minute mean of body temperature for participant 1

Normal core body temperature is not observed in Figure 4.11 for participant 5, who reported disturbed sleep. The RCSQ scores for this participant are shown in Figure 4.5, with the poorest

sleep occurring on Monday night (with a score of 51.8). Higher actigraphy is also observed on Monday night. Suddenly waking up increases the body temperature and pulse rate, as data show for the 3 days. Three peaks in the pulse rate and actigraphy are observed on Monday between 01:00 and 03:00 when the participant woke, as reported in the daily log. The participant reported in the daily log that woke and slept several times during the night in the 3 days.

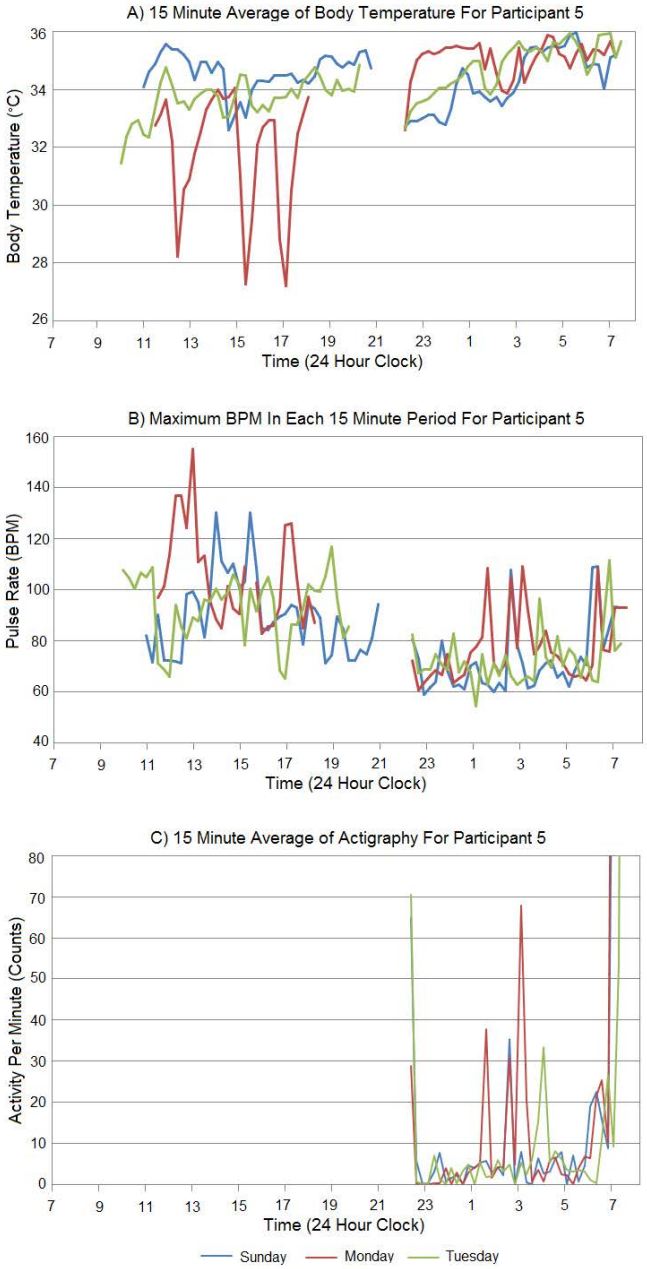


Figure 4.11 15-minute mean of body temperature for participant 5, who reported disturbed sleep during the 3 nights

The recordings of participant 1, who did not report disturbed sleep, show normal patterns of body temperature in Figure 4.12 and lower variations in the pulse rate and actigraphy than those of participant 5, as shown in Figure 4.11.

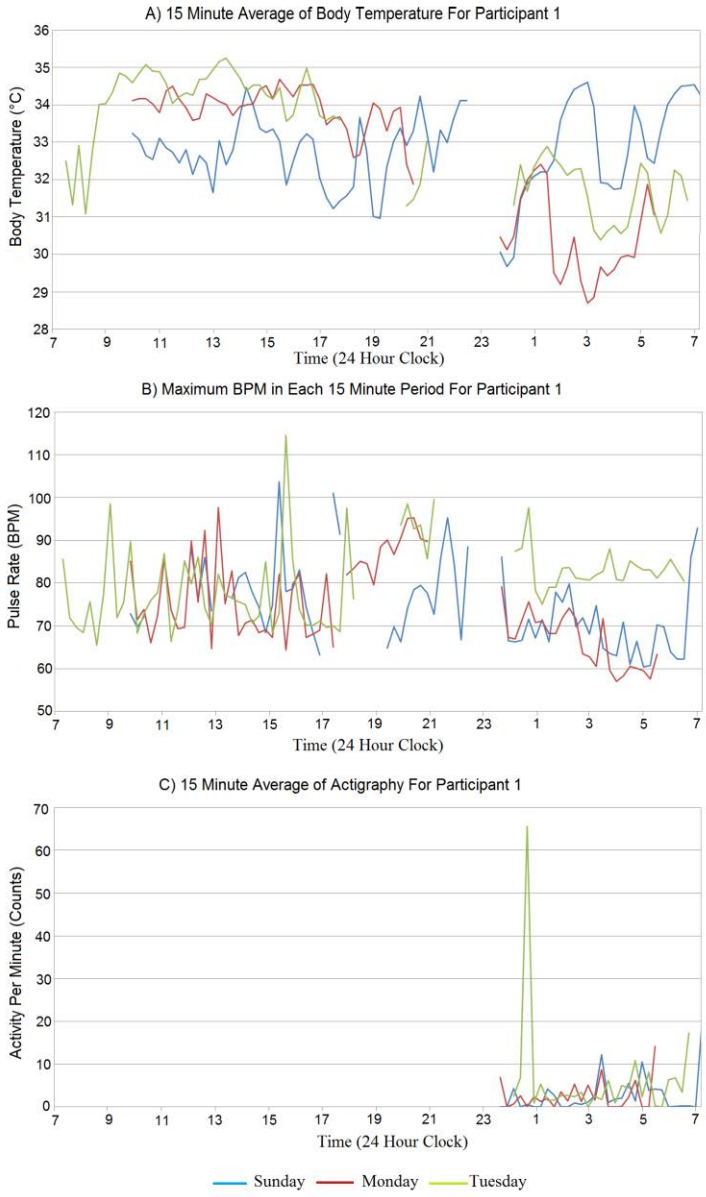


Figure 4.12 15-minute mean of body temperature for participant 1, who slept continuously in the night

4.4 Histograms

Histograms are useful data summaries by means of a graphical representation of the distribution of data. Variables are split into intervals or bins. Each bin contains the number of occurrences of data with values in the range of the bin. The property of plotting distribution of data was used to show clinicians a way in which to summarise and understand the behaviour of data. Discussions with clinical participants recommended visualisations that could summarise data, observe trends and make comparisons of data. On the other hand, scatterplots and numerical datasets were suggested by clinicians to be used for detailed observations. It was suggested that averages of data over long periods of time (days) could also be used to observe trends and make comparisons.

4.4.1 Comparing Data with Histograms

Figure 4.13 shows the histogram of 15-minute average MET for participant 1 on Sunday (the most active day). This figure shows that on Monday (B), activity falls in the range of light intense activity (lower than 2.9); in contrast, on Sunday (A) there is activity in the range of moderate intense activity ($3 \leq MET \leq 6$). More moderate intense activity would generate more and higher bars in bins 3 to 6. In the interviews with clinicians, as presented in Chapter 5, and focus groups with GPs, as shown in Chapter 7, participants found that histograms of data would be an easy way in which to compare trends of data over long periods of time by observing shifts of the bars. Furthermore, this could be used as a way in which to summarise data. Clinicians suggested that histograms of energy expenditure could be useful in observing patients‘ fitness before and after a surgery or fever in histograms of body temperature.

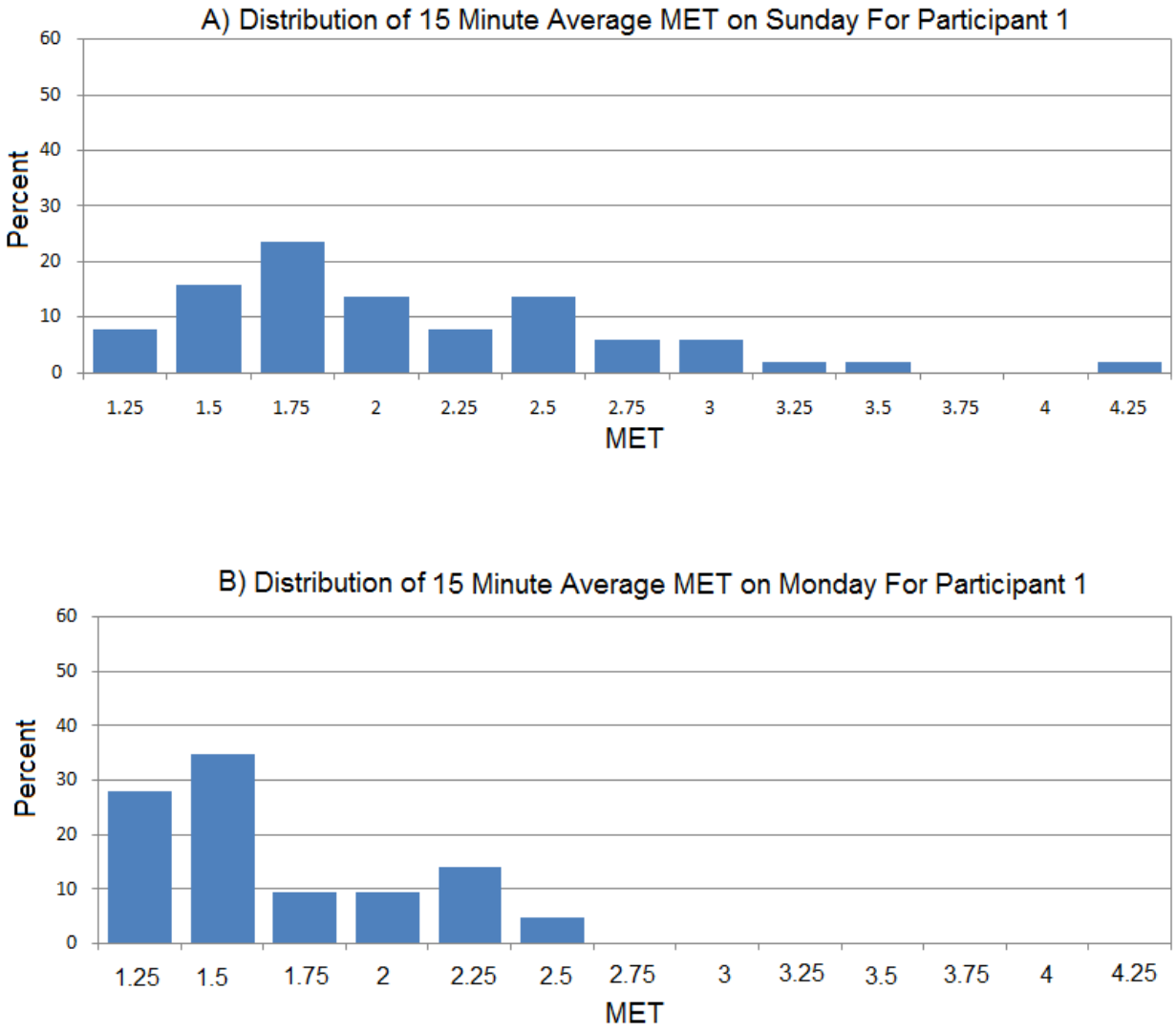


Figure 4.13 Histogram of 15-minute MET average for participant 1 on Sunday (a) and Monday (b)

4.4.2 **Measuring Data Reliability**

Clinicians answered in the interviews that one barrier to the adoption of a medical device is data being inaccurate. CircadianSense does not record continuous valid data, as shown in the recordings of pulse rates in Figure 4.14, because of movement or detached sensors. Clinicians were shown Figure 4.14, which shows daytime minute-by-minute pulse rate recordings. Evident gaps of data are present in the pulse rates. Clinicians were asked how they would use data with few or many gaps in valid data. The answer was that it would depend on the percentage of valid data, giving direction to the use of data, e.g. diagnosing a pathology or establishing trends. However, as discussed in Chapters 5 and 7, clinical collaborators did not find necessary continuous recordings so important. The reason exposed was that, in general, continuous

observations of patients are not necessary, as physiological signals change slowly over time, even in inpatients. Typical observations of data are made in periods up to 8 hours. It is more important to see trends of data than to observe quick changes in physiological signals. However, this would not apply to cardiac patients, wherein quick changes are indicators of problems.

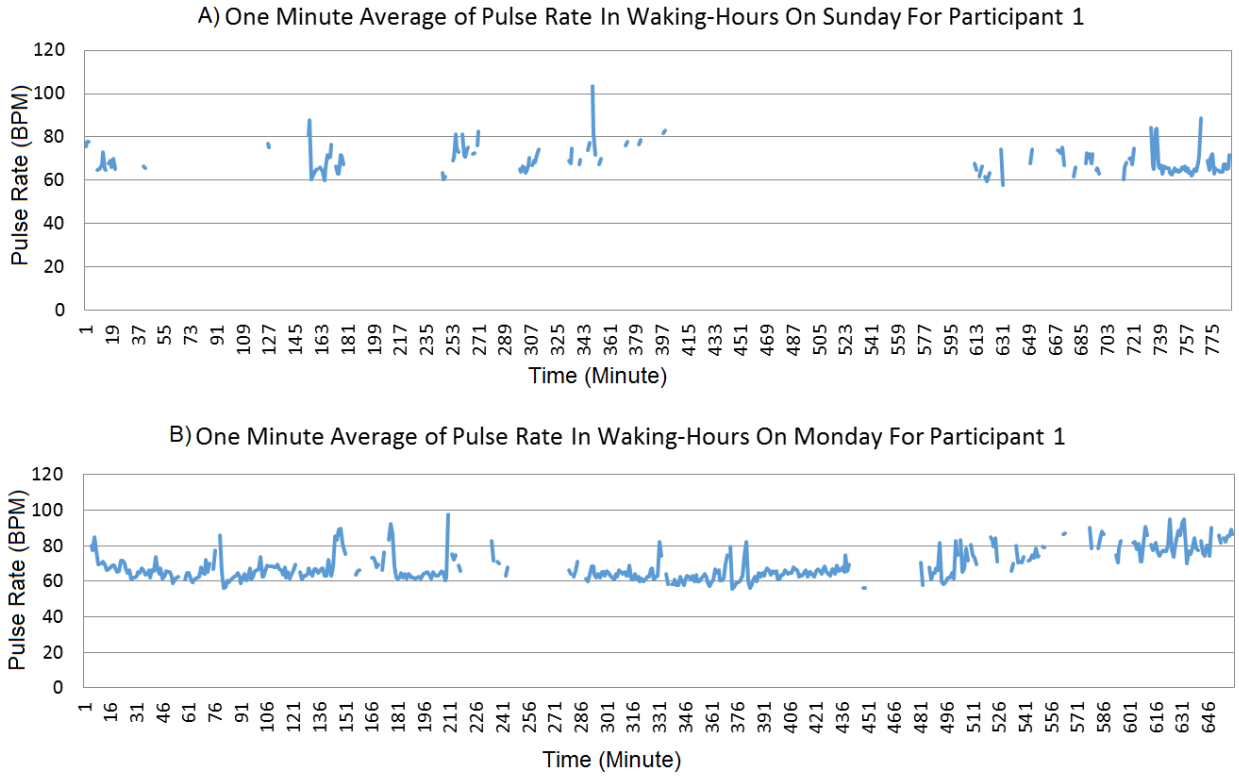


Figure 4.14 1-minute average of pulse rate recorded on A) Sunday in waking hours and B) Monday in waking hours for participant 1. Participant was most active on Sunday and there are more gaps of missing data compared to Monday

Data Losses. Pulse was detected with an optical sensor on the carotid vein on the neck and signal reliability was susceptible to neck movement. The 15-minute mean values were calculated only from valid 1-minute intervals. For example, if there were only 5 minutes of valid data, the 15-minute mean value would be calculated from the 5 minutes alone. The maximum and minimum would also be taken from the 5 minutes. If there were only 1 valid minute of data in a block of 15 minutes, the mean, maximum and minimum values would be the same. Figure 4.15 shows the number of valid minutes vs MET. Lower values of MET have more valid minutes of pulse data. The number of valid minutes decreases as MET increases. A discussion with a member of the Committee of Medical Research, as presented in Chapter 7, recommended including conditions in which the medical device provides accurate and reliable data, e.g.

environmental variables of temperature, humidity, vibration, electrical noise, conditions of the patient, such as age, weight and height, or any condition that could affect the accuracy of data. This measurement of the pulse rate vs. MET could serve for clinicians to determine how many valid periods of pulse rate data there are in the averages by analysing the MET values.

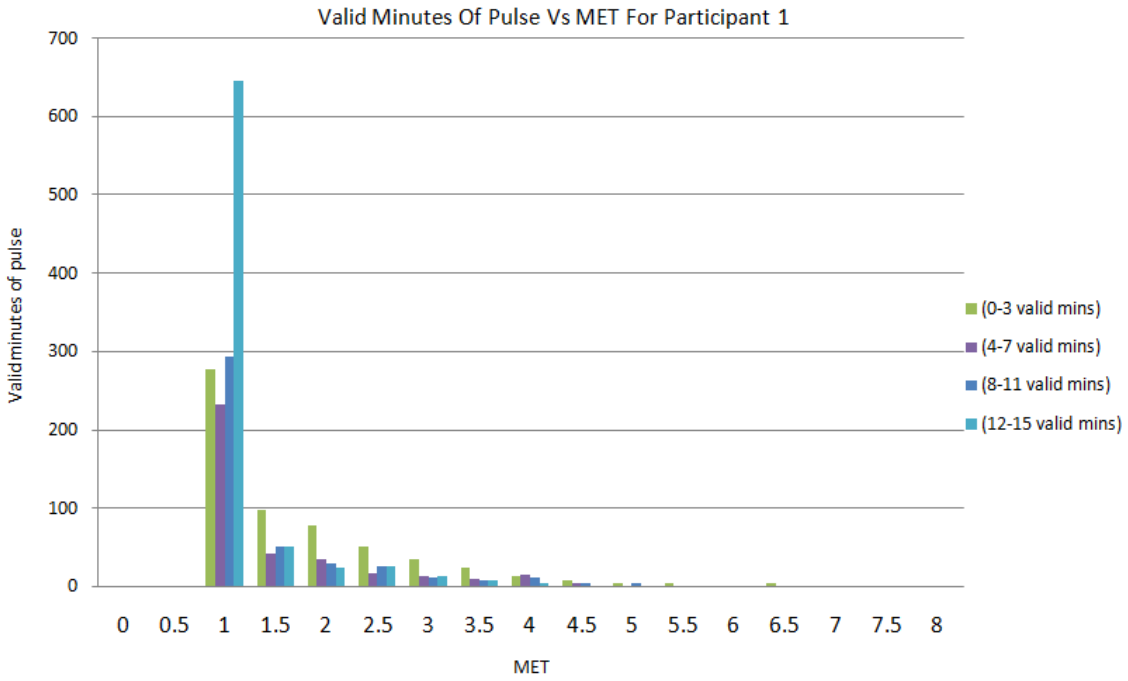


Figure 4.15 Valid minutes of pulse vs. MET

4.5 Heat Maps

A heat map is a simple two-dimensional colour representation of values. The colour assigned to the variable depends on magnitude. Heat maps of CircadianSense data were created with the aim of summarising the dataset information and providing a visual representation of the data recorded. The heat map originally only included colours, but after an initial assessment by the main clinical collaborator it was recommended to put the correspondent value in the cells of the heat map. There were opinions as to how to highlight abnormal values. Anaesthesiologists recommended tailoring the colours to the patient and highlighting abnormal low and high values with a different colour. However, GPs in the focus group recommended setting the normal or expected range of signal values on the age and condition of the patient. This could be achieved by recording data of a big group of different patients to determine the expected values on

different conditions. After knowing the expected values the range could be set and the abnormalities highlighted.

Figure 4.16 shows part of a heat map in waking hours with icons representing activities performed by participants. The colour of cells for pulse rate and MET at 12:15 and 13:00 on Monday are greener because of the physical activity performed.

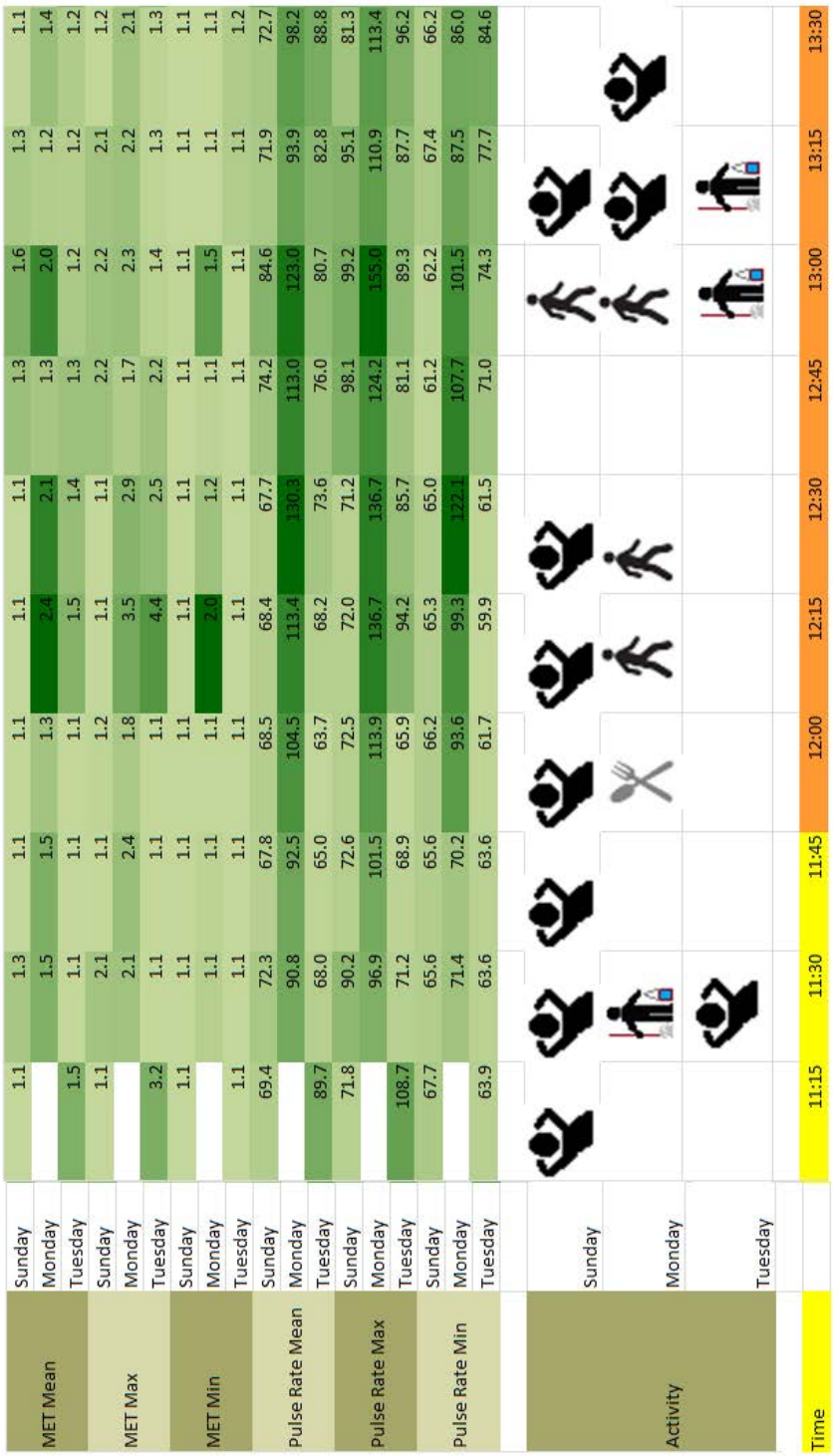


Figure 4.16 Part of heat map of participant 5 in waking hours

Figure 4.17 shows part of the heat map of participant 5 in sleeping hours. This participant, who has disturbed sleep, shows an increased actigraphy and pulse rate when waking up. These changes are observed as greener cells for those variables at the times at 2:45 on Sunday and Monday at 2:45 and 13:15 when reported in the daily log with regard to waking up. Monday was reported by participant as the worst night‘s sleep as shows Figure 4.5.

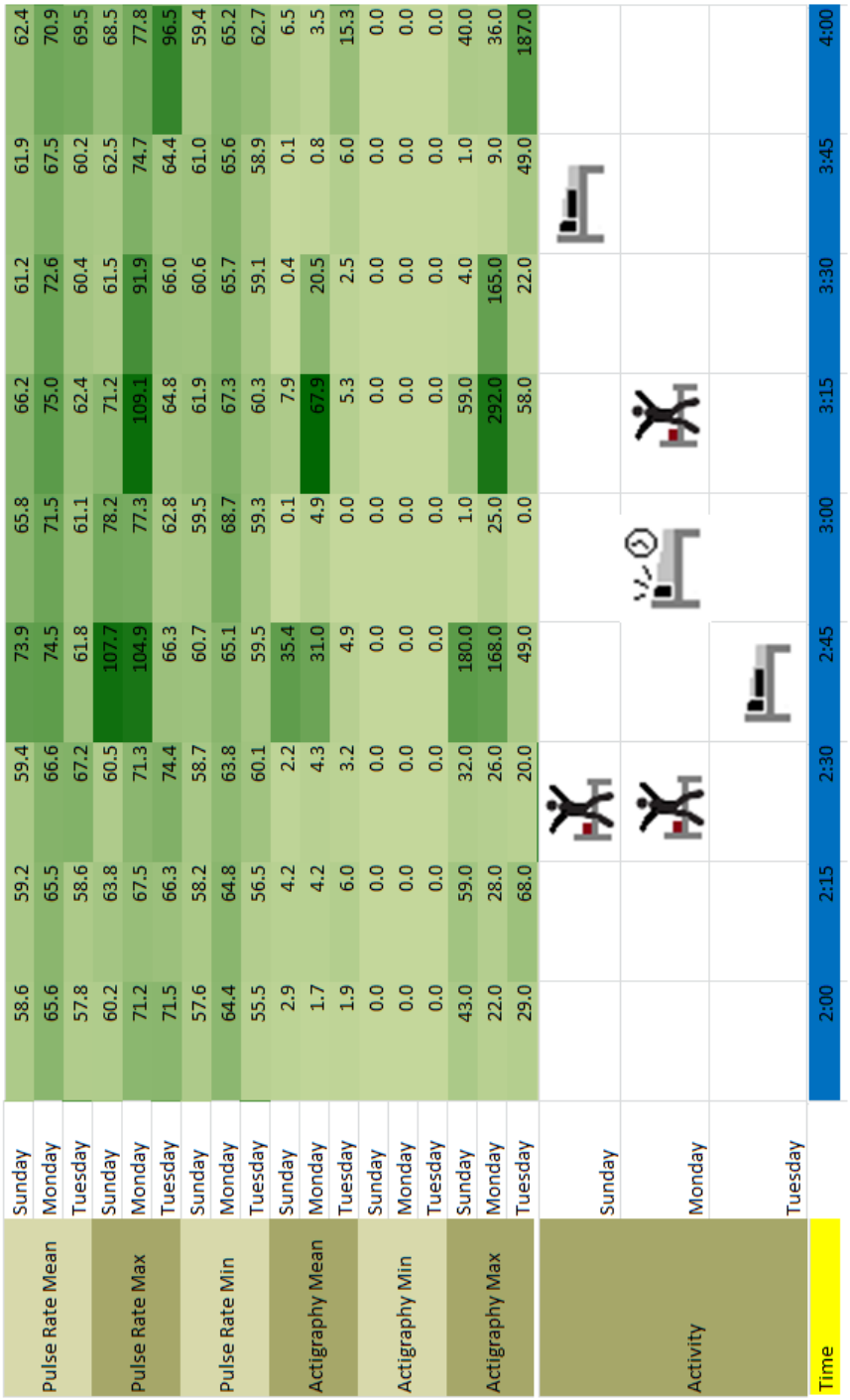


Figure 4.17 Part of the heat map of participant 5 in sleeping hours

Participant 5 reported in the daily log that a bee, which suddenly appeared in the flat, scared her. By examining Figure 4.18 at 14:00 on Sunday there was an increase of the maximum pulse rate but low MET. The mean pulse rate didn‘t vary because it was a short event triggered by stress.

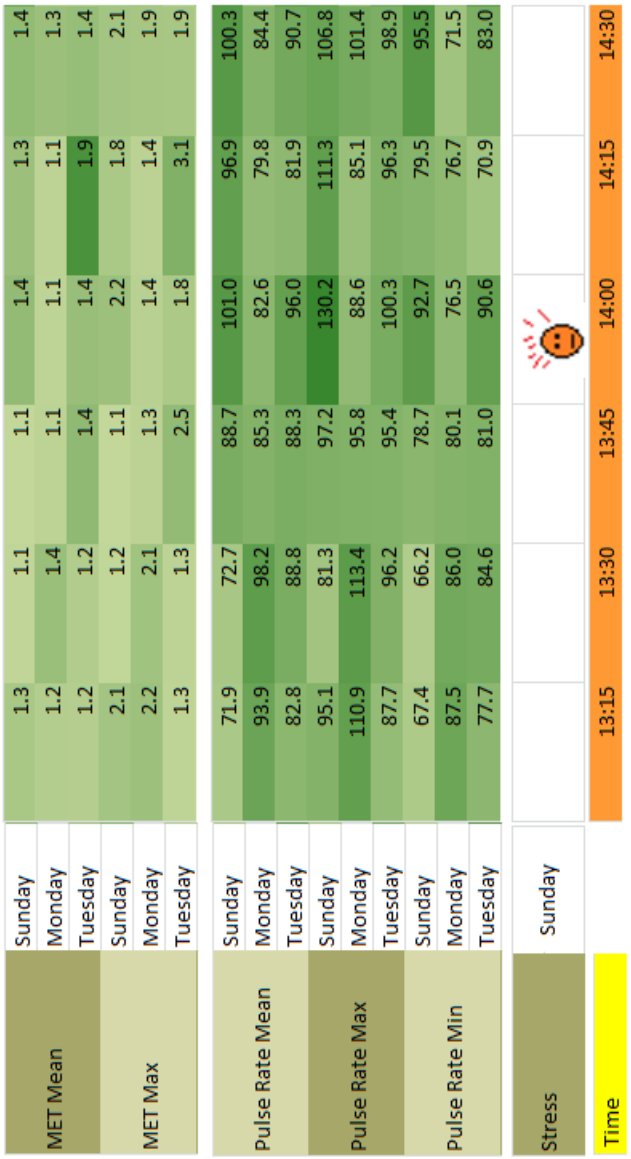


Figure 4.18 Zommed-in view of heat map of participant 5

The explanation and interpretation of the colours of the cells, magnitude, and information in the daily log reported by patients were given to clinicians, who agreed that the behaviour appeared as expected. It could easily be used to quickly detect abnormally high or low values. The icons of the activities registered in the daily log also matched the colours of the heat map, but it would depend on whether activities are annotated by patients at the correct time.

4.6 Dynamic Visualisations

Dynamic visualisations were created using Google‘s _Motion Chart‘ in Google Sheets. Motion Chart is a free interactive chart in Google‘s online spreadsheet which is similar to Excel. The interactive selection allows users to choose variables to animate and the properties that will be changed, e.g. changes of the size of the bubble, position, and colour based on the amplitude of the signals. An example of this visualisation is shown in Figure 4.19, wherein the values of the pulse rate and MET are plotted for several days and can be played to show their change over the 24-hour period. In the example, the size of each bubble represents phasic EDA at that time and the colour represents body temperature, the position on the Y axis for the MET value, and the position on the X axis for the pulse rate. This visualisation was discussed in interview II with clinicians, as presented in Chapter 5, but was not found to be an intuitive and a very fast way in which to show information.

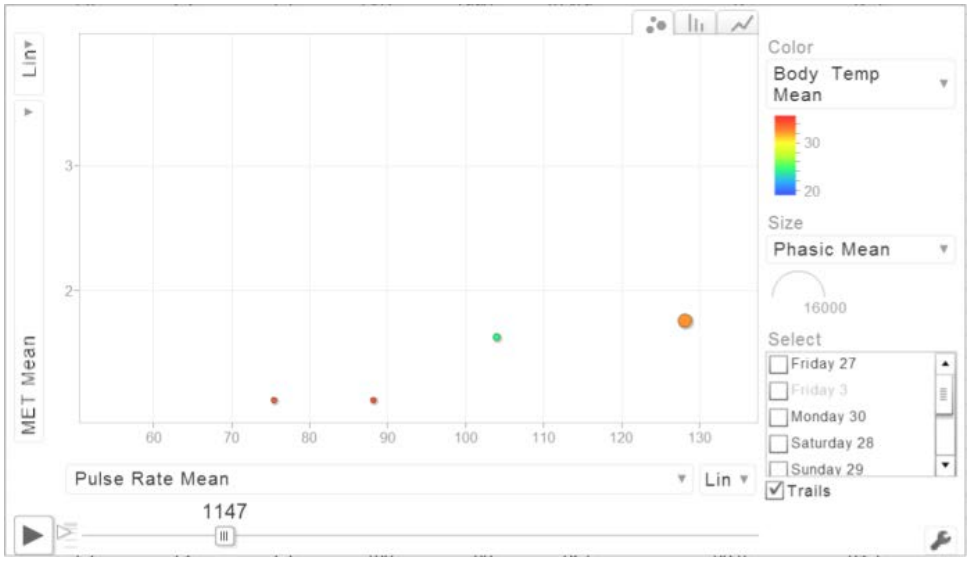


Figure 4.19 A snapshot taken during a Motion Chart Visualisation of EDA (size of bubble), body temperature (colour), pulse rate (position on X axis) and MET (position on Y axis)

4.7 Summary

This chapter presented data preparation and visualisation of CircadianSense‘s objective and subjective data of interest for clinicians. Scilab was used to process data because it is widely used, is a free academic and scientific software with multiple libraries for numerical computation. However, data processed was converted to CVS files readable by Excel, which is common software used in the home and office. Excel would enable clinicians to manipulate and interact with data. However, as per the results of interviews and focus groups with clinicians, the time available with patients was sparse. Analysis and processing are not tasks that clinicians would be interested in undertaking. Manipulation of visualisations would be limited to the selection of signals to be displayed with different time averages. The improvements suggested by clinicians go in the direction of exploring visualisation that could be used to make comparisons of data over long periods of time and observe trends of data.

CHAPTER 5
CLINICAL STUDY INTERVIEWS AND ASSESSMENT RESULTS

5.1 Introduction

This chapter describes the clinical study of two semi-structured interviews. Interviews were audio-recorded with permission from the participants. Audio and annotations of interviews were qualitatively analysed. Firstly, semi-structured interviews were conducted to explore personal experiences with wearable devices, gadgets, and possible scenarios and ideas for adopting medical wearable prototype systems and relevant medical information to be collected. Relevant topics from the first interviews served as a guide to exploring in more depth in the following semi-structured interview for possible medical implications of data collected by CircadianSense and assessments of visualisations. The evolved proof-of-concept CircadianSense was the result of experimental testing by the research team, recruited participants, and clinical collaborators. All of these participants provided feedback in order to make changes to the system so as to improve the comfortability and reliability of data. As CircadianSense is intended to be used in clinical settings or daily life activities, an assessment was made by all participants by scoring features and a comfort assessment of all of its on-body sensing units to identify areas of improvement for further refining of the system, as discussed in Chapters 6 and 7, with larger participation in focus groups with general practitioners and wearers in Mexico.

5.2 Participants

Table 5.1 summarises participants‘ use of CircadianSense and their interview participation. The four interviewed anaesthesiologists are clinical staff of Queen Elizabeth Hospital Birmingham, working at the point of recruitment in Anaesthesia and Critical Care at the QEHB. Two male participants and two female participants took part in the interviews. One of the participants has worked on research projects involving interactive technology for the rehabilitation and issues of

pain management, sleep, and general well-being. This main clinical collaborator was the first to participate in both interviews I and II due to her experience of research into technology for medical applications. The other three participants were cited depending on their time availability. Recruitment was conducted through invitation by the first researcher. Consent forms and information sheets provided to clinicians are shown in Appendix A. All clinical participants were invited to send via e-mail information that they felt was missing in the interviews but important to consider. Clinician 3 recommended by e-mail the use of materials used in plastic surgery to reduce skin irritation. Clinician 1 made suggestions about visualisations of heat maps and histograms by e-mail.

Table 5.1 Participants, use of CircadianSense and interviews

Participant	**Use of CircadianSense**	**Interviews**	**Other feedback**
Clinician 1	Short-term trial + Hospital simulation	I and II	Discussions and two e-mails
Clinician 2	3 days + 3 nights	I and II (II by Skype)	
Clinician 3	3 days + 3 nights	I and II	Discussion and one e-mail
Clinician 4	Short-term trial (no data was recorded)	I and II	

5.3 Interview I

Interview I explored future scenarios and possible outcomes for wearable patient-monitoring systems like CircadianSense, and ideas for visualisations of the data were presented for consideration and discussion. As shown in Table 5.1, four clinicians participated in interview I. Feedback from this interview informed further work, including work on data visualisation, and defined the content for interview II. The interviews were transcribed, summarised and a compilation was made for qualitative analysis.

5.3.1 Interview I – Questions

The questions used in interview I were designed to learn about the clinician's personal experience of wearable monitoring systems and to explore their views on future patient-monitoring systems, including benefits, advantages, disadvantages and barriers to adoption. The questions are listed in Table 5.2. The proposed environmental and physiological variables to record were selected according to their feasibility and recommended in the literature review, as shown in Table 3.2 and Table 3.1, respectively. Questions were asked to determine possible additional signals to record and applications.

Table 5.2 Interview I system questions

System questions asked in Interview I
Q1: What, if any, is your past experience with wearable sensing systems/gadgets? Imagine a future scenario when a basic (core) CircadianSense system could be prescribed and, optionally, sets of different sensors added on. Q2: Compared to CircadianSense, what sensors would be ~~–c~~ore" and what might be optional? Q3: What do you think would be the potential for a system like this? Q4: How could it benefit clinicians? Q5: How could it benefit patients? Q6: Would there be any disadvantages? Q7: What do you imagine would be the barriers to adoption?

The question responses and comments are summarised below in the order shown in Table 5.2. Where responses were varied, examples of individual reports are provided.

5.3.2 Interview I – System question responses

Q1: Experience with wearable devices or gadgets

Only clinician 3 reported no experience with wearable devices or gadgets for medical applications. The remaining clinicians were familiar with activity gadgets to count steps and measure energy consumption. Clinician 1 reported experience with not only wearable devices or

gadgets to measure activity and sleep but also medical devices at the hospital to measure patients‘ parameters through telemetry. Clinician 4 also reported his experience with a wearable device (polysomnography) for a sleep study. However, these devices listed are confined to the hospital environment.

Q2: Core and optional sensors

All variables recorded by CircadianSense, as shown in table 3.2, were recommended by all clinicians to be either core or optional. A core sensor was listed by all clinicians: pulse rate. Clinicians, in addition to variables recorded by CircadianSense, listed as core sensors those of interest used in particular diseases. For example, clinician 1 recommended oxygen saturation in obstructive sleep apnoea and added accounts of blood pressure and blood sugar. However, clinician 1 also commented that it „depends on what it is used for". For clinician 2 the core sensors would be body temperature, ECG, and peripheral flow for Raynaud‘s disease. Optional would be sound levels and variables that change over hours or days. Clinician 4 was interested in respiratory rate, blood pressure, and heart rate. Optionally listed as core sensors were accelerometers and heart rate to compare the activity of patients for fitness.

Q3: Potential

The clinicians suggested the monitoring of patients in intensive care (including sensing of factors for delirium) and a wide range of applications wherein ambulatory real-world sensing would be beneficial, including the monitoring of people with obstructive sleep apnoea, of geriatrics, e.g. prostate problems, the assessment of physical activity for people with obesity, preoperative assessment, postoperative cardiac patients, and general assessment of patients‘ fitness and well-being.

Clinician 3 anticipated more scenarios for applications. Listed were intensive care, obstructive sleep apnoea, geriatrics, identifying and comparing how much environmental conditions of the hospital affect episodes of delirium, sleep in the intensive care unit (ICU) and somnolence, assessing physical activity of people with obesity, the elderly with prostate problems, postoperative cardiac patients, preoperative assessment, and fitness and well-being.

Q4: Benefit for clinicians

Clinicians 1 and 2 reported that the benefit would be that of gathering accurate data and comparing objective data with information reported by patients. Clinicians 1 and 2 also observed that data gathered in the patient‘s environment would provide information on the behaviour of signals. Clinician 3 found as benefits saving money in sleep studies, data potentially guiding treatments, helping to improve environmental conditions in the hospital, and data helping to assess the effectiveness of treatment. Clinician 3 gave examples in which gathered data can be used, e.g. comparing before and after an intervention, comparing events of delirium, and assessing how machines used in sleep apnoea interfere with sleep of the sufferer and partners. Clinician 4 reported as benefits continuous monitoring, an early-warning system, better focus on resources and interventions in the hospital based on data recorded, and assessing the effectiveness of interventions.

Q5: Benefit for patients

All clinicians agreed that the benefit of CircadianSense for patients would be that of monitoring patients in the real world. Clinician 1 reported that CircadianSense would provide accurate and extra information of patients and not only what they report in the appointment. Clinician 2 also observed as benefits a cost-effective system with which to gather data in a real scenario and patients not staying in the hospital. Clinician 4 reported as a benefit continuous monitoring.

Q6: Disadvantages

Clinicians 1 and 2 reported discomfort in respect of wearing the system and sensors. Clinician 1 reported usability of the system and accuracy and meaningfulness of data. Usability items included the time during which to wear the system as well as the system being difficult to use. Clinician 2 suggested that the system can interfere with the activities that patients perform, and wearing the system can be time-consuming, as well as costly if it is damaged. Clinician 3 found as disadvantages that the system has to comply with safety regulations, and infection control. Clinician 4 reported that the system creates a lot of data which requires data processing and analysis, as well as the cost of maintenance of software. Clinician 4 also found as a disadvantage infection control.

Q7: Barriers to adoption

Clinician 1 reported on data not being useful, accurate and relevant, and the lack of usability regarding whether the patient is able to use it. Clinician 2 mentioned the time in which to download data and analyse it, adding an extra step in the management of the patient, interfering with what patients do, and whether clinicians do not trust the device. Clinician 3 reported as barriers the cost and effectiveness of the system. The clinician needs to be familiar with the system. Clinician 4 also reported cost and resistance to changes by clinicians.

5.3.3 Interview I – Data and visualisations

The sequence of data and sample visualisations viewed in interview I are shown in Table 5.3 together with the questions asked and the points at which comments were invited.

Table 5.3 Sequence of data and visualisations presented to clinicians

Interview I. Data and ideas for visualisations presented to clinicians
D1: Datasets in Excel Question: Are you familiar with Excel?
D2: Scatterplots of variables including energy expenditure (as MET), pulse rate, actigraphy, and body temperature Comments invited.
D3. Data granularity. Example scatterplots of mean MET with the three granularities (15 minutes, 1 hour, and portions of the day) Question: What granularity do you find more useful?
D4. Uncertainty. Scatterplots of mean pulse rate with granularities of 15 minutes and 1 minute. Question: How many valid minutes of data are required for a valid 15-minute summary?
D5. Heat map visualisation examples in Excel Comments invited.
D6. Icon fields Comments invited. Question: Is the set of icons intuitive? Is anything missing?
D7. Histograms of 15-minute mean MET Comments invited.
D8. Motion chart visualisation example Motion chart with different variables for axes, bubble size, and colour. Comments invited.

The question responses and comments are summarised below in the order shown in Table 5.3. Where responses were varied, examples of individual reports are provided.

D1: Datasets in Excel

All clinicians were familiar with Excel and also with bar charts, histograms, heat maps, and scatterplots.

D2: Scatterplots of variables including energy expenditure (MET), pulse rate, actigraphy, and body temperature

Scatterplots of different variables recorded and shown to clinicians were understood. Explanation of variables was given to clinicians. For example, an increase in actigraphy, pulse rate and body temperature of one participant with disturbed sleep, as shown in 4.11, also shifts in the circadian cycle of body temperature of participant 1 when sleeping at different hours, as shown in 4.12. All clinicians reported that the behaviour of the signals was as expected.

D3: Data granularity

Clinician 1 reported that the granularity to be used depends on what condition one is examining. Displaying data with averages of portions of the day provides highly summarised information; on the other hand, 15-minute mean granularity gives much more detail of the variable. Clinician 3 also reported that summaries are important and low granularity can be used for data that does not appear to be correct. Clinician 2 reported as preferable granularities 1 hour and portions of the day. Clinician 4 reported that when looking at the dataset there is too much data in it, but when data is visualised it is easier to interpret.

D4: Uncertainty

Clinicians were shown daytime minute-by-minute pulse recordings, as shown in 4.14, during activity, where many gaps in the data were visible due to the removal of invalid observations. The clinicians were then shown 15-minute averages of the pulse rate, as shown in Figures 4.10 and 4.11, calculated for the same data using any and all valid 1-minute instances. This data appeared to be more complete and had few gaps.

The pulse rate is one variable that is susceptible to having unreliable data. It was explained to clinicians that the 15-minute mean pulse rate variable was calculated on the number of valid

minutes. That is to say, if there are 7 minutes with valid data the mean, maximum and minimum are calculated for the 7 minutes. Clinicians were asked the following question: How many valid minutes of data are required for a valid 15-minute summary?

Clinician 1 reported that the percentage of invalid minutes per period of 15 minutes to discard data is 50% or 75%, but also mentioned that the percentage depends on the pathology. Clinician 2 reported ideally 0% and no more than 50%. Clinician 3 reported that it is more important to have constant readings in the hospital so as to see trends. Clinician 4 reported no more than 20%, although he also mentioned that ~~"~~the more significant and the more variable, the more continuous readings". An example of this would be cardiopathy.

D5: Heat maps

Clinicians were shown and explained a heat map of users and their opinions were asked. Clinician 1 asked if ranges could be individualised. It was also observed that heat map overviews may help to test hypotheses by observing when high or low values are present and the possible variables that triggered that condition or the relationship with other variables, including data from the daily log visualised as icons, as shown in Figures 4.16 and 4.17. Clinicians 2 and 3 observed that abnormal values are easily identified, since they present lighter or darker tones than those of the rest of the values. Clinician 4 observed that heat maps contain a lot of information but highlight the exceptions, and could be used as an early-warning system by tailoring the ranges.

D6: Icons

Icons represented information that clinicians were interested in being annotated in the daily log, the discussion of the icons suggested by clinicians is presented in section 4.2.2. The evolution of the set of icons is shown in Figure 4.2. a) shows the proposed icons shown to clinicians. b) shows the changes suggested by main clinical collaborator, c) changes suggested by the other 3 clinicians and d) changes recommended by GPs in focus group 3.

D7: Histograms

All clinicians agreed that histograms can be used to summarise data. Clinician 1 reported histograms as being useful in helping to explain associations between signals. If there were an

increase in pulse rate or body temperature, more bars would be seen on the right side of the histograms. Clinician 3 reported that histograms could provide information on the fitness of a person before an intervention and identify people at risk. In this scenario, histograms of energy expenditure would show changes in the distribution of the bars to the right for more physical activity. Clinician 4 reported that histograms render data easy to compare. If one variable were observed over several days, comparisons of the histograms would indicate a reduction or increase of the variable.

D8: Motion charts

Motion charts were presented to clinicians. These motion charts were with datasets wherein different combinations of variables were chosen to modify the size, colour, and x and y positions of the bubbles, as shown in Figure 4.19. Clinician 1 reported that motion charts were found to be difficult to interpret and depend on brain capacity to maintain data information while things move quickly on the screen. However, motion charts could be a way in which to demonstrate a phenomenon or recognise a disease by comparing how data moves. Clinician 2 reported that it can be useful for people who are used to analysing data like that, suggesting that it can be used to compare patients‘ data behaviour. Clinicians 3 and 4 reported that data is displayed quickly. Visualisations need to be intuitive and not require too much clinician training. Clinicians need to be trained to identify what normal data looks like.

5.3.4 Summary

The clinician‘s responses to system questions in interview I helped to define usability refinements made to CircadianSense and guide work on data analysis. The responses of clinicians suggest that the variables recorded could extend the use of CircadianSense to other applications, such as the assessment of general well-being, preoperative and postoperative assessments, and the assessment of patients‘ fitness. Furthermore, more variables could be added, such as respiratory rate and peripheral flow for other conditions such as Raynaud‘s disease and sleep apnoea.

The responses of clinical participants are in concordance with the benefits reported in the literature review. The benefits comprise reducing costs, and observation of patients‘ data in their environment (and not only in the hospital) with a reduction of hospital resources. These

recordings would complement reports of the patient and provide early warnings for different conditions and assessment of the effectiveness of treatments.

In addition to issues reported in the literature of discomfort and usability, clinicians‘ concerns were related to complying with safety regulations, and infection control. Particular attention has to be paid to the variables to be recorded, analysed and visualised to provide relevant and useful data to clinicians, as irrelevant data would be a barrier to adoption. The system records raw data and this information can be displayed in various forms that need to be explored so as to produce and present useful and meaningful data. A system that is easy to use for both users and clinicians is a relevant feature. However, for clinicians this includes data that is easy to analyse in a short period of time, as the time for training and analysing data is limited. This includes time in which to extract conclusions from visualised data, since data processing and analysis are time-consuming tasks that could add an extra step.

In data visualisation there was an emphasis on simpler and more intuitive visualisations. Despite having been anticipated as an interesting way in which to view multidimensional data over time, the negative responses regarding motion charts meant that they were not pursued further. Instead, better use of histograms was investigated, using examples of other visualisation with the aim of possibly understanding relationships between data and observing trends and making comparisons.

Literature on wearable health-monitoring devices has focused on improving the reliability and accuracy of data. However, clinicians‘ responses suggest that observations of trends are more important in monitoring diseases. Gaps of data were not seen as a problem, except for diseases wherein quick changes indicate a condition.

5.4 Interview II

Interview II began with a reminder of the CircadianSense system, sensors, and a description of data of two participants (1 and 5). Data of these two participants was chosen because one of the participants has disturbed sleep, aspiring towards differences between these two participants showing a difference in the visualisations to explain their data behaviour. The sequence of visualisations and questions is summarised in Table 5.4.

Table 5.4 Sequence of data and visualisations presented to clinicians

Interview II. Data and visualisations presented to clinicians
D1: Scatterplots of variables of energy expenditure for two participants (as MET) with the three granularities (15-minute mean, 1 hour, and portions of the day) Comments invited.
D2: Histograms of 15-minute mean MET for two participants Comments invited.
D3: Heat maps Comments invited.
D4: New set of icons Comments invited.
Q1: How could these (visualisations) be used for the following? Circadian cycle, sleep, sleep apnoea, preoperative evaluation, postoperative evaluation, lifestyle evaluation, rehabilitation, and intervention evaluation

D1: Scatterplots

Scatterplots were reported as being useful for comparison when data of several days is overlapped, as presented in Figures 4.11 and 4.12. Clinicians recommended averages of data over long periods of time to observe trends and make comparisons. On the other hand, averages of short periods of time enable observing abnormalities but it is a time-consuming task.

D2: Histograms

All clinicians reported that histograms are useful for comparison with how bars are distributed in recordings of several days. If detailed information were required it could be provided by averages of data in short periods of time in the dataset or scatterplots, although scatterplots would be preferable due to the easy way in which to see low and high values.

D3: Heat maps

Despite attempting to make the heat maps more intuitive, clinician 2 reported that heat maps were not easy to interpret: "*Okay if you are interested in detail but frustrating otherwise*". Other clinicians reported that abnormal values can be easily detected, although the ranges need to be adjusted to highlight the abnormal values.

D4: New set of icons

These were reported as being good for a general overview. Another icon was recommended for distinguishing between healthy and unhealthy snacks and meals. The final set of icons is shown in Figure 4.2

Q1: How could these data visualisations be applied in the following?

In interview I, possible applications of sleep apnoea, preoperative and postoperative, rehabilitation were anticipated with data collected and complemented with other variables, such as blood pressure, blood sugar and pulse oximetry. These applications were discussed with clinicians and summarised in Table 5.5. However, the applications for particular conditions of the patients were commented upon by clinicians according to their expertise or interest. Clinicians were also asked to comment on the possible visualisations for the applications suggested.

Table 5.5 Summary of Q1 suggestions for clinical application

Application	**Variables to monitor**	**Examples of clinical application**	**Possible visualisation examples**
Circadian cycle (Clinician 1)	All including diaries and RCSQ + blood pressure	Impact of rest on shift workers	Heat maps to see abnormal values
	Heart rate, temperature, ambient light, actigraphy	Sleep disorders, neurology, psychiatry	Scatterplots
Sleep (Clinicians 1, 3 and 4)	All including diaries and RCSQ	Community sleep assessment, 1 week of recordings	Scatterplots, histograms
	REM, actigraphy	Clinical psychology	Heat maps
Sleep apnoea (Clinicians 1, 3)	All including diaries and RCSQ; CO2 levels, oxygen saturation and blood pressure	Diagnosis of sleep apnoea, impact of CPAP intervention, 24 hours of recordings	Heat maps to see abnormal values

	REM, actigraphy	Clinical psychology, neurology, respiratory specialist	Heat maps
Preoperative evaluation (Clinician 4)	All including diaries and RCSQ; blood pressure and CO2 levels	Risk assessment before surgery, 3 days and 3 nights of recordings	Heat maps
	Pulse, oxygen saturation, ECG, body temperature, blood pressure	Cardiac patient	Histograms
Postoperative evaluation (Clinician 2 and 4)	All including diaries and RCSQ; what variables to add depends on what is evaluated; they can be oxygen saturation and levels of activity	Bariatric surgery, 1 day of recordings	Histograms to see trends and scatterplot with overlaid data of several days
	Oxygen saturation, REM, actigraphy, blood pressure and general sleep assessment		
Lifestyle evaluation (Clinician 1 and 2)	All including diaries and RCSQ	Weight loss guidance, fitness, levels of activity in diabetics	Histograms to see trends
	Sleep assessment, ECG, stress	Occupational health	
Rehabilitation (Clinician 4)	All including diaries and RCSQ; oxygen saturation and blood pressure		Scatterplot and histograms of MET
		Physiotherapy	
Intervention evaluation (Clinician 4)	All including diaries and RCSQ		
	Sleep assessment, melatonin, pre- and post-data.	Joint replacement, pre- and post-evaluation	Scatterplot and histograms of MET

5.4.1 **Summary**

Simpler overview visualisations with fewer variables were preferred. The variables to display should be those that are closely related, e.g. pulse rate, body temperature, and energy expenditure. Three clinicians had the opportunity to wear the system to collect data. They made recommendations to improve CircadianSense, e.g. suggesting wireless telemetry of patient data to surgeons, with an option to set alarms according to sensed data. In general discussion surrounding the system format there were suggestions for wristband solutions, combining sensors into one or two positions with wireless communication, real-time monitoring, and alternatives to adhesive attachments and/or decreasing the system weight. One clinician, who wore the system at night, found the processor box to be uncomfortable and big.

All clinicians were interested in visualisations to make comparisons over periods of days and to observe trends. Scatterplots of averages of hours or longer and histograms give the opportunity to contrast the behaviour of the data.

In addition to registering in a daily log typical information on food, stimulants, sleep quality or physical activity of the patient, emotional states of the person were recommended because of the influence they have on disease. Further feedback from other clinicians and one researcher recommended CircadianSense validation using a sleep laboratory and a study with 100 healthy participants recording over 7 days and nights. These recordings were suggested by clinicians to be used for training purposes and compare visualisations of different patients. Time in which to extract conclusions from data, including all of the steps necessary such as processing, analysing and visualisation, should be straightforward and not time-consuming because of the little availability of time that they have.

5.5 Participant Evaluation of CircadianSense

Assessment of CircadianSense was conducted using the questionnaire shown in Figure 5.1. The original maturity assessment questionnaire was published by Pantelopoulos and Bourbakis (2010) (as shown in Table 2.1 of Chapter 2), which comprises 16 features (F1–F16) for rating and weighting by users/patients, clinicians, and system designers/engineers. This questionnaire was used as a starting point, as it contains many of the features recommended in the literature for wearable health-monitoring systems. However, as discussed in the literature review in Section 2.8, the methodology followed by Pantelopoulos and Bourbakis (2010) to assess and compare the maturity of wearable health-monitoring systems reported in the paper is not clear. This is a generic questionnaire in which some of the features might be important for some WHMSs but not relevant for others. Moreover, more features that have been reported both in the literature and by clinicians need to be assessed, e.g. hygiene and disinfection (also reported by clinicians in interview I), metrics of data not compatible with clinical standards, and the lack of understanding of how algorithms calculate variables (Jeon and Finkelstein, 2015). An average of the weights and scores of the features from these three perspectives would lead to wrong conclusions; for example, a feature could be important for a clinician or a user but not for a manufacturer. In this condition a low score could wrongly conclude that it is not an important feature. Furthermore, not all features are equally important to users or clinicians and even the relevance of the feature depends on the application of the WHMS. The use of this questionnaire was used to find room for improvement of CircadianSense through an assessment and comments of the features by participants, clinicians and engineers.

The omission of clinical hygiene was particularly notable; therefore, a new feature (N17) was added. Moreover, with the increase in security concerns over the period of the research, it became apparent that a system such as CircadianSense could be a potential security concern.

Wearers of the system were advised not to use the system at airports or train stations and to be mindful of security concerns. The possibility of a security alert was added as a new feature (N19). Computational & storage requirements (F8) in the original questionnaire made an unclear contribution and was removed, as was wireless assessment (F13). Reliability (F11) and fault tolerance (F14) were combined as one feature. Wearers, clinicians and engineers were asked to assign weights and ratings from 1 to 5 to the features listed in Figure 5.1 as a patient/wearer, clinician and/or engineer/system designer.

Feature	Feature importance 1: not at all 5: very high			Feature description (and rating scale)	Feature rating for CircadianSense prototype			Feature rating for CircadianSense's Potential		
	Wearer/ Patient	Clinician	Engineer		Wearer/ Patient	Clinician	Engineer	Wearer/ Patient	Clinician	Engineer
Wearability (F1)				For example, system comfort, weight and size. Rating: 1: very poor 5: very good						
Intrusion (F2)				For example, interference with patient movement, behaviour or daily activity. Rating: 1: very poor 5: very good						
Aesthetic issues (F3)				Affecting the patient's appearance. Rating: 1: very much 5: not at all						
Potential for security alert (N19)				Could the system be construed as a security threat, e.g. at an airport? Rating: 1: very much 5: not at all						
Data security (F4)				Encryption and protection of patient data. Rating: 1: very poor 5: very good						
Ease of use (F9)				For example, ease of putting on and taking off, and switching on and off. Rating: 1: very poor 5: very good						
Access to data (N20)				Ability to access recorded data. Rating: 1: very poor 5: very good						
Maintenance (F5)				Recharging batteries and any servicing while in use. Rating: 1: very poor 5: very good						
Real-life application (F6)				Applicability to real-life and real health conditions. Rating: 1: very little 5: very much						
Performance in real-world use (F10)				Rating: 1: very poor 5: very good						
Availability of results (F7)				Timeliness of data and results. Rating: 1: very poor 5: very good						
Reliability (F11+F14)				Rating: 1: very poor 5: very good						
Cost (F12)				Rating: 1: very poor 5: very good						
Scalability (F15)				For example, potential to add sensors. Rating: 1: very poor 5: very good						
Decision support (F16)				Support for data interpretation. Rating: 1: very poor 5: very good						
Clinical hygiene (N17)				For example, disposable electrodes. Rating: 1: very poor 5: very good						
Data presentation (N18)				Presentation of data for clinician and user. Rating: 1: very poor 5: very good						

Figure 5.1 Set of features used to assess CircadianSense

Literature reports that comfortability and appearance become less relevant when a user of a medical device perceives higher usefulness of the system. All of the features assessed in Figure 5.1 cannot be considered equally important. Discussions in the interviews found that barriers to adoption include not trusting devices, data collected being not relevant or meaningless that are closely related to features of real-life application (F6), performance in real-world use (F10), reliability (F11), interference robustness (F13) and fault tolerance (F14). More features identified in the literature and by clinicians that were pointed out as being important were hygiene and data presentation so as to extract conclusions from visualisations to compare and observe trends. These new features were included as clinical hygiene (N17), data presentation (N18) and access to data (N20).

The assessment of the features of Figure 5.1 was made to find issues of CircadianSense that could be improved. Respondents in the assessment of the features of Figure 5.1 are shown in Table 5.6. One clinician was not available and didn‘t participate in the assessment of CircadianSense.

Table 5.6 CircadianSense assessment questionnaire respondents

Participants	**Respondents**	**Description**
Wearers	10	One UoB-recruited participant plus six engineers and three clinicians
Engineers	6	Three undergraduate students and three members of the research team
Clinicians	3	QEHB clinicians

As anticipated by the literature and the results of the clinical interviews, issues related to reliability and evidence of perceived usefulness of data recorded and meaningful data were the aspects considered more important. As shown in Figure 5.2 and the numerical results in Table 5.7, the weights of real-life application (F6), performance in real-world use (F10), data security (F4), reliability (F11–F14), clinical hygiene (N17) and access to data (N20) were considered the most important features for clinicians. Wearability (F1) was a highly weighted feature for users, clinicians and engineers. However, aesthetic issues (F3) is evidently more important for users than for clinicians or engineers.

Table 5.7 Results of the weights for the features

Feature	User	Clinician	Engineer
Wearability (F1)	4.35	4	4.16
Aesthetic issues (F3)	3.6	2.33	2.6
Data security (F4)	3.45	5	3.83
Access to data (N20)	3.5	4.83	4.83
Real-life application (F6)	4.6	5	4.6
Performance in real-world use (F10)	4.55	5	5
Reliability (F11+14)	4.3	4.66	4.6
Clinical hygiene (N17)	4.6	5	3.5
Data presentation (N18)	4.3	4.66	4.5

The assessment of feature weights by users, clinicians and engineers is shown in Figure 5.2.

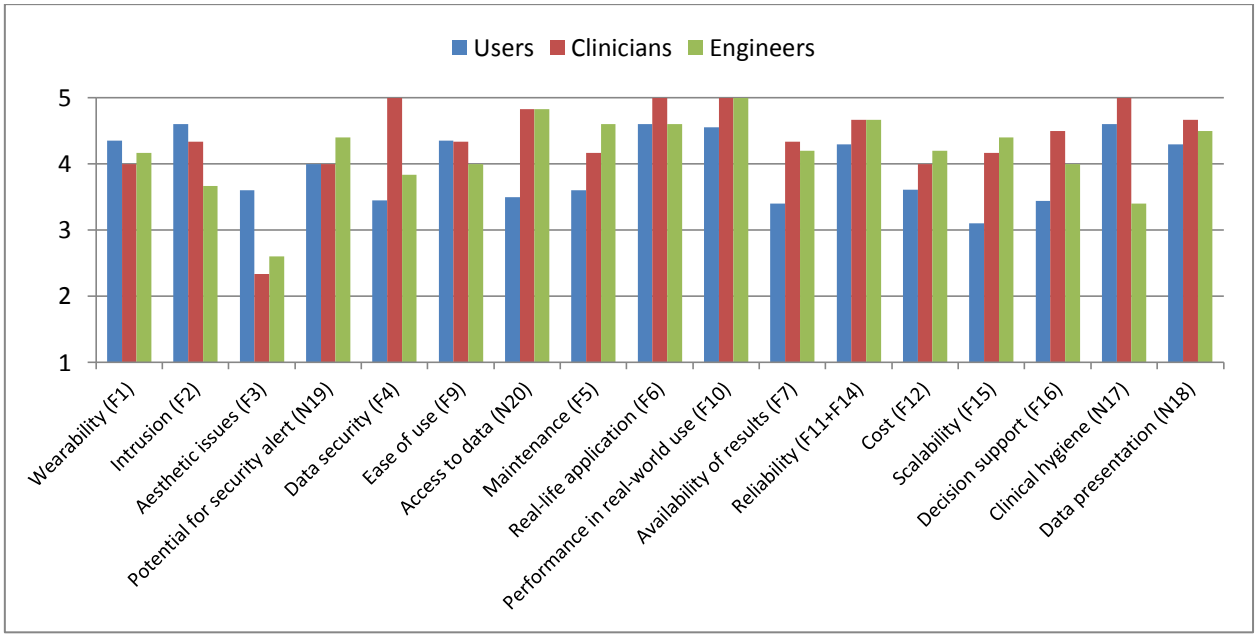


Figure 5.2 Assessment of feature weights by users, clinicians and engineers

The feature ratings for CircadianSense by users, clinicians and engineers are shown in Figure 5.3.

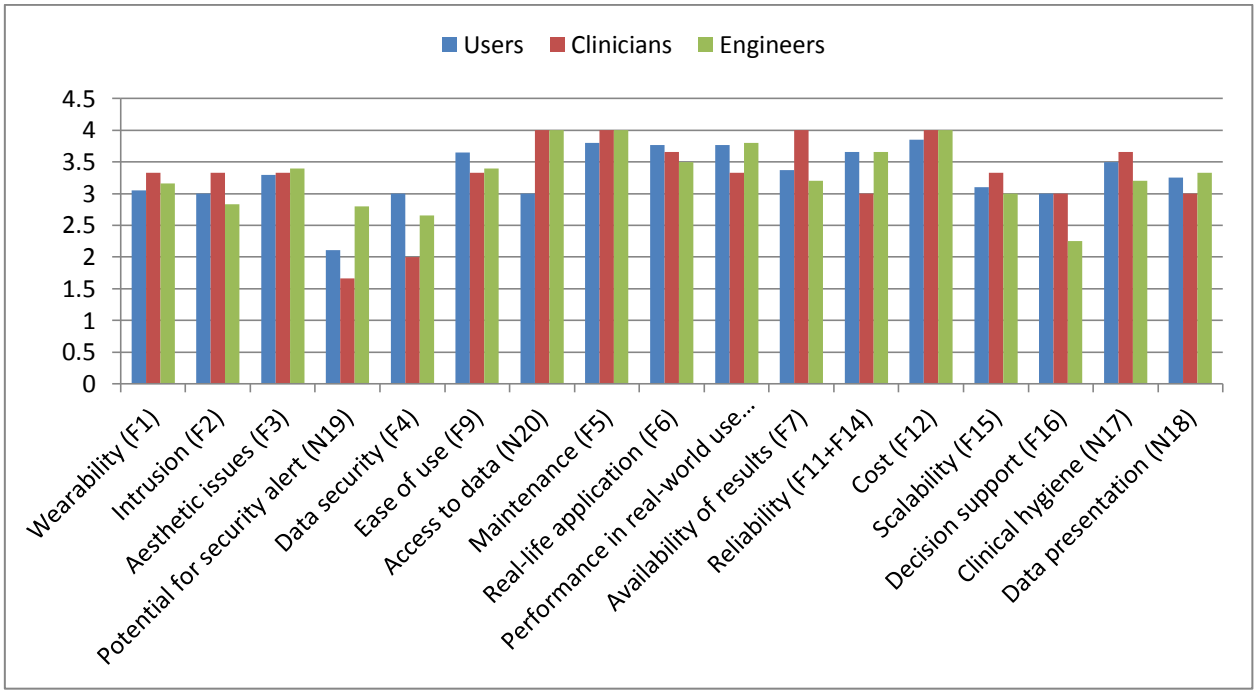


Figure 5.3 CircadianSense ratings by users, clinicians and engineers

The ratings of the features with the highest weight by users and clinicians are shown in Table 5.8.

Table 5.8 Ratings of the features of CircadianSense

Feature	User	Clinician	Engineer
Wearability (F1)	3.05	3.33	3.16
Aesthetic issues (F3)	3.3	3.33	3.4
Data security (F4)	3	2	2.66
Access to data (N20)	3	4	4
Real-life application (F6)	3.77	3.66	3.5
Performance in real-world use (F10)	3.77	3.33	3.8
Reliability (F11+14)	3.66	3	3.66
Clinical hygiene (N17)	3.5	3.66	3.2
Data presentation (N18)	3.25	3	3.33

Comfortability or wearability (F1) and aesthetic issues (F3) could not be so important for a system that has to be worn for only a short period of time. However, the intended use of CircadianSense is for periods of days, which made important the assessment of these features and were discussed in detail. It was clear, however, while testing the system that different on-body sensors were perceived differently. The participants‘ assessment of comfortability for each sensor is shown in Table 5.9 (respondents who did not use the sleep system did not provide responses regarding the sleep sensors).

Table 5.9 Scores of feature wearability for CircadianSense

Wearability (F1)	**Importance weight**	**CircadianSense rating**
User	4.35	3.05
Clinician	4	3.33
Engineer	4.16	3.16
Aesthetic issues (F3)	**Importance weight**	**CircadianSense rating**
User	3.6	3.3
Clinician	2.33	3.33
Engineer	2.6	3.4

The components assessed and shown in Figure 5.4 between uncomfortable (2) and ~~–ok~~” (3) were: the optical pulse sensor with an average of 2.22 for waking hours, and electrooculography (2.36) electrodes and the optical pulse sensor (2.86) for sleep. The scores of CircadianSense components show that the pulse sensor and EOG electrodes were the most uncomfortable components of the system. Four participants experienced skin irritation from sensor attachments, e.g. from EDA and EOG electrodes and sticking plasters for temperature and pulse sensors. Two participants reported that the sleep processor box was heavy.

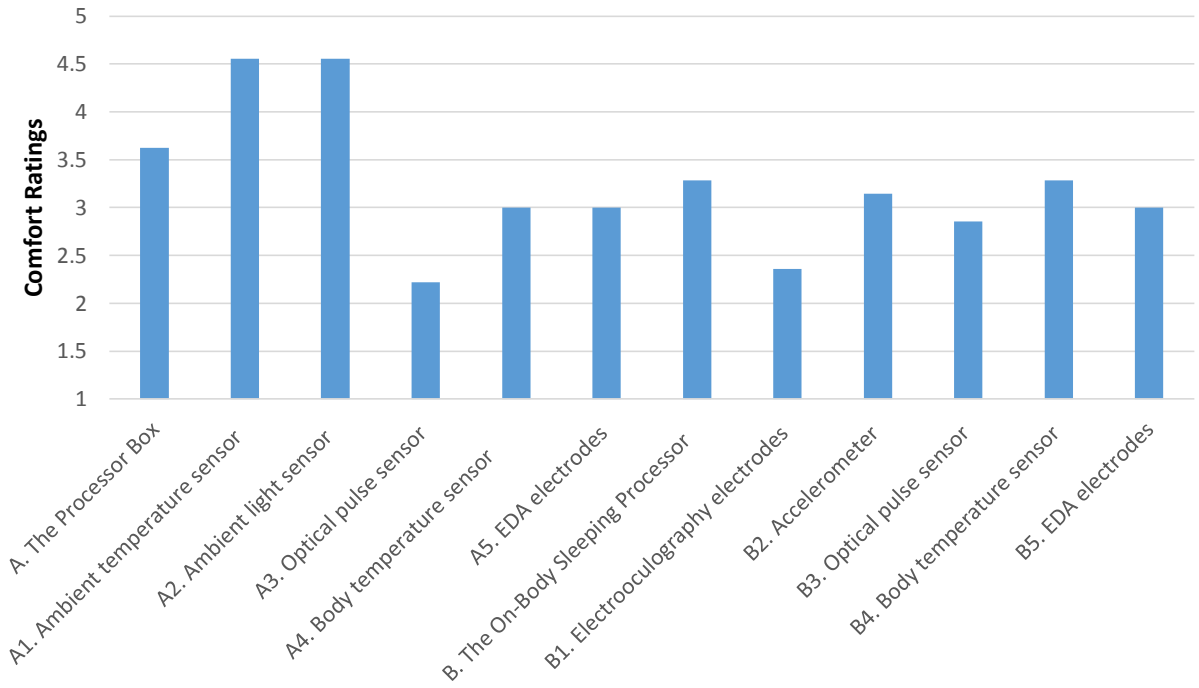


Figure 5.4 Results of individual assessment of comfortability for CircadianSense components (1 = very uncomfortable, 5 = did not notice)

5.6 Discussion

5.6.1 Sensors and hardware

Potential benefits of a system such as the CircadianSense system were identified by all participants. A real-world, multi-parameter monitoring system has applications beyond investigation of the circadian cycle, also being suitable for more general use in terms of assessing interventions and treatments and establishing a prognosis. Currently, in general practice, physiological parameters can only be sampled in the surgery, clinic or laboratory and the only continuous data ‗acquired' is that of the patient's own subjective recollections. CircadianSense, by comparison, provides continuously monitored objective data, which would not replace patient reporting but could provide valuable additional diagnostic data. For many conditions, it was observed that this could result in a considerable economic benefit if patients were able to acquire data in their own homes rather than occupying hospital beds.

The potential drawbacks of the system are mainly concerned with regulatory requirements as well as technological acceptance by the users. Regulatory requirements include medical device approval from organisations such as the UK's Medicines & Healthcare products Regulatory Agency. A potential barrier to system uptake would be if patients found the system to be overly intrusive or if it interfered with their everyday activities. Although much progress has been made in terms of wearability and comfort, CircadianSense is an early clinical prototype and there is scope for improvements. Ideally, these would be informed by participation of all stakeholders, including real patients from selected cohorts as well as nursing staff and carers.

There was a broad consensus on the idea of a core sensing system, with additional optional sensors depending upon on the assessment required. However, there were different suggestions for the core sensor set. There would possibly be more than one set of core sensing systems, depending on the general application.

Relevant features for clinicians and users were real-life application (F6) and performance in real-world use (F10) as shows the weights in Table 5.7; however, the only way in which to provide evidence of meaningfulness and usefulness of data recorded is by conducting the collection of data of different patient cohorts in various scenarios and its usefulness for monitoring and

diagnosis of diseases to increase the ratings given in Table 5.8 by clinicians and wearers. Much of the literature on WHMSs recommends as future work the collection of data of patients. However, this step should be included in the development of the system so as to provide evidence of the benefit of the WHMS and to support its use.

Most of the wearers of CircadianSense were young students who are used to sharing data on social networks. The feature of data security (F4) was not important for these participants but could be more important for older people, who are not very active on social networks. However, many ethical issues arise when there is collection of data of patients. From this perspective, clinicians weighted this feature with 5 compared to a 3.45 weight average of wearers. Norms and regulations for medical data privacy should be observed and not dismissed, as it was not a very important feature for one of the perspectives. Clinical hygiene (N17) was weighted as very important by clinicians and participants. Disinfection and hygiene protocols are part of the medical procedures of clinicians and are continuously observed in hospitals and patient management. Surprisingly, there is little discussion and evidence of clinical hygiene being taken in the design and use of a WHMS.

A system being assessed with only a simple weight or score might lead to losing the opportunity to detect aspects to improve of the WHMS. For example, the feature of wearability (F1) was scored with 3.05 by wearers. From this it could be concluded that wearability or comfortability is ~~"~~good" for CircadianSense. However, a more detailed discussion with wearers found that the perceived uncomfortability of sensors is different. Pulse and EOG sensors were found to be the most uncomfortable elements of CircadianSense. Electrodes for EDA measurements left skin irritation on some participants after one day or more days of use. It was not rated as very uncomfortable, but issues of skin irritation need to be addressed for a WHMS that is intended to collect data for long periods of time. Furthermore, sticking plaster left skin irritation after several days of use. One clinical participant indicated that materials used for plastic surgery could be suitable for attaching sensors. These materials are indicated for long periods of use. Changes in EOG, pulse sensors, Ag/AgCl electrodes, and sticking plaster are recommended to increase comfortability. Averaging the weighting or scores of features of wearers, clinicians and engineers can lead to wrong conclusions and eventually produce a not clinically relevant device, as not all of the features have to be considered equally important. Clinical participants opened

areas of discussion to determine the relevant features and issues in the development of CircadianSense. The ratings of the features of CircadianSense in Table 5.8 shows that wearability, aesthetic and data security are necessary to improve.

5.6.2 **Data Visualisation**

The representation of uncertainty was an important issue in data visualisation. Physiological parameters were recorded with reliability as low as 50%. Views were mixed regarding how critical this was (ideally, of course, reliability would be 100%), but it was clear that the importance of reliable data was dependent on the application.

A key function of data visualisation was to indicate abnormalities in the recorded parameters to clinicians. In some cases this can be highlighted by identifying parameters outside of pre-set maximum and minimum thresholds. In general, it was the simpler and more familiar visualisations that the clinicians favoured, such as line charts, bar charts, and histograms.

Visualisation of data is an important task recommended in the literature so as to deliver useful and meaningful information to clinicians for purposes of diagnosis, prognosis and assessing treatments. However, there is a lack of information and discussion surrounding how to deliver relevant multivariable data to clinicians. In the interviews, clinicians suggested that visualisations should provide a way in which to summarise data and compare and observe trends in a quick and straightforward manner. The dataset was initially created in Excel, which is common software used in the home and office. However, during the interviews, clinicians expressed the little time that they have with patients. One concern was in relation to who would analyse and process the data recorded if a system like CircadianSense were available. It seems that visualisation should be available when the clinician wants to interact with data without adding steps to prepare or process data recorded. Visualisations of interest for clinicians comprised histograms and scatterplots of data averaged in long periods of time in order to observe trends and compare data. Moreover, there was an interest in displaying behavioural and emotional states of patients for a complete picture of the factors that have an influence on the disease. Comments of clinicians regarding the data collected of different physiological and environmental variables show the expected patterns, e.g. an increase in pulse rate when the wearer performed physical patterns and circadian rhythms of body temperature in conditions of

no disturbed sleep. Relevance of visualisation could be assessed if data of different patient cohorts were used to display data and determine whether there are differences. If differences are present in the visualisation of patients‘ data the feature data presentation (N18) could be scored more objectively by clinicians.

5.6.3 **Limitation of the Clinical Study**

Limitations of this clinical study included the number of wearers and clinicians who participated in the study. The experience and area of work of anaesthesiologists are confined to a hospital. A different perception of WHMSs could be complemented with a larger number of clinicians with different expertise and a larger number of wearers. Moreover, the one-on-one interviews without more clinicians did not enable clinicians to share ideas and discuss features in detail.

Evidence of CircadianSense for real-life application (F6), performance in real-world use (F10) and reliability (F11+14) was partially provided (as shows the low ratings in Table 5.8), as the data collected was from healthy participants. Data of healthy wearers and discussions concluded that the behaviour of data was as expected.

This work was extended by inviting 23 general practitioners who participated in four focus groups. In the focus groups, themes and topics relevant to CircadianSense were discussed in more detail to identify more issues and features relevant to the WHMS.

The results and discussions shown in this chapter are particular to solutions similar to CircadianSense, e.g. a WHMS for long-term recordings of raw data of different signals for offline processing without diagnosis or detection of abnormalities in real-time. A WHMS with different characteristics, applications or uses might need different features and address issues other than the ones detected in this study.

CHAPTER 6
FOCUS GROUPS RESULTS

6.1 Introduction

In the proof-of-concept study of CircadianSense based on one-on-one semi-structured interviews with anaesthesiologists, themes emerged that required deeper exploration. These key topics were 1) limitations and improvement of the information provided by patients to clinicians, 2) selection of objective and subjective variables related to the health problem, 3) ways in which to visualise and summarise multivariable data recorded, and 4) exploration of features desirable for a WHMS. This chapter shows a qualitative methodology followed for deeper investigation into the aforementioned themes. This study consisted of four focus groups conducted in the city of Leon, Mexico with general practitioners. Twenty-three general practitioners participated in four focus groups divided into three groups each. This approach was taken to allow group interaction between participants and the moderator, as well as sharing experiences and ideas. At the end of the chapter the results of the focus groups are analysed and presented. The results of the focus groups, along with the results presented in Chapter 5, were used to improve the WHMS developed.

6.2 Design of the Pilot Studies and Focus Groups

Two pilot studies were conducted with only one clinical participant. The aims of the pilot study were to refine the set of questions for the focus groups, identify potential problems or issues, such as repetitive or confusing questions, and estimate the time during which to conduct the focus groups. The answers of the participant provided ideas for new questions. After the two pilot studies the set of questions was refined for each one of the first two focus groups. The questions of the pilot study are shown in Table 6.1.

Table 6.1 Questions of pilot study 1

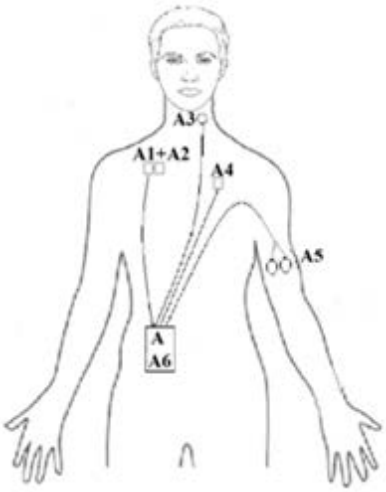
Pilot study 1 Objectives: Find limitations and issues in the information provided by patients Find relevant clinical data to be collected Find features desirable for a WHMS Set time and refine questions
1 How do you assess patients‘ conditions when you meet them? 2 What problems do you encounter when assessing patients? a) What information is missing when you talk to the patient? 3 How could patient assessment be improved? 4 What additional information would be useful? 5 When would you like to receive this additional information? 6 How would you like to receive this additional information? 7 What additional recorded variables would be useful? 8 Recorded variables can be subjective, objective, daytime and nighttime, physiological, environmental and activity-related (mention two or three examples). What would be useful to record? 9 Imagine that a wearable 24-hour patient-monitoring system is available that can record all useful information. a) Would you use it? b) When would you use it? c) What do you imagine it would look like? d) What would stop you using it for patients? e) How long would patients wear it? f) When would you have access to the data (anytime during recording or only at the end of the recording)? 10 Would patients have access to their own recorded data? 11 What features should the wearable system have?

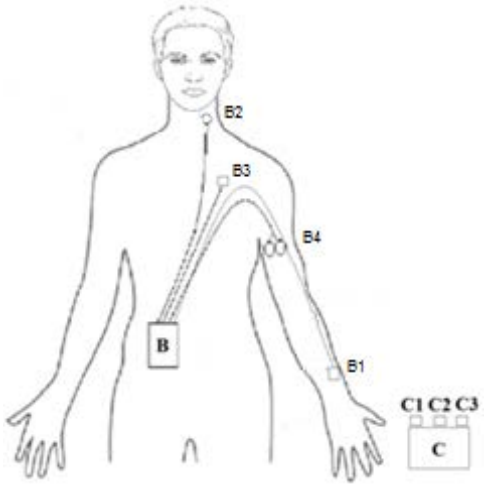
This pilot study lasted 1 hour and 15 minutes. It was found that it was necessary to help participants of the focus groups to think about possible ambient, physiological and behavioural variables. Therefore, question 9 was divided into categories of nighttime and daytime, as shown in Table 6.3, which contains the questions asked in focus group 1. Question 9 a) was removed

from the questions for focus group 1, questions 9 c) and 11 (as asked) were found to be repetitive, and question 9 e) was removed and asked in focus group 2. In focus group 2, as shown in Table 6.4, there is a list of possible uses for a number of conditions in which this question could fit better.

Table 6.2 Questions of pilot study 2

Pilot study 2 Find variables of interest listed in pilot study 1 and also recommended by literature Make improvements to the daily log Discuss possible visualisations and summarisations of data Set time and refine questions
1. This is a sketch of the system and the position of sensors both in waking and sleeping hours. What changes or recommendations would you make?





Waking-Hours System: A. On-Body Waking-Hours Processor A1. Ambient temperature sensor A2. Ambient light sensor A3. Optical pulse sensor A4. Body temperature sensor A5. EDA electrodes A6. Accelerometer	Sleeping-hours System: B On-Body Sleeping Processor B1. Accelerometer B2. Optical pulse sensor B3. Body temperature sensor B4. EDA electrodes Ambient Sleeping Processor C1. Ambient temperature sensor C2. Ambient light sensor C3. Ambient noise meter

The list of variables recorded is as follows:

Waking hours	**Sleeping hours**
Skin temperature	Skin temperature
MET	Actigraphy
Pulse rate	Pulse rate
Electro dermal activity	Electro dermal activity
Ambient light	Ambient light
Ambient temperature	Ambient temperature
	Ambient noise

What variables would you remove or add?

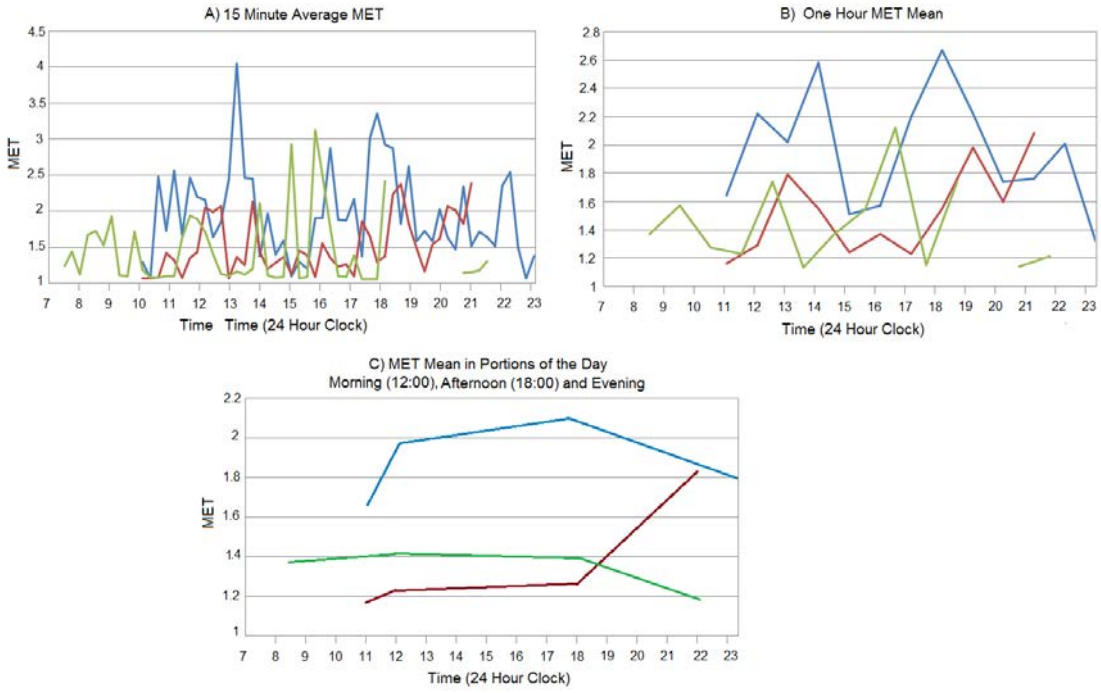
2. This a daily log proposed. What other information would you add or remove?

   Participant:_____ Date:_____

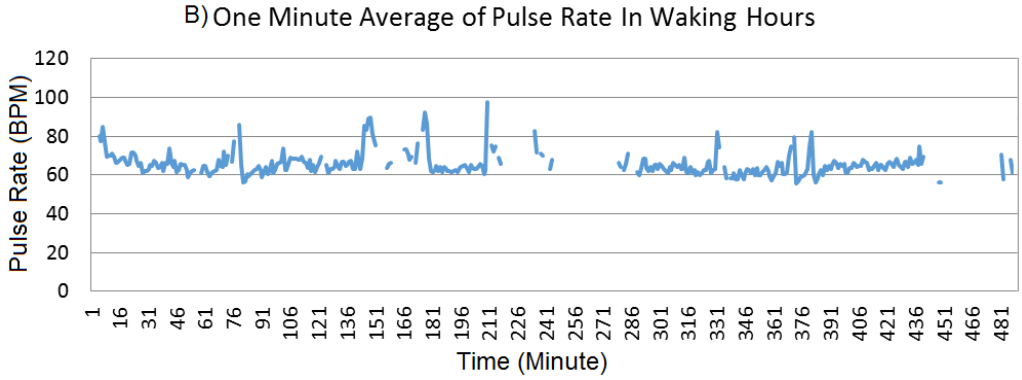
Time	Acitvity (light, moderate, intense)	Meals, snack (light, medium, large)	Stress	Stimulants Medicine	Sleep Naps	Any changes in behaviour due to wearing the system	System comments (sensor detached, removed)
6:00							
6:15							
6:30							

3. How do you imagine you would access recorded patient data? What would you prefer? (Any format or application software?) What device or devices would you use? How would you like the information to be displayed?
4. What could be the possible medical applications of the wearable system if the recording variables are the ones in the table?
5. There are variables that might be of interest but are not possible to measure in an ambulatory manner, e.g. blood sugar, blood pressure, etc. If you were interested in those variables, how would the protocol include them? For example, a patient going to the clinic to get blood sugar tested every day.

6. This is an example of energy expenditure. What periods of time would you like to average variables recorded?



7. This example of a pulse rate contains missing data. However, the averages can be calculated for the valid data alone to avoid discarding the data recorded. How would you like to obtain a measurement of the percentage of valid data in the averages displayed?



8. How would you like to obtain a measure of the percentage of valid data in the averages displayed?
9. What would you do with data with few periods of valid data? Would it be useful?
10. How could data recorded be summarised and annotated in the patient record?

In question 1 of Table 6.2 the participant was asked to add changes to a sketch of a wearable system with a proposed placement for sensors. In question 2 a daily log was presented and the clinical participant was asked to add relevant activity and behavioural information to be registered. After conducting the pilot study these activities were found to be very restrictive and limiting participants' responses. These questions and activities were changed in the focus group so that participants could imagine the system and think about the system and information to be annotated in the daily log, as shown in Table 6.4 in questions 2 and 4. After conducting these two pilot focus groups the final sets of questions were written for focus group 1 (Table 6.3) and focus group 2 (Table 6.4).

Table 6.3 Set of questions of focus group 1

<table>
<tr><td>Focus group 1</td></tr>
<tr><td>Objectives: To identify limitations and issues of the information provided to clinicians by patients
To obtain ideas for gathering useful subjective and objective data relevant to the patient and its handling</td></tr>
<tr><td>1. How do you assess patients' conditions when you meet them?
a) How long do you have?
b) Who are your patients?
2. What issues or limitations (if any) do you encounter with information provided by patients and in the clinical assessment that you make when you meet them?
3. How could these issues be improved upon?
4. If you could receive more information to help diagnose patients or assess treatment efficacy,
a) What additional information would be useful?
b) When and how would you like to receive that additional information?
5. Imagining that a 24-hour patient-monitoring system were available, what variables would be useful to record in the daytime and nighttime?
<table>
<tr><td>Physiological During the Day</td><td>Physiological at Night</td></tr>
<tr><td>Environmental During the Day</td><td>Environmental at Night</td></tr>
<tr><td>Activity-Related and Behavioural During the Day</td><td>Activity-Related and Behavioural at Night</td></tr>
</table>
6. What would you use data recorded for?
7. What do you imagine the system would look like?
8. What features should it have? For example, size, cost, ease of use, etc.</td></tr>
</table>

9. What would stop you using it for patients?
10. When would you like to have access to the data (anytime during recording or only at the end of the recording)?
11. Would patients have access to their own recorded data?

The set of questions of focus group 2, as shown in Table 6.4, was refined and completed through both the pilot study and the answers of focus group 1.

Table 6.4 Set of questions of focus group 2

Focus group 2

Objectives:
To get recommendations for recording and assessing objective and subjective data, respectively
To identify ways in which to summarise and interact with data

Table 1 shows physiological, environmental, subjective and activity-related variables that could be used to help you diagnose, treat and understand some diseases listed in table 2. You can add more variables if you think that they are necessary and you can add more diseases.

Physiological variables	**Environmental variables**	**Subjective and activity-related variables**	**Non-ambulatory tests**

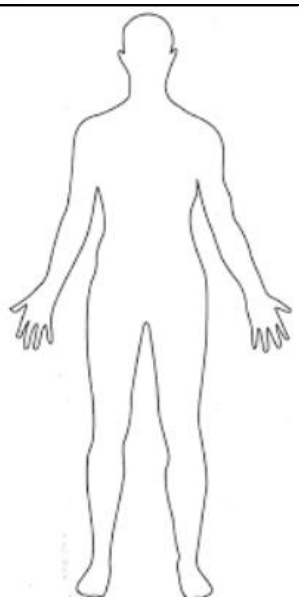
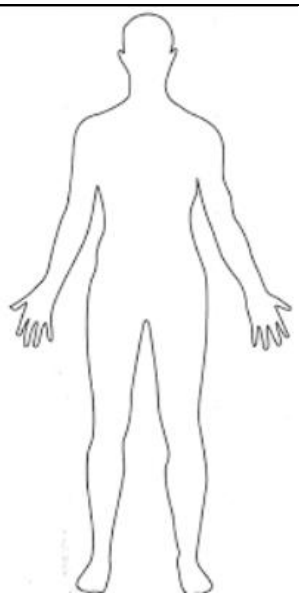
Table 2. With the variables of Table 1 and others that you think are necessary, add the variables of interest for better diagnosis and treatment of the diseases. Please start listing from the most important variable. Please also put a note indicating if that variable would be recorded during the night, day,

continuously or sampled and how often it would be.

Table 2. Variables to record for the monitoring, diagnosis, treatment and prognosis of various diseases

Disease	Physiological	Environmental	Subjective and activity-related	Laboratory tests

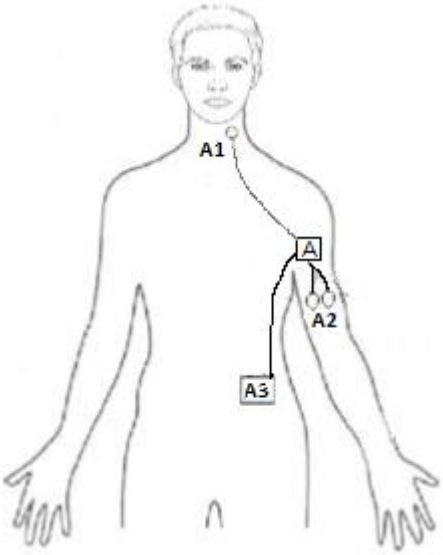
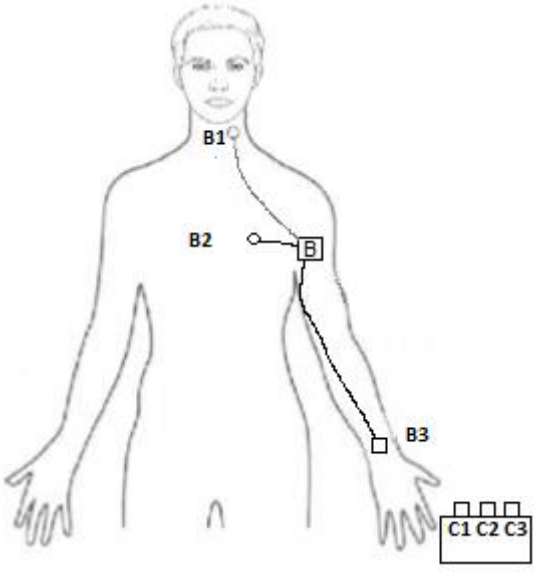
1. Please sketch where you would place the sensors for the variables of interest

	
Waking hours system	Sleeping hours system

2. If sensors are in distant places, how would you imagine connecting all sensors?
3. What activity-related and behavioural information would you be interested in for the diseases of Table 2? How often would that information be annotated? Paper, mobile? (for the daily log)
4. What would be the protocol for wearing the system for the diseases in which you are interested? For example, how often would the patient wear the system?

The set of questions of focus group 3 was selected after the analysis of the results of focus groups 1 and 2. This focus group centred on the analysis and assessment of visualisations. The system had not been built at this point and the data presented were those of CircadianSense.

Table 6.5 Set of questions of focus group 3

<table>
<tr><td>Focus group 3</td></tr>
<tr><td>Objectives:
Elicit opinions regarding preferences and thoughts in respect of the research prototype.
Receive feedback on scatterplots, heat maps, and icons used to summarise subjective information to determine changes and modifications for a better understanding and correlation of multivariable and multirate data.</td></tr>
<tr><td>1. Figure 1 shows a sketch of the placement of sensors on the body and the variables recorded. Is there any change that you would like to make?
<table>
<tr><td> 
</td><td> 
</td></tr>
<tr><td>Waking hours system:
A On-body waking hours processor
A1. Optical pulse sensor
A2. EDA electrodes
A3. Accelerometer</td><td>Sleeping hours system:
B On-body sleeping processor
B1. Optical pulse sensor
B2. Body temperature sensor
B3. Accelerometer

Ambient sleeping processor
C1. Ambient temperature sensor
C2. Ambient light sensor
C3. Ambient noise meter</td></tr>
</table>
</td></tr>
</table>

Figure 1 Placement of sensors in waking hours and sleeping hours

2. Examples of visualisations.
    i. Please see example 2.xlsx for visualisation of 15 minutes and heat map.
    ii. Please see three different granularities of data for MET in Figure 2.

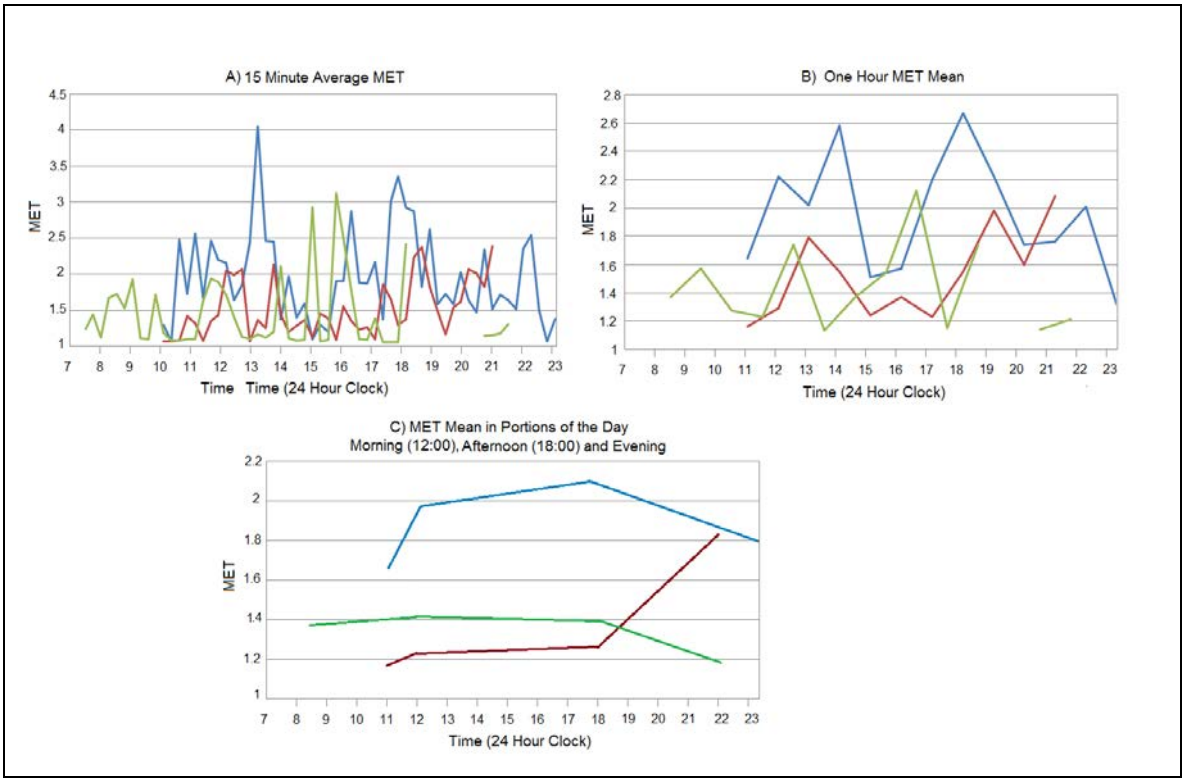


Figure 2 Three different granularities of data for MET. Figure A 15-minute average, Figure B 1-hour average, Figure C Portions of the day (morning, afternoon and evening). Sunday (blue), Monday (red) and Tuesday (green).

a) Are those averages useful?
b) Would you propose different data averages?

3. Objective and subjective data is summarised in the heat map
    a) Would that visualisation help you to extract relevant information?
    b) The set of icons is shown in Figure 3 to represent information in the paper log. Is there an icon that is missing or any that needs to be modified?

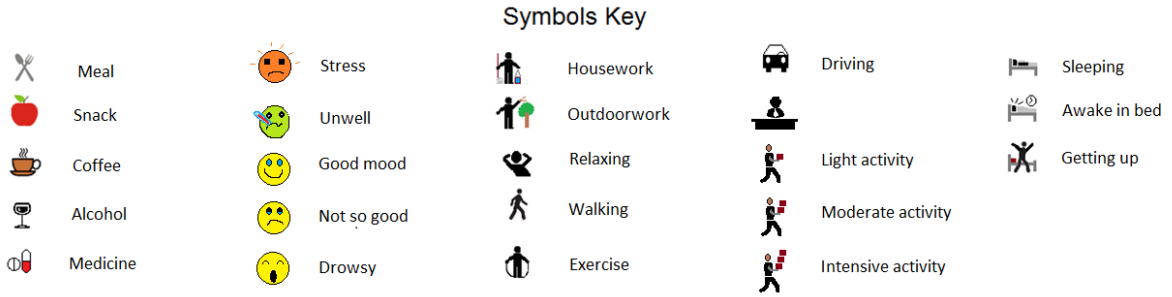
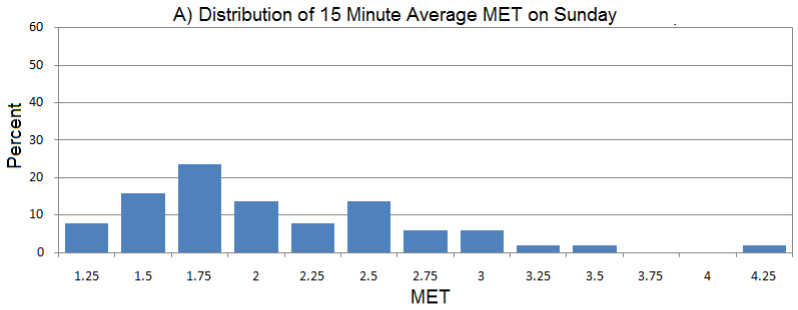
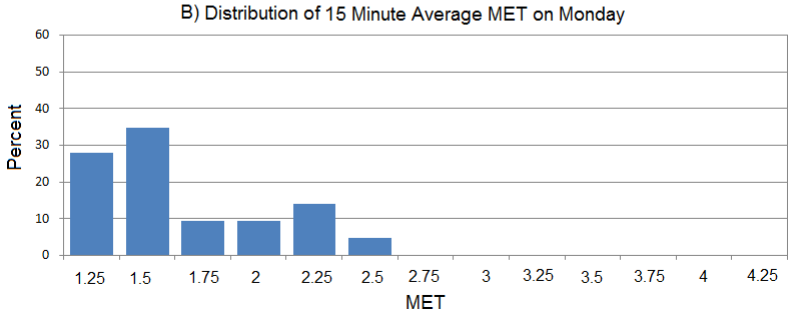


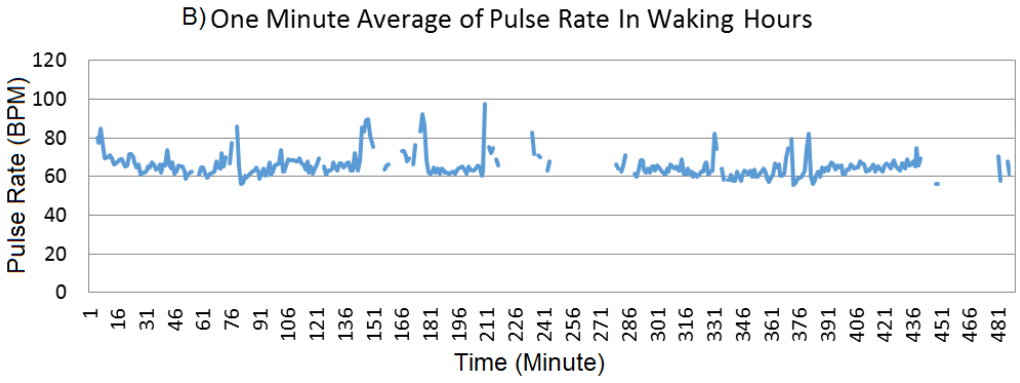
Figure 3 Set of icons

4. Would histograms help you to extract relevant information (example 2.xlsx sheet 2)?





5. How would you like to interact with this data? Any format, interface?
6. This example of a pulse rate (BPM) contains missing data periods of intense activity with MET, a question of uncertainty



a) Would a measure of the percentage of valid data in the averages be useful or important?
b) What would you do with data with few periods of valid data?

7. How do you imagine this sort of recorded data being summarised and annotated in the patient record?

6.3 Participant Description, Recruitment and Selection

Twenty-one participants worked for Foundation Best. This is a private organisation with pharmacies with consulting rooms in Mexico and Latin America. In total, 11,964 general practitioners work for Foundation Best. GPs' supervisor of the city of Leon in the state of Guanajuato, Mexico recruited participants for the focus groups. These participants freely volunteered to take part in the focus groups. The majority of GPs did not know one another, with the hope of a little degree of bias. Their participation in the focus groups depended on the time available due to their occupation. The other two participants worked for the Mexican Institute of Social Services (IMSS).

The average years of experience of participants was 8.48 (σ =10.863). Three participants had specialisation. Such specialisation was in family medicine, public health medicine, and anaesthesiology, with two diplomats in intensive care and advanced trauma life support. Forty per cent of participants reported experience with either medical gadgets or computer/phone applications for medicine. All participants use computers, tablets, mobile phones, and laptops. Only two GPs reported the use of computers in their office.

Table 6.6 Participants in the focus groups

Focus group	1			2			3			4		
Group number	1	2	3	1	2	3	1	2	3	1	2	3
Number of participants	8	5	5	8	6	4	8	5	5	6	6	6

Focus groups lasted between 50 minutes and 1 hour and 15 minutes. All participants signed a consent form prior to data collection. All focus groups were audio-recorded for further content analysis. Manual coding was conducted and a second researcher confirmed that the codings were comprehensive and exclusive. These codings are included in Appendix F.

Focus groups started with a general introduction, the objectives and purpose of the study, confidentiality, and the importance of opinions. General recommendations were taken into account for promoting a comfortable environment, such as a quiet place wherein participants sat around a rectangular table and could communicate with the moderator and other participants. Two recording devices were distributed upon the table. Participation was encouraged, emphasising that all participants should share ideas honestly and extensively. During the focus groups, notes of reactions of participants were taken.

6.4 Data Analysis

Recorded focus groups with accompanying moderator notes were transcribed using Microsoft Word. Each question was analysed to identify recurrent themes, as shown in appendix F. Representative quotes were added for a picture of the focus group comments.

6.5 Results of the Focus Groups

6.5.1 Results of Focus Group 1

Participants of the focus group expressed problems of communication between GPs and patients. These include receiving very short answers from patients, patients hiding symptoms and mistaking symptoms with diagnosis. GPs explained these problems of communication as being due to the types of patients to whom they attend. Some patients derive from rural areas and the majority of patients are low-education and low-income people. Some patients want a quick solution to their problem with medicine acting as a ~~"m~~agic pill". Some patients also think that the more medicine is prescribed, the better the treatment is. The availability of medical information on the Internet has created problems of disbelief. For example, patients find what

they think the diagnosis and the treatment are and when they do not match with the diagnosis and treatment stated by GPs, it might create distrust in respect of the diagnoses and treatment.

Improvements of the limitations and issues of the information provided by patients, as recommended by GPs, fall into three categories: 1) better relationship between the GP and patient, 2) improving the attention and more time with the patient, and 3) more laboratory and clinical tests and more information on the environment of patients, such as work environment, hours worked per day, socioeconomic level, information on stress or anxiety experienced by the patient, hours slept, sleep quality, and amount and quality of food and stimulants (including coffee, alcohol and cigarettes). GPs would require specific information of some patients and conditions; for example, for the elderly or people with prostatic problems, the amount of water drunk, times that the person went to the toilet, cigarettes smoked, alcohol or stimulants taken, sugary drinks, and drugs. GPs know that a change in the behaviour and habits of chronic patients is necessary for better disease control.

–*Medication is not the solution. They need to change their behaviour, alimentation, exercise. In chronic diseases they want a medicine that cures everything like a magic pill*."

However, radical changes might encounter resistance by patients; therefore, GPs recommended cutting patients' habits slowly and improving the relationship between GPs and patients.

To the question –Imagining that a 24-hour patient-monitoring system were available, what variables would be useful to record in the daytime and night?", vital signs were listed by all GPs. These included heart rate, blood pressure, body temperature, and respiration rate. Stress and sleep quality assessment were also variables listed as being very important. Their answers for assessing these variables were by means of measurements of skin pH or diaphoresis for stress, EEG analysis, and measurements of melatonin or serotonin for sleep. Further discussion with clinicians showed that they are not interested in the values of those variables but they are the ways in which they know how to assess sleep and stress. Simpler, cheaper and easier ways of assessment would be better and accepted.

Additional environmental variables to temperature, noise and light were suggested for specific health conditions, e.g. altitude (as it affects haemoglobin and blood pressure) and assessment of pollution in the environment of the asthmatic.

Features that would stop prescribing the use of a WHMS are similar to those reported in the literature. These were uncomfortable and difficult devices to use for both patients and clinicians, and if they were costly. Other features reported by the three focus groups include a device outputting wrong measurements or not being calibrated, and a device that produces skin reactions or puts the patient‘s life at risk by interfering with pacemakers or cables that could tangle around the neck. Features that clinicians expect from a WHMS include accurate measurements, standardised data, ease of use, and being adaptable to fit different patients and not visible. The conception of the WHMS by GPs was that of clothes with embedded sensors such as T-shirts, vests and belts. However, clinicians discussed possible problems of clothes fitting different patients, personal preferences of clothes, and even the uncomfortable use of a vest in hot temperatures. One group recommended something of personal use for hygiene and the reason for a patient‘s preference. More options were suggested such as sensors in an armband alone or connected to other devices. Participants of one focus group realised that sensors in a belt or watch could not be possible because some of the measurements are taken on the chest, such as ECG and temperature, thus recommending something covering the chest and arm connected with several electrodes.

The time during which to access data clinicians suggested being at the end of the time prescribed for wearing the system but every 8 hours or any time in patients with severe conditions. Clinicians recommended a printed format to report data recorded. They preferred printed data because they do not carry laptops, as it can attract thieves. Only two clinicians use computers in the office and the little use of computers was also for safety reasons, although participants suggested that an electronic database could be accessed remotely by clinicians. All groups agreed that patients should have access to their own data. The reasons were that patients have the right to access their data, they could have a second opinion, they could see a doctor if witnessing abnormal values, some patients could use this data to change their behaviour for better disease control, and this could be good for diseases that are developing but have no symptoms.

6.5.2 **Results of Focus Group 2**

Reports of stress, anxiety and sleep quality and efficiency were recommended by clinicians because of the role that they play in the disease. However, clinicians also suggested gathering causes that could lead patients to stress, e.g. the socioeconomic level of patients and other personal information such as the place of work, hours worked, and problems of anxiety, stress or anger. The interest in these factors is that they might affect the emotional state of the patient and the behaviour of physiological signals without an apparent cause. The complete list of variables is shown in Table 6.7

–*Many times the patient does not have enough money to buy food. It can lead to depression; then it can lead to hypertension or diabetes. Everything is chained. One thing leads to another. It is not a metabolic factor — it is multifactorial. It is not the same an educated patient than other without formal education who might think I can eat or drink this or that and it doesn't affect my health. An educated person is aware of what they have to do or avoid.*"

–*Sleep quality affects mood and stress and they affect diabetes*."

–*Negative emotional states change parameters of vital signals, blood pressure, pulse, glucose levels without apparent physiological causes*."

Table 6.7 Variables of interest

Physiological variables	**Environmental variables**	**Subjective and activity-related variables**	**Non-ambulatory tests**
Pulse rate	Light	MET (1 rest, 10 very active)	Glucose
Respiration rate	Noise	Sleep quality both objective (actigraphy) and subjective	Insulin
Body temperature	Temperature	Stress both objective (EDA) and subjective	Cholesterol
	Pollen	Pain	Blood pressure
Oxygen saturation	Altitude	Mood	
	Pollution	Personality tests	
		Tests for the elderly, such as memory and	

		functioning	
		Time of medication and food	
		Food quality	
		Time when the symptoms occurred	

One group of clinicians recommended tests and information depending on the target population. The information of interest and tests are different for bulimic or elderly patients.

Clinicians preferred sensors connected wirelessly, as wires could be dangerous when the person is sleeping. This concern over patients‘ safety also appeared in focus group 1, wherein clinicians asked whether the patients wearing the WHMS would include children or people with psychiatric problems.

Clinicians recommended a rechargeable device that could last at least 3 days without recharging. The diary and the subjective reports were recommended in paper form, as some patients do not know how to use smartphones, although a mobile phone or a computer connected to a database would be preferable.

In the daily log, recommended registering the time when the person took medicine, when the patient felt the symptoms, and the amount and quality of food and drink to determine a possible connection between these factors. This information of patients is typically forgotten during the appointment. Mood and stress were recommended to be reported per day or in three blocks during the day because it is considered that those factors do not change quickly.

Regarding the question of for how long the patient would wear the WHMS, all groups made a distinction for diagnosis and control. The protocol for different health problems (diabetes, hypertension) would be the same.

–Daily until we control the problem. The goal is the control. At least 1 week, but if the disease is not under control, extend it 1 week more."

–In general, we control diabetes in the hospital in 1 week. So, the system would be worn 1 week, then once a month and then once every 3 months."

–In general, wear the system 1 week and then if the patient responds to treatment, wear the system once a month, but if they don't respond, extend 1 week more."

In control there were different opinions ranging from 1 day a month to once every 2 weeks. Again, however, it depends on the disease and the type of patient.

–I would say twice a week, because chronic patients try to cheat you by modifying their habits 1 or 2 days before the appointment. If they are monitored at least 2 days a week, you force them to stick to the treatment."

6.5.3 **Results of Focus Group 3**

In the third focus group, participants were shown graphs of information collected with CircadianSense. These graphs showed data in averages of 15 minutes, 1 hour, and portions of the day (morning, afternoon and night). The recommendation was to display averages of 20 or 30 minutes. Time averages of 1 hour or 1 day could be useful in comparing trends over a period of days, and shorter averages to see more detailed information.

–Twenty-minute averages is the minimum because cardiovascular effects are seen after 20 minutes of physical activity. Patient could forget or ignore events lasting shorter. However, shorts events in periods of 1 hour or longer could not been seen, for example, physical activity."

–Normally, we take measurements in shifts of 8 hours. There are variations every 15 minutes but they are not indicators of a problem. The averages depend on what I want to see. Averages of 8 hours to compare trends."

With regard to highlighting values of data recorded in the heat map, clinicians suggested standardised values, depending on the cohort of patients, instead of tailoring individual ranges.

–Maybe a range of values, something like ages of 30 to 40, 41 to 50. Standardised them by ranges based on group of ages. You can use your criteria and explain, for example, arrhythmia, hyperthyroidism. Gender affects but with little effect. If a person has hyperthyroidism and the

pulse increases at night, you can prescribe more medicine. Standard values will give you an idea of the treatment."

Information to be included in the daily log would depend on the health condition. However, a basic data to be registered and represented as icons suggested by GPs is presented in Figure 4.2 d) section 4.2.2.

Concerning the question of "How would you like to interact with this data? Any format, interface?", one participant stated:

"*A panel with different vital signs. I select what I want to see. It can be Excel. Something like medication, what they took and at what time, and then compare, for example, MET, pulse. Is there correlation? I want to see only graphs and the numbers in the graphs when we click on it. If we don't see anything abnormal then we don't lose time, because it is a lot of information. Compare with three, four patterns, for example, medication, pulse, etc. An app linked to our phone. No CDs.*"

In all of the groups, concerns over accuracy of the data recorded arose. GPs were interested in the participants whose data was recorded to validate the ranges of measurements for different cohorts.

"*Was it tested on people? Do you know the number of people? Ten is not a representative sample. If you say 100 or 1000*."

"*Was the study with healthy people? You need more people, more groups to see variations and catalogue them, get a range of valid measurements; we can have patients with heart failure or renal problems and the signals vary too much and maybe the device cannot detect them*."

Clinicians were not familiar with histograms. Histograms of the pulse rate were shown to clinicians and they showed interest in histograms, as they could be a way in which to summarise data.

—In this graph (histogram) you can see if something is wrong with the pulse. It is a summary. If we see something abnormal in the histogram we can get the answers of what and when by looking at the scatterplots. We are not very mathematical. We go from general to particular."

—This graph is useful. For fever we can see high bars for high temperatures; when fever is controlled, bars in the low ranges. Bars in the right side of the histogram for a tachycardia."

Missing information in the measurements was not seen as being important for observations of the patterns, trends or behaviour of signals in chronic diseases, as GPs take measurements of variables with a separation of hours or even days. For example, body temperature is taken in the appointment, while blood pressure and glucose levels are taken one or two times a day. These discrete measurements taken with differences of hours allow them to see the behaviour of the signals. However, highly accurate and continuous measurements would be necessary for arrhythmias or those diseases in which quick variations could be indicators of an abnormality.

In general, GPs suggested visual summarisations of data that could be provided by histograms or scatterplots with data averages of 8 hours, days or even weeks. Averages of hours or minutes would be used if an abnormality were observed in larger averages. GPs suggested including in the clinical history of the patient only graphs that showed an abnormality, and including averages of data of days or weeks to compare trends.

6.5.4 **Results of Focus Group 4**

Three groups of six GPs participated in focus group 4 with the objectives of assessing and recommending features relevant to a WHMS and particularly to an evolved CircadianSense prototype. Clinicians were shown the features of Table 2.1 and presented new features recommended in the literature and by clinicians who participated in the interviews, as shown in Figure 5.1. An introduction to a WHMS to be constructed called PatientSense was given to GPs, as well as the intended use. Participants were asked to assess the relevance of the features to PatientSense and determine whether there were more to be included.

In general, features of wearability (F1), aesthetic issues (F3) and operational lifetime (F5) would be important for the patient. However, one group suggested that a heavier device or aesthetic

issues would be less important if information collected could change radically the diagnosis or management of the disease.

Real-time application (F6) would depend on the application. If it were for a health problem that could put the patient‘s life at risk, it would be very important. However, for PatientSense this was not an important feature, as data would be collected over days and presented to GPs for its analysis. Although if there were a possibility to include this option for conditions that have no symptoms but are developing, it could be beneficial.

Computational & storage requirements (F8) would depend on the application. It would be more important for a Holter monitor and not for body temperature, which would require few observations during the day. For PatientSense this requirement was listed as being important.

Real application (F6), performance and test in real cases (F16), reliability (F11), interference robustness (F13) and fault tolerance (F14) were indicated as being very important All groups agreed that a GP‘s decision is based on accurate measurements. When data is not reliable the diagnosis and evaluation of a patient can lead to incorrect results. Reliability and fault tolerance are expected both in the process of recording and in the transmitting process. A device must provide evidence that the data collected is useful for diagnosis and monitoring. This can be achieved with trials and studies to show that information which is collected is useful.

–*If we don’t trust the device we won’t use it*.”

Ease of use (F6) would be important for the patient, as there are patients with little technical skills or who are physically impaired. For clinicians, it includes interaction with data. If management of data is a complex process an extra person would be necessary to download and process data. Preferable would be a database with patients‘ data accessible by clinicians with all data and visualisations available.

Cost (F12) was considered as important; again, however, if the device provides evidence that helps to improve diagnosis and treatment to the benefit of the patient, cost would be not so important.

Scalability (F15) was considered good in adding more sensors for monitoring more diseases.

Regarding decision support (F16), the general opinion is that decision support is only an aid for clinicians, as even laboratory-interpreted X-ray images are verified again by clinicians. Decision support should not be given by the system to the patient, because if it is not accurate it can create mistrust in the clinician‘s diagnosis or create false expectations if the device is not detecting a health condition (or vice versa). The diagnosis should be given by a clinician.

Performance and test in real cases (F10) is very important for any WHMS, because if it does not produce relevant data with which to detect conditions or severities its use will not be prescribed. The system has to be tested with a broad number of patients in order to provide evidence that the system is capable of measuring and detecting different patterns of data of different patient cohorts.

Clinical hygiene (N17) was a very important feature, given that if the WHMS is worn in the hospital or home of the patient it can be a focus of infection for others users — a patient can have open wounds, fluid or blood that can contaminate the device. The system should follow disinfection control, which happens with medical tools.

With regard to access to data (N20), it would be better that all data be easily accessible by clinicians, who would select the graphs, zoom-in on data, and access behavioural data anytime and before the appointment. Processing of data would not be part of their activities. In chronic patients or patients who do not stick to treatment it would be better if data could be accessed anytime and have communication with patients to state the undertaking of more physical activity, eating less sugary food, or other medical recommendations.

Data presentation (N18) was considered part of access to data (N20) with the appropriate medical standards. Data could be presented as both numerical values and graphs, the selection of days and time during which to be visualised, and the variables of interest. Data should include behavioural data of the patient. There is a trend in Mexican Health Services in which medical records are being digitalised in a database with the aim of sharing information of the patient with

different doctors and specialists of public hospitals so as to reduce cost and time of treatment. This information includes laboratory tests, patient records, and medical images (X-ray, tomography), but there is no information of patients regarding habits such as food, physical activity, stress, sleep quality, and any information that affects the patient‘s condition. It would be good for the diagnosis to include habits and behavioural information of the patient in that database.

The selection of an appropriate set of tests and information of the patient was also recommended. Physiological and environmental signals need to have appropriate behavioural data of patients and habits. The information to gather depends on the age and condition of the patient. Necessary would be tests of stress, sleep, habits and anxiety, tests of memory or functioning for the elderly, and detailed description of the food eaten for people with bulimia, anorexia or obesity. The information has to be selected according to the type of patient.

Data encryption and security (F4) was not very important for the clinicians, as the patient receives laboratory tests printed on paper and sometimes this information is read by many people before it is received by the patient. However, data being encrypted is better, although it needs to be under a medical standard because patients have the right to share that information with other clinicians for a second opinion.

6.5.5 **Ethical Issues**

There was the opportunity to discuss this study with the secretary of the Medical Research Committee of CECYPE. CECYPE is a company that provides preclinical and biomedical research on human pharmacology clinical studies, medical devices, nutraceuticals, functional food and bioequivalent drugs. The main duty of the secretary of the Medical Research Committee is to evaluate procedures to be followed in the protocols for the services provided by CECYPE. The first comment was that a medical device, particularly a wearable health-monitoring device, cannot be generalised and assessed, as proposed by Pantelopoulos and Bourbakis (2010). The design and the assessment have to be personalised based on the use, application and medical requirements.

The assessment should include a feature of biocompatible materials. Do the elements of the system produce skin reactions? If yes, inform the user of the possible risks, even if they happen one time out of 1000. Indicate when and how these risks could happen. Users have the right to be informed of any risk, even if it is almost imperceptible.

A feature of a WHMS should include non-invasive measurements. Invasive measurements create problems of sterilisation, protocols of sterilisation and disinfection, and use of an operation room. These conditions, in general, are not met in universities or at home. Invasive measurements should include strict protocols of disinfection, description of procedures, risk assessments, and actions to take to preserve user integrity.

All users, participants and people involved in the process of the design, testing, data collection should be well informed of both actual and possible applications of the study and device, e.g. if there are possible uses of the data or system for the army. Any participant should be aware of the aim of the study and decide whether they will participate or not.

Data encryption has to be a priority. Genomic studies have given the opportunity to detect possible hereditary problems in the future of a person, but if that information is in the hands of a company it can be used to not hire that person, or a health insurance company could deny the service if they see that it is very likely that the person will develop an expensive health condition. We do not know whether in the future as medical algorithms progress, it will be possible to detect neurodegenerative conditions from readings of the pulse rate or body temperature. There can be future implications for users if this data is not encrypted and anonymised.

It should comply with safety norms, even if they do not apply to the country wherein the medical device is developed. Medical norms should be followed, ensuring that the system and procedures are updated so as to meet the medical safety norms.

The device should be validated with clinical studies. It would be preferable to have a group of reference and a group of patients and see differences in data between these cohorts. The Federal Commission for the Protection against Sanitary Risk (COFREPIS) in Mexico has the

competence of sanitary regulation of the production, commercialisation, import and export of health-related drug technologies, among other duties. Evidence of products tested with at least 20 to 25 people is required by COFREPIS. Healthy subjects have to provide evidence of their condition by means of at least chemical analysis, blood tests, X-ray tests, blood pressure, and electrocardiograms. It is not enough if a person says that they are healthy because there are no evident health problems. Patterns of physiological signals are different when a person has a health condition, even if they are not evident. The selection of participants should be very strict and provide medical evidence of the condition. For example, statistical data of age is not enough to describe subjects, as there is chronological and vascular age. This means that a person who suffered a disease in childhood or adolescence can show more arterial stiffness than that of other older people who have been more active. The conditions of subjects determine the variability of physiological signals. A person who has a medical condition can mask other medical problems, which affects the variability of signals. For example, in people with diabetes, metabolic syndrome is common. In metabolic syndrome, problems of increased blood pressure, high blood sugar, and abnormal levels of cholesterol or triglyceride are commonly observed.

There should be the inclusion of a medical expert in the research, design and assessment of the system. The clinician is one important user of the product or technology to be designed. It is necessary to determine what they want and how they want the information. For example, the pulse rate can be measured by counting pulses in 15 or 10 seconds and then multiplying by 4 or 6, respectively. But another way is by measuring the frequency between two beats. The first visualisation shows pulse rate readings that are very stable, and is commonly used by an anaesthesiologist, who is observing the trend of the pulse rate in surgery. It is normal to have a variability of 4–5 beats in 1 minute. Higher variability in 1 minute can be an indicator of cardiovascular problems. For a cardiologist a useful representation of the pulse rate is the frequency between beats, who observes the variability so as to determine a heart condition — an average of the pulse rate per minute would not provide useful information for a cardiologist.

Included in the protocol should be the methodology and conditions in which the system was tested, e.g. temperature, humidity, vibrations or any condition that can affect the reliability and accuracy of the device, which should be assessed and informed. If clinicians know in which

condition the system is not reliable, they can dismiss that data or the user might avoid its use in those conditions.

The decision support feature would depend on the application but, in general, the decision should be made by the doctor or specialist. A medical device will not be able to give correct information on a psychosomatic patient. The relationship between the patient and doctor is more important. Decision support should be used to complement the diagnosis but the decision relies on the clinicians based on their observations and mainly on their relationship with patients.

An assessment considering the manufacturer‘s opinion can reduce the quality of the medical device. For a manufacturer, cost can be very important and lead to a selection of a more uncomfortable or unreliable sensor to the detriment of the usefulness of the device. Opinions of clinicians and users should be considered more important.

Importance of the features depends on the relevance of the data provided. Wearability (F1) and aesthetic issues (F3) are important but they need to be evaluated, because a system used for 5 minutes is not the same as one used for several hours.

6.6 Discussion of the Results

Not all features that were proposed by Pontoapulos and Bourbakis (2010) are part of the solution of CircadianSense and PatientSense. Data gathered on an SD card is processed offline and presented to clinicians. Therefore, real-time application (F6), interference robustness (F14) and decision support (F16) should not be assessed. Much of discussion in the literature review has been surrounding automatic decision support; however, this should be complementary information, as reported by clinicians, because even when the clinician receives the interpretation of X-ray images there are errors made by radiologists. Automatic decision algorithms are not 100% accurate. This could create mistrust for patients and clinicians, who could abandon the use of the device. Ethical issues arise if the system wrongly diagnoses, creating false hope (or vice versa). Moreover, diseases are affected by multifactorial causes such as behavioural and activity-related variables. Psychosomatic patients have no measurable physiological causes and only a good relationship between the patient and doctor can find psychological causes.

Features of real application (F6), performance and test in real cases (F10), reliability (F11) and fault tolerance (F14) were considered very important both for clinicians and for users. The usefulness of the device and the relevance of the device could be assessed once data collected facilitates the diagnosis or prognosis. Usefulness of data collected affects the importance or relevance of other features such as wearability, aesthetic issues or cost.

In the interviews with clinicians, hygiene and compliance with regulations are important features to be included. A medical device that is intended to be used by patients in the hospital or at home can be a focus of infection. It is necessary to include a disinfection protocol.

Time during which to extract conclusions has been a barrier for clinicians because of the little time available that clinicians have. An automated process of data is preferable to provide visualisations to clinicians. In this scenario the clinician would only select variables to visualise and use more zoomed-in views of data. It is important for clinicians to have ways in which to summarise, observe trends and compare data. Despite Excel being a program familiar to clinicians, the answers suggest that they are not interested in manipulating data. Their interest is in manipulating views of data, selecting variables, observing trends of data and making comparisons.

The assessment of the features for a WHMS cannot be generic and depends on the application of the device. Validation of the device should be part of the design process, i.e. testing the system in different scenarios, conditions and different patient cohorts.

Behavioural and activity-related information of the patient to be registered so as to complement objective records of physiological and environmental signals have to be selected according to the type of patient. There is not a generic solution because the information to collect depends on the targeted disease and the type of patient.

The secretary of the Committee of Medical Research considers that new features should be included. These include that the devices should comply with international medical standards of safety for patients. If there is a remote risk for the user it should be informed. Testing procedures

should be rigorous with a protocol establishing patient descriptions, a description of cohorts to observe the validity of data, and procedures followed in the study. It is not enough if participants say that they are healthy, as it needs to be verified with rigorous medical exams. Variability of physiological signals changes depending on a number of factors, such age, actual diseases or those suffered in childhood.

The methodology should include information on how the system was tested and inform in which conditions the system is unreliable. Medical participation is important so as to determine what information they want and how they want it, e.g. the number of decimals, the size of the data averaged, etc. A representation could be important for some clinicians but not for others, who could receive useless data.

Elimination or reduction of discomfort and risks for patients can be achieved by building a system using biocompatible materials and non-invasive measurements. It is also necessary to inform any person involved in the project, both users and designers, of the possible uses of the device and data for ethical reasons.

Literature reports that for young people it is common to share personal information via social networks and data encryption might not be relevant. However, data improperly handled could have ethical and legal issues if from the data it is possible to detect neurodegenerative diseases as algorithms advance.

CHAPTER 7
DESIGN IMPROVEMENTS AND ASSESSMENT

7.1 Introduction

This chapter describes an improved CircadianSense called PatientSense based on the results and assessment of anaesthesiologists and wearers, as described in Chapter 5, and the results of the focus groups with general practitioners, as presented in Chapter 6. The system was worn by 16 users who assessed the system and identified areas of improvement. The assessment had the aim of finding issues and improvement, rather than making a comparison with other devices, since the features relevant to the WHMS depend on the application.

7.2 Factors to be Improved

Improvements to wearability and comfortability were recommended in the study with clinicians and participants in the first stage of CircadianSense. Changes to firmware were also made in order to increase fault tolerance and the reliability of data.

7.2.1 Size and Weight Reduction

The enclosure used for CircadianSense was a generic plastic box with three standard AA rechargeable batteries. The size and weight were recommended to be reduced. The enclosure was found to be uncomfortable by some wearers during the night. Miniaturisation and comfortability were pursued by selecting other sensors and changing their placement on the body, and a 3D-printed enclosure to fit all hardware. In CircadianSense, batteries were removed and recharged through an external battery charger by the researcher and then installed in the device. In PatientSense the recharging of batteries can be done by any common mobile phone USB charger

connected to an external mini USB connector without participation of the researcher. A Feather Mo processor board compatible with Arduino IDE was used to reduce the size of the hardware. The board has a built-in micro SD card slot. The mini USB port of Feather M0 was used to recharge a lithium-ion polymer battery. The 3D-printed enclosure and body and pulse sensors are shown in Figure 7.1.

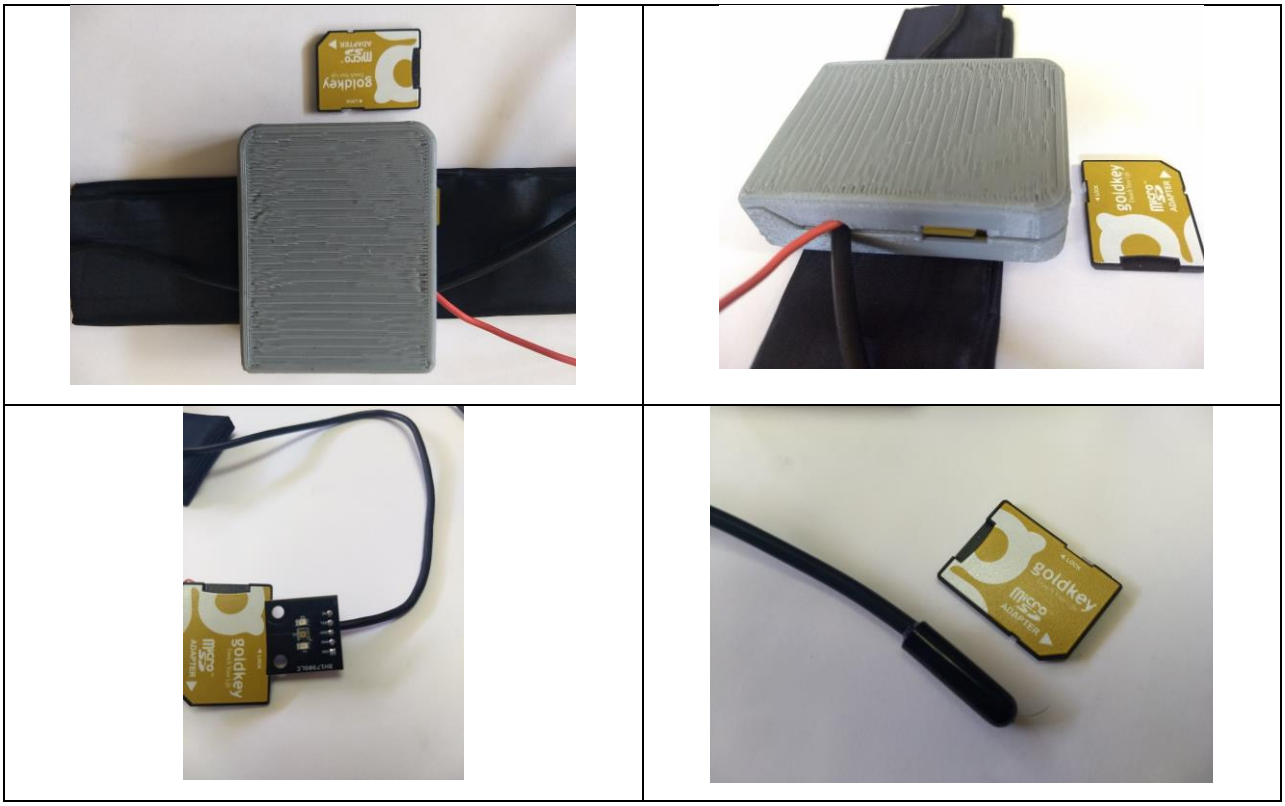


Figure 7.1 3D-printed enclosure of PatientSense and sensors of pulse and body temperature

7.2.2 Sensor Changes

EOG for REM detection

Identified risks included skin reaction due to the Ag/AgCl electrodes used both in EOG and EDA measurements. Tests demonstrated that the longer the use of Ag/AgCl electrodes, the more noticeable they were. These Ag/AgCl electrodes left skin irritated in some participants. The irritation of skin was accumulative over time. The main interest of EOG measurements was in easily detecting REM episodes using power spectral changes (Virkkala et al., 2008) without an expert to interpret data. However, tests showed that detection was evident in only two of five participants. Hang et al. (2013) there are variations of amplitude and frequency band of slow

wave sleep (SWS) signals between individuals which make difficult to model and characterise. Virkkala et al. (2015) concluded that the reliability of REM detection is affected by the sleep efficiency such as people with insomnia, PLM, medication, chronic pain or other medical conditions and the quality of the EOG signals could be affected by the electromagnetic fields at home and the correct placement of the electrodes by the subjects. Considering the poor results of REM detection using Virkkala et al. (2008) analysis, the lack of comfortability of the wires running from the processor box to the face and the skin irritation produced by the Ag/AgCl electrodes, the detection of this variable was not included in PatientSense. Moreover, in the focus groups, issues of safety arose during the discussion, wherein a major concern was the risk of the wires running on the back of the head, which could tangle around the neck.

GPs who participated in the focus groups were more interested in a simpler indicator of sleep quality, rather than identifying stages of sleep or the measurement of secretion of hormones during sleep. A simpler method with which to detect changes in sleep quality and which is less invasive can be achieved with actigraphy.

Measurements of EDA

EDA measurements with Ag/AgCl electrodes produced skin irritation in some participants after several days of wearing the electrodes; in one case the skin irritation was produced after 1 day of use. Cables from the wrist to chest and then to the processor box were found to be uncomfortable and with possible task interference when wearing sleeveless clothes. A change of placement to the upper arm was achieved with the aim of increasing comfortability and less interference of wires. Ag/AgCl electrodes were replaced by conductive fabric to measure EDA. Conductive fabric does not require gels and there is no risk of skin irritation.

Pulse sensor

The optical pulse sensor used in CircadianSense was a very simple circuit that amplified the signal from an optical detector. Reliability of the data decreased in conditions of high movement, although both anaesthesiologists and clinicians suggested that continuous recordings of signals are not necessary for the observations of trends of behaviour of data. Pulse Sensor Amped used in CircadianSense was replaced by BH1790GLC, a more accurate wearable pulse sensor also attached onto the carotid artery with a sticking plaster.

Light Measurement

In the interviews and focus groups the presentation of data in scientific or medical standard formats was recommended. The light sensor used in CircadianSense detected light changes with an LDR presenting data not in a scientific metric, labelling extremes of the measurements as bright and dark, as shown in 3.20. This LDR sensor was replaced with a TSL2561 sensor, which records light conditions in lux that is a measure of the light intensity, as perceived by the human eye. CircadianSense recorded light both in waking hours and sleeping hours. During waking hours, environmental conditions changed quickly and GPs did not find relevant measurements of ambient signals. PatientSense records light only in sleeping hours.

Body Temperature

A commerical logger device called iButton is a recorder of temperature that uses the DS18B20 sensor from Maxim Integrated. This sensor has been used in a number of studies of circadian rhythms, as reported in the literature. Measurement of body temperature by the analogue temperature sensor used in CircadianSense was replaced with the DS18B20 digital sensor. The output of the analogue sensor used in CircadianSense was amplified with an operational amplifier which increased the size of hardware and power consumption.

Actigraphy and Energy Expenditure

The two analogue accelerometers ADXL337 used in CircadianSense had to be characterised to determine the offset voltage and the sensitivity for each axis as described in section 3.9.2. This sensor was replaced by accelerometer MMA8452Q that does not require a characterisation. It has an inter-integrated circuit protocol (I2C) for data communication.

7.2.3 Ambient Variables

Ambient variables at night were listed as being important by anaesthesiologists and clinicians as objective measurements of the sleep hygiene environment. As indicated by GPs, sleep quality plays an important role in many conditions; for example, poor sleep can affect diabetes, hypertension or mood. During the day these ambient variables were not required to be recorded, as people are exposed to these changes in daily life activities and their effect is mainly in sleeping hours.

People with hypertension or allergies could require accounts of other environmental variables, e.g. altitude for patients with hypertension and humidity and pollution for people with allergies or asthma. However, these variables are targeted towards a very specific group of patients, with little relevance to the majority of patients.

Ambient temperature was changed by the DS18B20 sensor, the LDR used to measure ambient light was replaced by TSL2561, and noise measurement was performed with the circuit used for CircadianSense and presented in Section 3.10.3.

7.2.4 Behavioural and Non-Ambulatory Measurements

GPs recommended in the focus groups a log diary similar to that outlined with anaesthesiologists. However, more information from patients being registered was discussed, e.g. information on symptoms felt and the time when they occurred to correlate symptoms with medication, food or stimulants. It was also recommended to annotate the type of food in order to separate sugary food or junk food from healthy food. For people with obesity or eating disorders the information to be annotated would focus on the type and amount of food and tests of the emotional state of the person. The elderly or people with prostatic problems could require information related to the amount of water drunk and times that the person went to the toilet. Levels of physical activity were also required to be registered but it would be explained to patients what activities fall into those categories depending on patients‘ conditions, such as age, weight, or physical conditions. Additionally, this information would be complemented with results of tests of anxiety, stress, anger or information describing the environment of the patient, e.g. hours worked, the environment wherein the person works and lives, the socioeconomic level or any information that can affect the mood or stress of the person. This information might explain symptoms that have no signs observed by the doctor in the patient. Furthermore, the results of laboratory tests prescribed should be available at the moment of the appointment.

Blood pressure or glucose levels cannot be measured in ambulatory fashion. Commercial devices can be used to measure these variables and annotated in an extra column of the daily log. Again, however, the information to be registered would depend on the patient‘s condition.

Stress and sleep quality were found to be factors that can affect diseases and their correct assessment and control are important. Stress was required to be annotated in the daily log. However, there was a mixture of opinions on the frequency and annotation. Recommendations included shifting from being annotated in three blocks during the day to only once in a day. GPs explained that people in a city are exposed to different elements that can affect stress or anxiety, such as traffic, running late to work or other common problems. However, the problem for the patient is when stress is a constant component in their daily life. The recommendation was to report stress in blocks of the day: morning, afternoon and night. The log diary proposed and discussed with GPs is shown in Figure 7.2 and the icons representing the information in the daily log are shown in Figure 4.2. The discussed daily log is a generic document that could be modified depending on the target population and the information relevant to the disease.

Name:_____ Date:_____

Time	Activity (light, moderate, intense)	Meals, snacks, water Report detailed information	Stress and mood at least once a day	Stimulants (cigarettes, alcohol, drugs, medicine, caffeine)	Sleep, naps	Symptoms	Measurements prescribed by clinician (glucose, blood pressure)
6:00							
6:20							
6:40							

Figure 7.2 Daily log proposed by GPs

7.2.5 **Improvements to Firmware**

After testing CircadianSense in real environments through the research team, clinicians and users, there were some flaws that were improved upon in this iterative design. CircadianSense created only one file on the SD card for the total amount of hours of recording. However, in the presence of a low-voltage battery or disconnection of the SD card without stopping the recordings, the file was corrupted, losing all data or damaging the SD card. In CircadianSense this file stored data for up to 3 days. This problem was fixed by creating on the SD card a file every 10 minutes. The only lost data would be the last 10 minutes of recordings, leaving the other files intact.

There was no low-voltage detection in CircadianSense. In the presence of low voltage, CircadianSense hardware reinitialised the system continuously, deleting the file created. In PatientSense, Feather Mo monitors the voltage of the battery, putting the processor in sleep mode when low voltage is detected.

The list of sensors and the communication protocol are shown in Table 7.1 with the sampling rate.

Table 7.1 List of sensors used in PatientSense

Sensor	Protocol	Sampling rate
Ds18B20 (temperature)	One wire	1 Hz
BH1790GLC (pulse rate)	I2C	32 Hz
TSL2561 (light)	I2C	1 Hz
MMA8452Q (Accelerometer)	I2C	48 Hz each axis
EDA (conductive fabric)	Analogue	48 Hz
Sound	Analogue	100 Hz

The schematic of the waking hours PatientSense subsystem is shown in Figure 7.3. The subsystem for sleeping hours is similar without the EDA circuit.

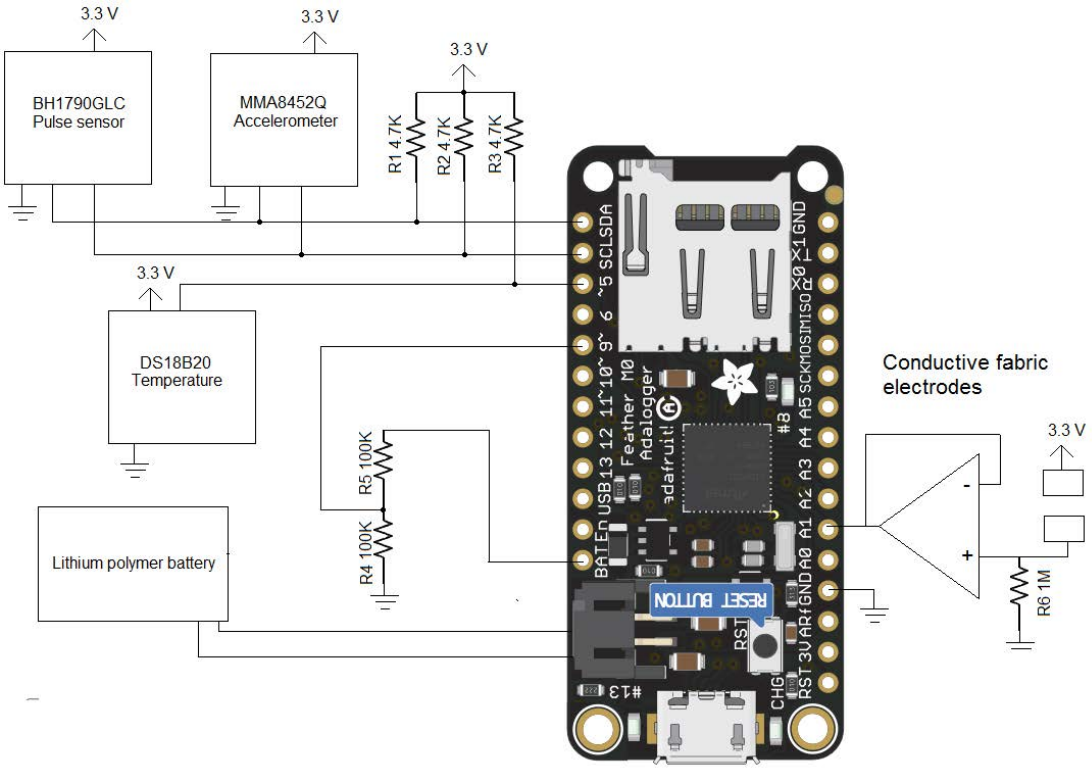


Figure 7.3 PatientSense waking hours subsystem

The subsystem to record ambient variables in sleeping hours is shown in Figure 7.4.

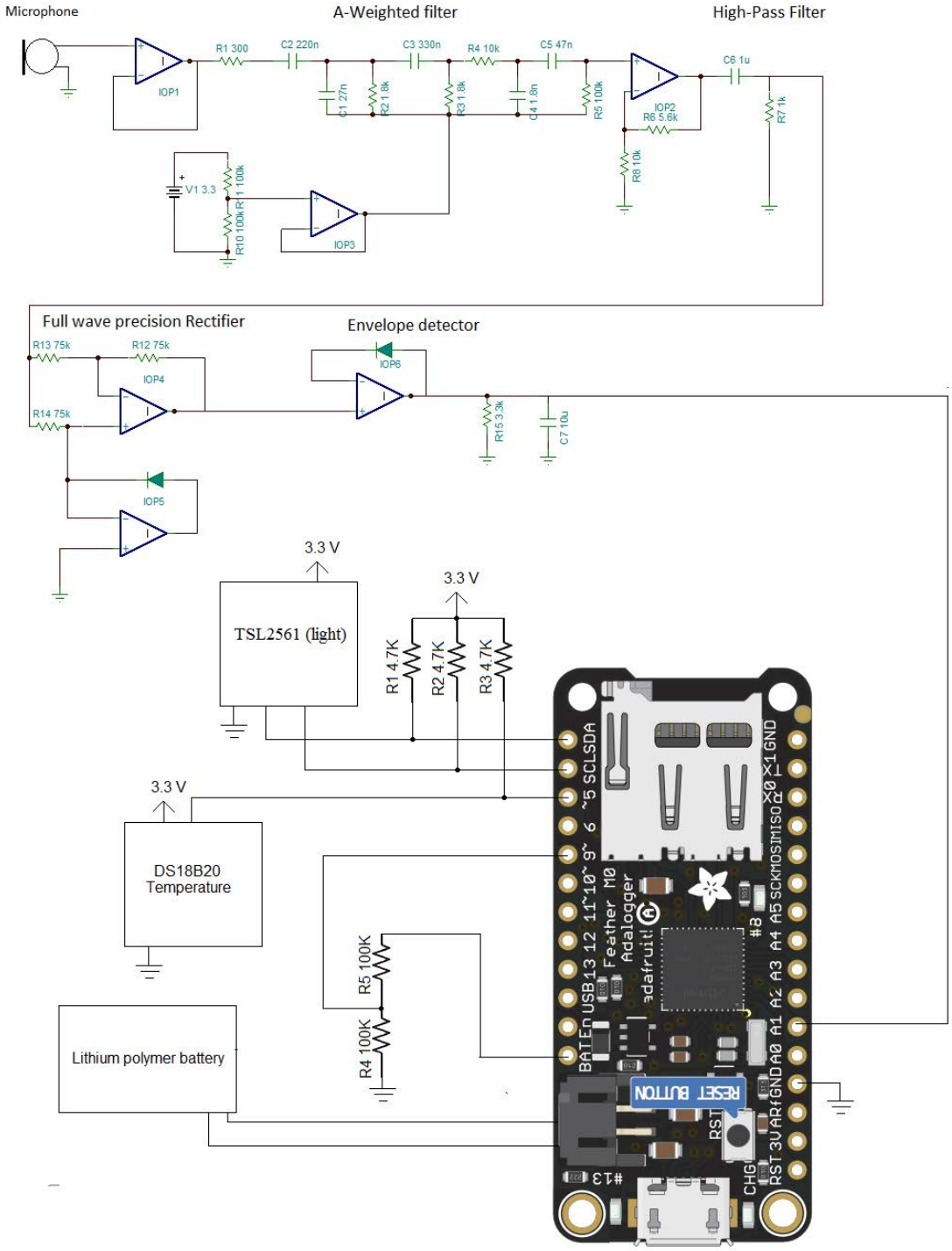


Figure 7.4 Ambient variables for sleeping hours PatientSense subsystem

7.3 Wearers of PatientSense

Sixteen participants took part in this study. All participants signed the consent form and were informed of the nature of the study. Twelve participants were students of engineering, 10 of whom were undergraduate students of electronic engineering with specialisation in biomedical systems. These participants are familiar with medical devices and medical terms such as EEG, ECG, body temperature, EMG, and have knowledge of medical standards and norms for patient safety. Age 21 ($\sigma = 0.6$) comprised 10 males and two females. All of them have used a wearable device or mobile phone app related to medical application, e.g. pulse oximeters, energy expenditure, step counters, and sleep quality apps.

Four non-student participants were also recruited, age 32 ($\sigma = 12.7$). One participant is a retired nurse, one is a housewife and two are young male workers. Only the nurse reported experience with wearable devices for medical applications. Participants were instructed to wear the system for 36 hours (including only one night) and complete the daily log. All of them were informed that they could withdraw from the study anytime and the information collected would be destroyed. Data collected would be anonymised and not shared without their permission. Table 7.2 shows data recorded from recruited participants.

Table 7.2 Data recorded from wearers

Participant	Data collected
11 students	29.5 to 37.8 hours
1 student and 2 non-students	1 night and 1 complete period of waking hours 16.3 to 21.4 hours
1 non-student	5 hours; battery was not fully charged and the processor was put in sleep mode
1 non-student	Battery discharged and data not recorded

Data collected was processed in Scilab and exported to Excel. Data was averaged in blocks of 20 minutes, 1 hour, 8 hours. This data was visualised and presented to GPs.

7.4 Assessment of PatientSense

The assessment of PatientSense was made by both wearers and clinicians. The assessment of PatientSense was made from the perspective of clinicians by 17 GPs who work in the city of Leon Guanajuato in Mexico. These 17 clinicians participated in three groups each. Wearers assessed PatientSense from the perspective of users. 15 out of 16 wearers also assessed the system of the device with the aim of finding areas of improvement and were invited to make recommendations as to the features assessed. All features listed in the questionnaire of Pontalopulos and Bourbakis (2010) and new features discussed in the focus groups and interviews were included in the assessment. The secretary of the Committee of Medical Research was contacted to provide comments on the features of PatientSense. An overview of PatientSense and the nature of the study were explained to all participants. The assessment of weights by wearers and clinicians is shown in Figure 7.5.

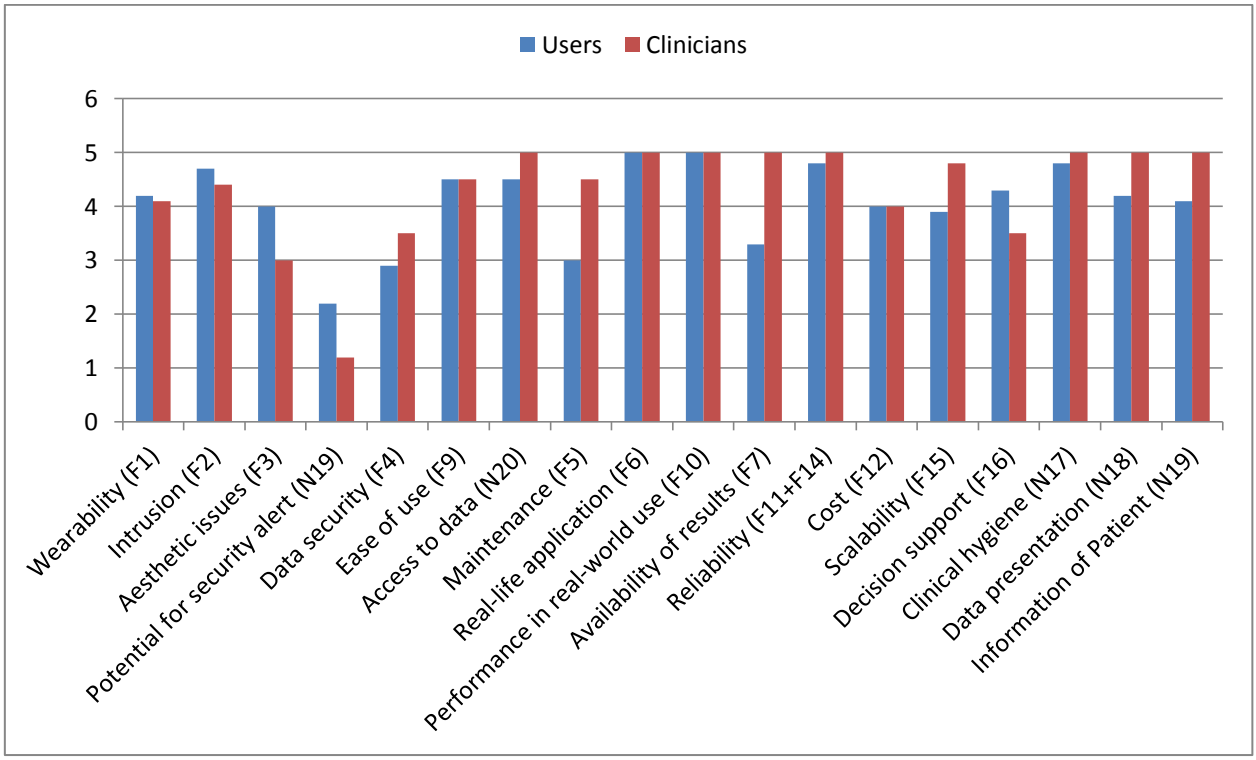


Figure 7.5 Assessment of feature weights by users, clinicians and engineers

Access to data (N20), real-life application (F6), performance in real-world use (F10), availability of results (F7), reliability (F11+F14), clinical hygiene (N17), data presentation (N18) and information of patient (N19) were the features with the highest score for weighting.

Results of the ratings of CircadianSense and PatientSense in Table 7.3 show an improvement in the scores of wearability and aesthetic..

Table 7.3 Results of the rating scores for CircadianSense (CS) and PatientSense (PS)

Feature	Users CS	Users PS	Clinicians CS	Clinicians PS
Wearability (F1)	3.05	3.9	3.33	4.1
Intrusion (F2)	3	3.9	3.33	4.2
Aesthetic issues (F3)	3.3	3.7	3.33	3.8
Potential for security alert (N19)	2.11	2	1.66	2.2
Data security (F4)	3	3.8	2	4
Ease of use (F9)	3.65	4.2	3.33	3.8
Access to data (N20)	3	3	4	4
Maintenance (F5)	3.8	3.8	4	3.8
Real-life application (F6)	3.77	3.9	3.66	3.8
Performance in real-world use (F10)	3.77	3.5	3.33	4.2
Availability of results (F7)	3.375	3.5	4	3.8
Reliability (F11+F14)	3.66	4.2	3	3.8
Cost (F12)	3.85	3.5	4	4.2
Scalability (F15)	3.1	2.5	3.33	2.8
Decision support (F16)	3	Not assessed	3	Not assessed
Clinical hygiene (N17)	3.5	3.12	3.66	3.5
Data presentation (N18)	3.25	4.2	3	4
Information of patient (N19)	Not included	4.2	Not included	Not assessed

7.5 Results

Wearability. This feature was rated as being very important. Users would prefer something more fashionable and smaller. The cable of the pulse sensor and its visibility on the neck were things that attracted the attention of other people. Three of the wearers changed their behaviour by wearing tall-necked clothes and one removed the pulse sensor when in the street. A change in the placement of the pulse sensor was recommended by wearers to make it less visible and more comfortable. GPs who did not wear PatientSense found small and light the subsystems appropriated to be worn by patients. There were no complaints from wearers when wearing the sleeping hours subsystem, as it occurred with CircadianSense.

Appropriate placement. All GPs agreed that the placement would depend on the variable to record and it is more important to record accurate readings. Six wearers suggested a change in the placement of the pulse sensor if it were possible or the use of a Holter monitor.

–Some of the fitness gadgets are worn as armbands and people are used to it; however, a wire and a sticking plaster in the neck is not common."

Aesthetic issues. In general, GPs mentioned that it would not be important if the system were worn under the clothes; however, the pulse sensor connected with a wire attracted the attention of people. It was more noticeable with V-neck shirts and difficult to cover during the summer. Moreover, all users mentioned that it was a theme of conversation when people noticed the wire on the neck, and also commented that in crowded places they did not like to use the pulse sensor.

Data encryption and security. GPs commented that data can be protected but it needs to be able to be read by any GP, as a patient has the right to receive a second opinion. Public medical services in Mexico are working towards the digitalisation of medical data in order to be shared by all medical services and doctors to reduce cost and time. Data encryption and security should follow the standards to be compatible with this platform.

The invited member of the Medical Research Committee was stricter and considers that any personal information has to be treated very carefully, even if it does not provide sensitive information on the patient. Any information in an academic research study should be used for that purpose and not shared out of this scope.

Operational lifetime. GPs recommended recording at least 3 days of continuous measurements. It was found to be a good idea to have a compatible port with mobile phone chargers to recharge PatientSense. Wearers and clinicians recommended an indicator when the system was charging and information on the remaining battery power when the system was worn. Wearers suggested wireless communication with a mobile phone to display this information.

Real application. For GPs this was a very important feature. If the system does not record useful data from patients the use of the device will not be prescribed. A recommendation of GPs was to test the system with different patient cohorts. Usefulness of data would be assessed if data delivered information to diagnose a disease or explain symptoms.

Real-time application. This was not the goal of PatientSense. However, both clinicians and wearers recommended that if one of the signals is out of the normal range it would be a good idea to trigger an alarm for patients and clinicians.

Computational & storage requirements. Clinicians asked for how long the system would record. Furthermore, students asked how much information an SD card could store. In a common 8 GB SD card, years of data can be stored. That is enough for monitoring chronic diseases for long periods of time. Students recommended wireless communication to backup information. If the SD card is damaged or lost, all data will be lost.

Easy to use. All users agreed that the system was easy to use, as it has only a button to record the system. However, there are no indicators to wearers that the system is recording or of the battery status. Wearers suggested wireless communication to download information collected to a mobile phone or computer. GPs asked questions about the process of displaying data once the SD has been removed. It was explained that for this proof-of-concept device, data is analysed and prepared by the researcher and exported to Excel. GPs are interested only in observing data

and not in the analysis or preparation of data, as it could require more time and training. One group of GPs suggested a system capable of uploading data in a database accessible on the Internet. GPs could access data anytime in the database to observe changes of data of chronic patients. GPs in focus group 2 recommended the use of a paper daily log, as there are patients who do not know how to use a mobile phone. Further discussion in the assessment recommended the use of an app on the mobile phone to register behavioural data with additional benefits for the patient, such as reminders for medicine, the intake of food and water for patients, and data being accessible by GPs.

Wearers also found it more difficult the use the printed daily log. It is more common to forget a sheet than a mobile phone. Their recommendation was also an app with icons or an easy way in which to introduce information of the daily log.

Performance and test in real cases. GPs recommended recording data from different cohorts because it is the only way in which to determine whether the system is capable of detecting differences in the data of patients. These differences might be indicators of the presence of disease or severity.

Reliability. This parameter was suggested to be assessed with data of many patient cohorts in different scenarios. There should be evidence of the conditions wherein the system provides reliable and accurate information.

Cost. Clinicians considered that the importance of cost can be determined by the meaningfulness of data. For users, cost is important in case the patient has to buy the system.

Interference robustness. This feature did not apply to PatientSense because data is stored on an SD card and there is no wireless communication between the sensors and the processor box. However, both GPs and wearers made suggestions to upload data to databases or mobile phones so as to interact with data at any time and observe the status of the system. In this condition this feature would be important to rate.

Fault tolerance. Clinicians were interested in determining in which conditions the system would produce unreliable readings, in order to avoid them. Questions regarding the influence of environmental factors on the system were asked. Is the system waterproof? Are the readings affected by temperature, humidity? The member of the Committee of Medical Research recommended validation of the system in various scenarios, including environmental and patients‘ conditions. Variability of signals depends on the disease, age, fitness of the person, and even medication. Testing the system with patients would be conducted to determine the condition in which the device provides reliable and accurate information and useful data for clinicians. These conditions would then be informed to wearers and clinicians, who would be aware of what conditions to avoid.

Scalability. GPs recommended adding plug and play sensors both for daytime and nighttime measurements. Adding sensors would depend on the disease and not all variables are relevant to the patient. A system that records many parameters of the patient that are not necessary would add discomfort for the patient.

Decision support. The system is not intended to provide diagnosis. In the case that the system provides a diagnosis it would be used as a guide, but the final decision should be made by the clinicians. Incorrect diagnosis given by a device could bring about false expectation (or vice versa), creating mistrust in the device. As discussed previously, the diagnosis should be given by the clinician to the patient.

Hygiene and disinfection. Patients wearing a system can be in contact with open wounds or fluids that can transmit diseases. In particular, the conductive fabric used to measure EDA was seen as a potential risk for patients if the fabric were not completely washed. Disposable conductive fabrics for personal use only were recommended. Plastic enclosures or wires should observe a protocol with which to disinfect and clean, considering that patients would be in contact with the system and transmit diseases of fluids when going to the toilet or any fluid from the nose or mouth to any of the elements of PatientSense.

Users commented that the wearable device would be preferably low-cost in buying it.

–People go to the toilet and touch the system. I would prefer use one bought for me."

The disinfection protocol was a feature recommended to be included. Any medical instrument goes through procedures of disinfection and it should apply to a wearable device.

Behavioural data of patients. There are emotional conditions of the patients that exacerbate the symptoms without apparent causes. When clinicians dig for a cause they may find that it is not because of a disease but rather conditions of stress, anxiety, and poor sleep quality. This information should be available to clinicians at any moment. PatientSense solution have a daily log for general health monitoring. But the information and tests depend on the type of patient and disease. Data to be collected would be different for a person with obesity and diabetes.

Potential threat. Cables and wires running over the body were not seen as a potential threat in Mexico. The system is worn under the clothes, except for the wire of the pulse sensor.

Data presentation. Visualisations of various physiological signals were presented to clinicians, as shown in Figure 7.6. As suggested in the focus groups the averages of 20 minutes were found to be short enough to observe abnormalities in the patient. Quick changes are not indicators of an abnormality. Increases in the pulse rate are observed after physical activity. However, if a high or low value of a physiological signal lasts several minutes it can be an indicator of a health problem. Scatterplots with averages of data over periods of hours were found to be useful in observing trends and making comparisons, but it would be necessary to collect data of several days. Histograms were also found to be useful in making comparisons and observing trends of data.

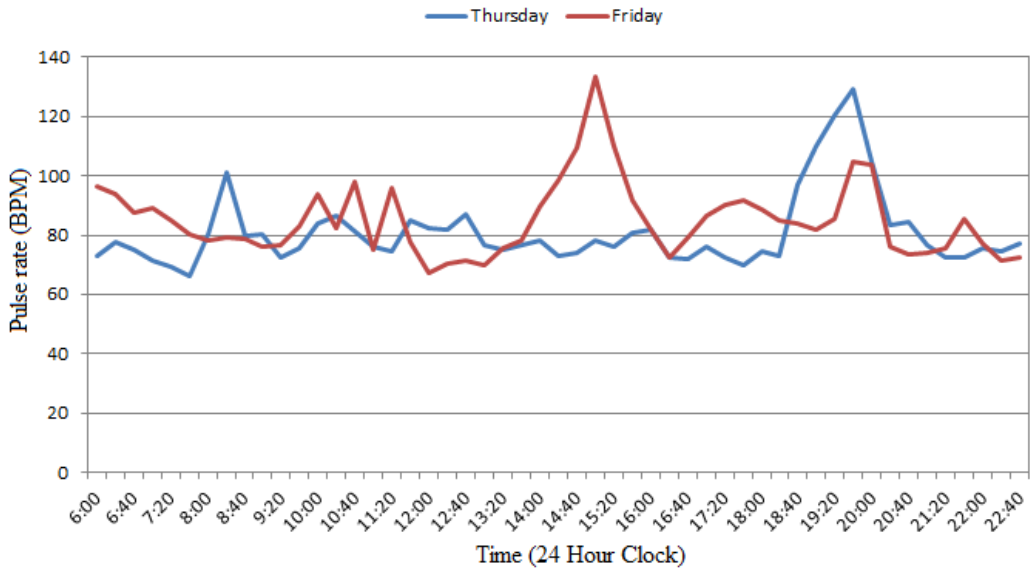


Figure 7.6 Visualisations of data recorded with PatientSense

One clinician recommended collecting data of different patients, classifying them in categories of age and disease. For example, it would be used to determine the range of expected values for patients with diabetes aged 30–40 and 41–50. If values are out of the ranges it could be an indicator of progression of the disease. Data of patients with hypertension, obesity, and cardiovascular problems of different ages would be categorised. Furthermore, it was necessary to provide evidence to clinicians that the system is capable of measuring data of different patients because variability and ranges are different.

Ethical issues

Discussion with the secretary of the Committee of Medical Research recommended in his experience the next features and changes:

Provide documentation of the protocol, which should be available to any person involved in the project. This should include consent forms and information sheets, detailed procedures to be followed, risk assessments and actions, and medical descriptions of participants with laboratory tests, always preserving information on the patients‘ anonymity.

Concerns and problems that were found in the study and use of the system designed were as follows: PatientSense was worn by a number of participants and there was no a protocol with which to clean and disinfect the device. There is no information on the liquids to use or the

procedures to follow to clean and disinfect the device. This should include the actions and procedures followed by the person assigned to the task. This is the first person that could be at the risk of infection. Patients claimed that they were healthy subjects but there is no medical evidence of this.

When a medical system in contact with a patient uses batteries the risk of an electrical shock is null. PatientSense uses a rechargeable battery but it is recharged with a mobile phone charger. If the participant charges the system with the system worn there is a serious risk of an electrical shock through the conductive fabric and the pulse sensor. There is no assurance that participants will follow the instructions of not wearing the system before recharging the battery. Additional circuitry is necessary for an electrical isolated USB port. PatientSense does not comply with safety norms. The feature of compliance with safety norms is necessary for any research before continuing with the study.

The pulse sensor worn on the carotid vein was also seen as a major issue to be addressed. The system is worn by a person in their daily normal activities. If there is an accident that breaks the pulse sensor, the broken pieces of the pulse sensor could cut skin around the carotid artery, which poses a serious risk for participants.

There is no evidence that the materials used for the cables and sensors are suitable for being in contact with skin over long periods of time, where allergies or skin reactions can be developed. An irritation produced on the skin on the carotid artery by the materials of cables and pulse sensors is also a serious risk for participants. A recommendation was to use other methods to measure the pulse rate or change the pulse sensor‘s position.

It is necessary to extend the tests with healthy participants and patients, providing evidence of the usefulness of the device and data. It was considered that features of reliability and fault tolerance are closely related because if the system fails in some conditions it is necessary to inform clinicians and patients of the conditions in which the device produces unreliable or inaccurate data, e.g. when person is driving a car, sleeping, and conditions of temperature and humidity. PatientSense does not provide evidence of environmental conditions in which data is

reliable and accurate. Tests changing temperature, humidity and vibration are recommended to determine these environmental conditions.

There is no data encryption and it should be included because data stored on the SD card can be accessed by any person. An SD card with a password is necessary to preserve information locked.

7.6 Summary

Participation of GPs provided feedback on improvements of PatientSense. There are no generic solutions and the data to collect depends on the patient and disease. This includes the selection of physiological, environmental and behavioural data. The selection of data to collect should be discussed with clinicians to determine what to record, how to record it and how it should be presented. Some variables could be relevant to a disease but not to other conditions. It would be preferable a scalable device to add or remove sensors and make more comfortable its use. The pulse sensor and its placement were found to be uncomfortable and very visible for wearers. However, the major concern is that it can be a risk for patients because it was placed on a carotid artery, where the sensor can cut the skin or produce an irritation. Hygiene and disinfection were also concerns for GPs and wearers because infection can derive from fluids. Despite the participants claiming to be healthy, there is no evidence to support it. Procedures of disinfection and cleaning should be rigorous, considering that PatientSense was worn in uncontrolled environments wherein fluids can contaminate parts of the device and be transmitted to other participants. Evidence of reliability, accuracy, real application, and useful visualisation can only be provided by collecting data from different patient cohorts to observe differences and trends and make comparisons. It is necessary to anticipate many scenarios wherein the device will be used and find risks for participants. Instructions for wearers were to recharge the battery when the system was removed. However, if this instruction is not observed there is the risk of an electrical shock for participants.

CHAPTER 8

CONCLUSIONS AND FURTHER WORK

8.1 Conclusions

As discussed with anaesthesiologists and general practitioners, a wearable health-monitoring system would provide several benefits in general practice, e.g. more accurate and continuous accounts of objective data of patients, assessment of the efficacy of treatments, and early warnings for different diseases. From the perspective of anaesthesiologists who work in a hospital setting it would also bring benefits in improving hospital environment, wherein the conditions do not promote good sleep in inpatients, and in reducing costs and hospital resources by recording the data of patients in their home and not occupying a bed in the hospital.

A wearable health-monitoring system recording physiological, environmental, and behavioural and activity-related information of the patient could extend applications to monitoring chronic diseases such as diabetes, hypertension and obesity. Anaesthesiologists listed applications of assessments of patients‘ fitness, general well-being and preoperative and postoperative conditions and sleep problems. But the WHMS needs to be accompanied by the appropriate selection of variables. In general, the vital signs are the core measurements required by clinicians. The relevance of the variable to measure is dictated by the importance to the condition to monitor, e.g. respiratory rate or humidity for people with asthma and respiratory and pulse rates for sleep apnoea. Patients‘ behaviour and habits have a strong influence on the behaviour of their condition. The decision as to what to measure and how to measure it should be informed by a clinician according to the target patients. There is not a generic solution and it also applies to the behavioural data to collect from the patient that is relevant for the doctor.

However, despite the possible applications and benefits of the WHMS, a significant challenge faced by designers of new medical devices is the limitation that testing cannot be performed with real patients without supporting evidence from testing with healthy subjects. The approach taken in this research to recruiting practising clinicians as study participants afforded a number of significant benefits:

- The study volunteers were able to give feedback both from a wearer‘s and a clinician‘s perspective.
- System requirements important for clinical use were identified at an early stage of the system evolution.
- Volunteers gave expert opinions regarding the usefulness of the acquired data and of the various options for visual presentation.

One good starting point was to include the features listed in the questionnaire of Pontalopulos and Bourbakis (2010) that are used for the rating the maturity of medical wearable health-monitoring systems. However, the approach followed by the authors can lead to wrong conclusions. The perspectives of users, clinicians and manufacturers should be assessed and addressed separately, as the features are not equally relevant to the three parties. There is no a general assessment for WHMSs, and the relevance of the features depends on the application and use of the developed solution. For example, real-time or decision support could not be part of the solution of the application. Many features have been reported in the literature but in a dispersed way. Interviews and focus groups opened areas of discussions for features relevant to WHMSs; although they were indicated as being very important by clinical participants, there is little discussion in the literature, e.g. clinical hygiene, data presentation, compliance with safety norms, data with scientific metrics, and providing evidence of usefulness of data recorded. The perceived benefit of the WHMS affects the relevance of other features, such as wearability, aesthetic issues, and cost.

Sharing personal information on social networks is common in young people. Privacy of physiological data might not be seen as important or relevant for this group of users. However, privacy should be treated as a priority and not as an optional feature of the system. It could be possible that neurodegenerative and chronic diseases be detected from physiological data in the

future with implications for the person whose data was recorded. Information collected should not be publicly available under any cause.

In academic research, protocols and ethical approvals are required. The documentation of the research specifies the nature of the research, description of the activities and procedures to follow, and description of participants. However, the research should be more rigorous for the selection and description of participants, be they healthy or with a condition. Variability of physiological signals depends on the condition of the person and it is affected by a number of causes, e.g. diseases suffered in the past, age, and fitness of the user. To label a participant as healthy should be after the results of medical tests and not because they are a young person without apparent health conditions. Medical research is based on observations and comparisons between groups of healthy people and patients with a condition.

The observation of differences in the patterns between different patient cohorts and healthy people can provide evidence of the usefulness of a WHMS. Relevance of data collected takes place when data is presented and it is possible for clinicians to identify a disease or severity. Recordings of healthy participants might not evaluate and provide evidence of the usefulness of the WHMS devices. However, participation of healthy users is a recommendation of the first stage in the development of treatments and designs of prototypes to identify issues and provide evidence of possible benefits of the treatment or application developed. Both anaesthesiologists and GPs recommended recordings of patients with different conditions and severities. For anaesthesiologists, data displayed would be used to identify severities and conditions by comparing data behaviour in the visualisations. Moreover, as they explained, they are trained by comparing data of patients with different conditions. For GPs it would be a way in which to validate the system, if it is capable of measuring accurate signals of different patients.

Missing information in the measurements was not seen as being important for observations of patterns or behaviour of signals in chronic diseases, as clinicians observe the trends of not continuous measurements, e.g. body temperature, blood pressure, or glucose levels. These discrete measurements taken with differences of hours enable them observing the behaviour of the signals. However, highly accurate and continuous measurements would be necessary for arrhythmias or those diseases in which quick variations could be indicators of an abnormality.

In terms of user feedback, all participants gave helpful insights. The relative comfort of the system was an important consideration. It was noted that comfort must be assessed in terms of the individual components of the system, rather than for the system as a whole. Furthermore, some system components seemed uncomfortable to participants at first, but became less bothersome over time, indicating a need to evaluate comfort longitudinally.

The main limitation of the research was the collection of data of healthy participants, although there is no medical support that indicates that they were healthy participants. Usefulness of data cannot be assessed without evidence that shows that there is a difference in the visualisations of different cohorts of patients. However, relevant features for a WHMS were discussed with clinicians that suggest that they should be part of the development of devices. These comprised clinical hygiene and protocols of disinfection, data presentation to observe trends and compare data, data being presented in a scientific format, and validation of the device to provide evidence of usefulness.

8.2 Research Questions

From the results presented in the thesis we can address the three research questions posed at the outset of this thesis:

> *Q1. How can we design, prototype and evolve a real-world, multimodal and long-term patient-monitoring system?*

CircadianSense and the evolved PatientSense could be described as early clinical prototypes. The iterative and inclusive design approach adopted highlighted benefits above those observed with more conventional participatory design approaches. Rather than defining a system specification and then adopting a participatory design approach, the approach used to define the proof-of-concept PatientSense was more fluid, speculative, and open to clinical input. Keeping participants involved in the design process through the evolution of the hardware prototypes was particularly useful, given the specific expertise of the volunteers: clinicians gave invaluable insights into the real-world challenges that the system would face in deployment, and engineers gave useful suggestions regarding technical challenges that would also need addressing. Ideally,

a complete design cycle from further evolution to productisation and commercialisation would involve large groups of subjects in testing and continued use by stakeholders, including, for example, nursing staff. The participation of clinicians gave direction in the selection of physiological, environmental and behavioural information. There are no generic solutions and the appropriate data to collect depends on the target patients. Clinicians reported that sometimes the signs do not match with the symptoms described by the patient, the symptoms have no apparent causes, and the reason reported is that emotional states, stress, and sleep quality of the patients affect their condition. The technological approach to monitoring health conditions should include these behavioural reports. Again, the solution cannot be generic and should be adapted to the patient and condition with the help of clinicians.

Q2. What features and issues need to be considered in a long-term wearable health-monitoring system to produce a clinically relevant device?

Features relevant to the WHMS depend on the application and the usefulness of data collected by the device, and affect the importance of other aspects such as cost and wearability. The feature that can lead to the adoption of the device for clinical use is the usefulness of data collected in providing evidence of success for diagnosis, monitoring and prognosis of diseases. The usefulness of data can only be understood by the collection of physiological, environmental and behavioural information relevant to the condition that facilitates finding relationships between data recorded and explaining the symptoms. Researchers have to anticipate all possible scenarios and determine if a sensor or its placement could affect the safety of patients and reliability of data. Irrelevant, unreliable or inaccurate data might lead to abandoning the use of the device. Features that have to be considered are hygiene, protocols of disinfection, validation of the device under different conditions and different patient cohorts and data presented in scientific format. People nowadays are used to sharing data on social networks. However, data privacy should be preserved independently of the preference of the patient or clinician to share information.

Q3. How can complex multimodal patient data be analysed, presented and visualised to provide trends, summaries and assessment of diseases?

Two characteristics should be observed in the visualisation to provide relevant information to clinicians, visualisations that enable observing trends and comparing data. Deterioration or improvement of the condition of a patient is generally observed over long periods of time. Averages of data over periods of hours or days and visualised as scatterplots can summarise data to observe the trends and behaviour of a disease and compare data over periods of days. Histograms also are visualisations that can be used to observe how data behaves and make comparisons. The limited time that clinicians have for patients constrains their participation and interest in selecting variables to visualise and selecting averages of data to be visualised to make comparisons and observe abnormalities. However, the analysis and presentation should be with their recommendation and using scientific metrics. A lack of understanding of how data was analysed and processed can cause distrust in data visualised. Evidence of the usefulness of the visualisation to compare data of patients can only be provided when data is collected from cohorts of patients with different conditions. If differences are observed in the visualisation then it can be used to train clinicians to diagnose and monitor based on the behaviour of data.

8.3 Further Work

The experimental work presented in this thesis was that of early-stage proof-of-concept testing with healthy subjects. The collection of larger datasets from a broader, more diverse set of healthy subjects is needed and there would be considerable scope for further work in the analysis of these datasets to provide useful understanding of normal patient data and to inform comparisons with patient data between different cohorts as well as comparisons within individual patient data, e.g. before and after interventions. There should also be engagement and collaboration with clinicians from specialisms relevant to different patient cohorts.

The collection of data of different patient cohorts can provide the evidence necessary to assess the usefulness of the device and the application for the diagnosis and monitoring of a disease. Are there visual differences in the data of patients with different diseases? Are there visual differences of patients with the same disease but with different severity? Positive answers to these questions are the evidence that the system is reliable, accurate, and provides useful and

meaningful data to clinicians. However, if there are no differences in the visualisation the following task would be to try different averages of data and explore other visualisations. The collection of data of patients with different diseases should include adjustments to the behavioural and activity-related information to be registered from the patient.

There are issues related to wireless communication in the medical field related to data security and compatibility with medical standards, although the system developed was not intended for wireless communication with other devices. Several benefits were reported in the study, such as monitoring the status of the battery, backing up the information on other devices, and displaying data on a mobile phone or computer for remote access by clinicians for monitoring and communication with patients.

It is easy to register information in a paper daily log, but for people used to mobile phones, an electronic daily log would be preferable with benefits both for patients and clinicians, e.g. programmed reminders of medication and medical recommendations, as well as remote monitoring by clinicians for better patient control.

PatientSense poses a risk of electrical shocks when the user does not follow the instruction of removing the device before recharging the battery with a USB charger. The conductive fabric used to measure EDA and the pulse sensor act as electric conductors that in an extreme condition could discharge a great amount of energy into the body of the patient. Indeed, the user has to follow the instructions but this is uncertain, leading to a system not complying with safety norms. A USB electrical isolator is necessary in the processor box.

Procedures of hygiene and disinfection have to be developed for the device. This risk is more noticeable in the conductive fabric, which is more difficult to disinfect and clean. Initially, the change in disposable Ag/AgCl electrodes by conductive fabric was achieved for the risk of skin irritation of the electrodes. However, this solution produced a more complex and risky effect for the user.

Encryption of data recorded is also necessary to be addressed for the protection of patients‘ information.

As recommended in clinical interviews, additional sensing of non-ambulatory measurements such as blood pressure, blood sugar and pulse oximetry can complement information collected by the device. This complementary information could easily be collected with commercial devices to help better monitoring and managing of chronic diseases.

A change in the method used to collect the pulse rate is also recommended by aesthetic and comfortability issues, but, more importantly, for risk-related reasons of having a sensor on a carotid artery.

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APPENDIX A CIRCADIANSENSE DOCUMENTS FOR THE CLINICAL STUDY

Electronic, Electrical and Computer Engineering, University of Birimingham

Assessment Number: ERN 13-0448

Hazard and Risk Assessment Summary

School/Dept: Electrical, Electronic and Computer Engineering

Assessor: Dr. Sandra I. Woolley

Location of Activity: Hospital and outside

Date of Assessment: 28th March 2014

Activity Assessed (Attach protocols): CircadianSense – A proof-of-concept system for unobtrusive multi-sensing of circadian parameters in real environments.

Assessment of Hazard and Risk											Control Measures Required
HAZARD (List only hazards from which there is a significant risk of serious harm under foreseeable conditions)	PERSONS AT RISK (See key, Indicate number)	PERSONAL HARM?			LIKELIHOOD of HARM?						
		F	Mj	Mn	Y	Pr	Po	R			
There are no significant risks associated with the use (as recommneded) of CircadianSense.											Recommended use of CircadianSense is described in the study protocol and participant information sheet. Actions taken are summarised overleaf.

Key

PERSONS AT RISK	
Ug	Undergraduate
Pg	Postgraduate
S	Staff
C	Contractor
V	Visitor
Pa	Patient
Pu	General Public
Yp	Young Person
Nm	New/Expectant Mother

PERSONAL HARM?	
F	Fatality
Mj	Major Injury
Mn	Minor Injury

LIKELIHOOD	
Y	Yes/ Very High
Pr	Probable
Po	Possible
R	Remote

Risk Significance	Y	Pr	Po	R	
F	✓	✓	✓	✓	✓ = Significant risk
Mj	✓	✓	✓	✓	
Mn	✓	✓	X	X	X = Insignificant risk

Major Injury: Loss of or broken limb
Loss of or damaged eye
Loss of consciousness
Acute illness needing medical treatment
Permanent ill health or disability

Date for Review: 27/March/2014

S. I. Woolley 28.3.14

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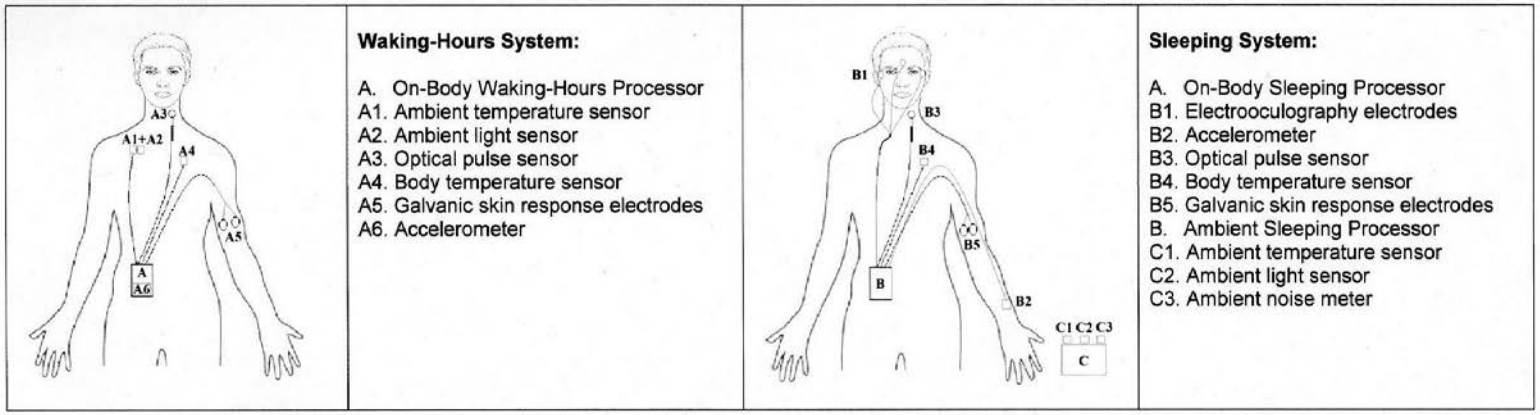
CircadianSense Recommendations and Actions Taken

CircadianSense is a system designed by the University of Birmingham's Human Interface Technology group for unobtrusive multi-sensing of circadian parameters in real environments. It was designed with the aim of contributing toward the clinical needs expressed for improved recording of patient data over longer terms and in the normal activities and real environments of everyday life. It has been successfully piloted in real use by the research team throughout the development period.

CircadiaSense consists of three compact, battery-powered, component systems: a sensing system worn under clothing during waking-hours and two sensing systems for sleeping; one worn and placed proximal to the sleeper, for example, placed on a bedside table. Each component system comprises a processor box which contains a processing unit, data storage unit and battery, and, an interface to a set of sensors. The figure below shows the component systems and locations of the sensors. The sensors are wired and the system does not radiate wireless signal energy. CircadianSense sensors measure physiological and ambient variables: body temperature, body movement, pulse rate, electrodermal response and night-time eye movement (electrooculography). An extra box placed proximally to the sleeping participant is used to record ambient temperature and light and noise level. The waking-hours wearable system can be worn either in a small waist bag or belt bag. The system was designed to be unobtrusive. With only the exception of a small sticking plaster and clip, it is completely covered by a short sleeved shirt or hospital scrubs. The system components are CE rated and the system does not use wireless communication and does not emit wireless radiation.



Waking-Hours System:

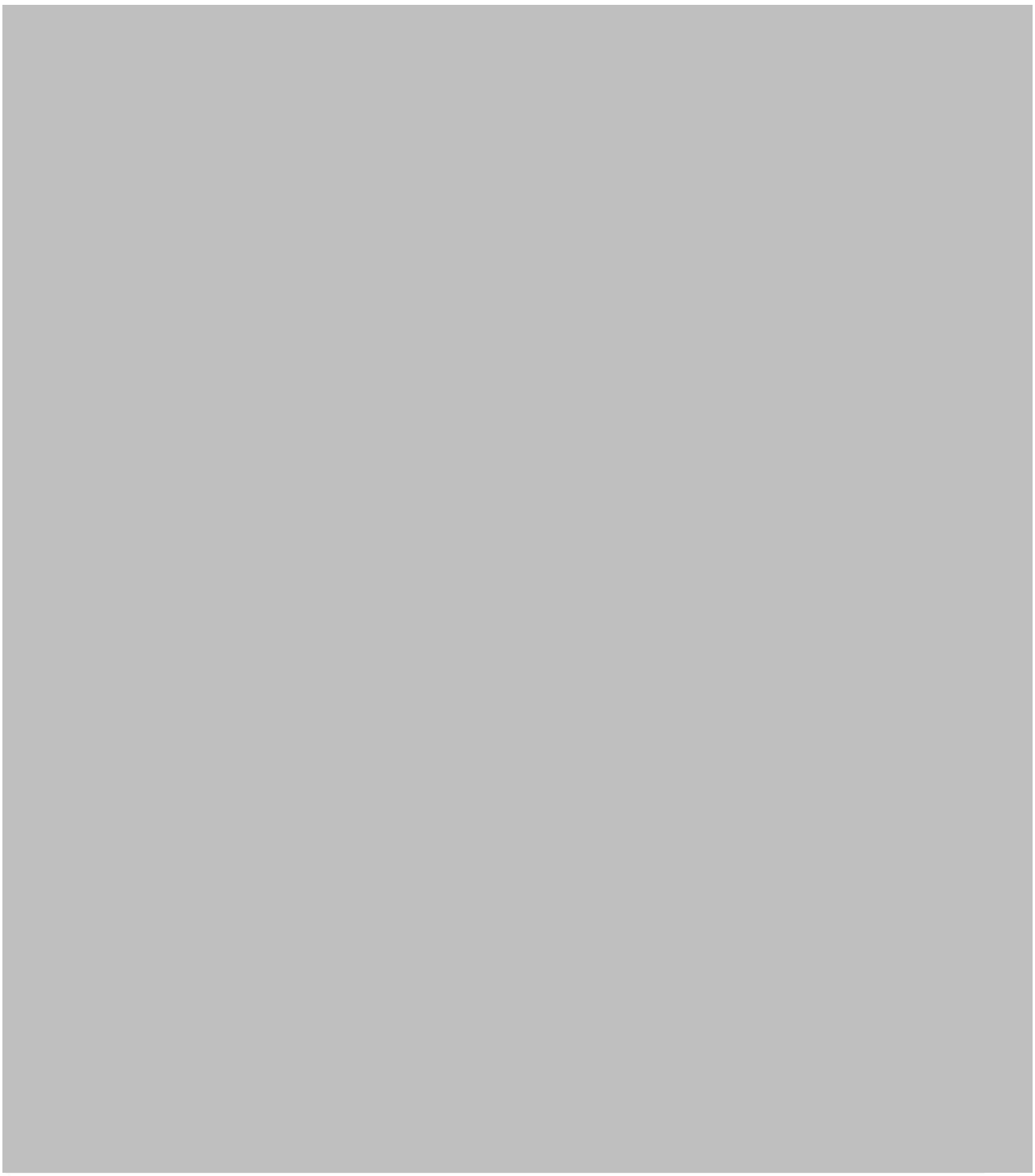
A. On-Body Waking-Hours Processor
A1. Ambient temperature sensor
A2. Ambient light sensor
A3. Optical pulse sensor
A4. Body temperature sensor
A5. Galvanic skin response electrodes
A6. Accelerometer

Sleeping System:

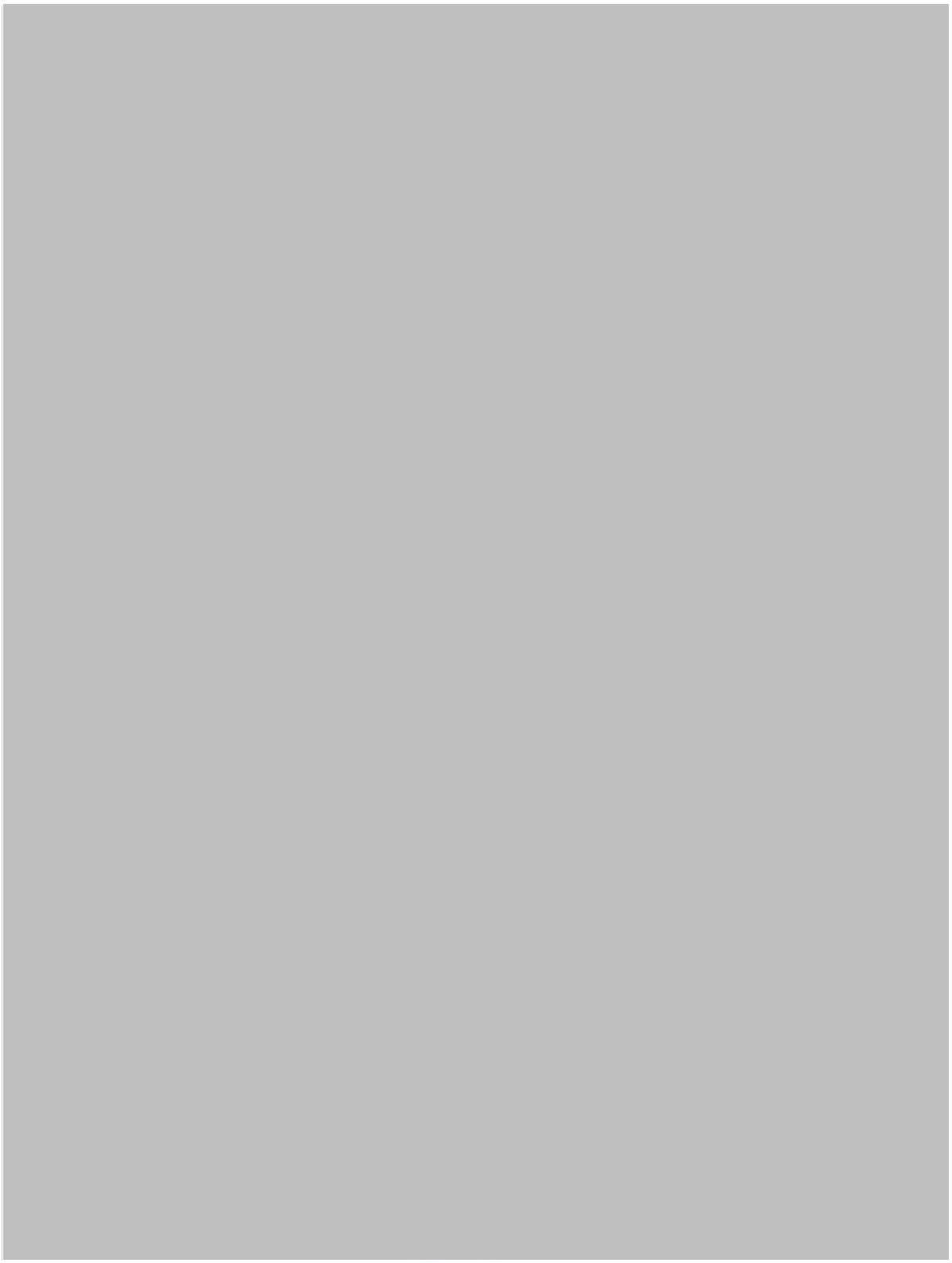
A. On-Body Sleeping Processor
B1. Electrooculography electrodes
B2. Accelerometer
B3. Optical pulse sensor
B4. Body temperature sensor
B5. Galvanic skin response electrodes
B. Ambient Sleeping Processor
C1. Ambient temperature sensor
C2. Ambient light sensor
C3. Ambient noise meter

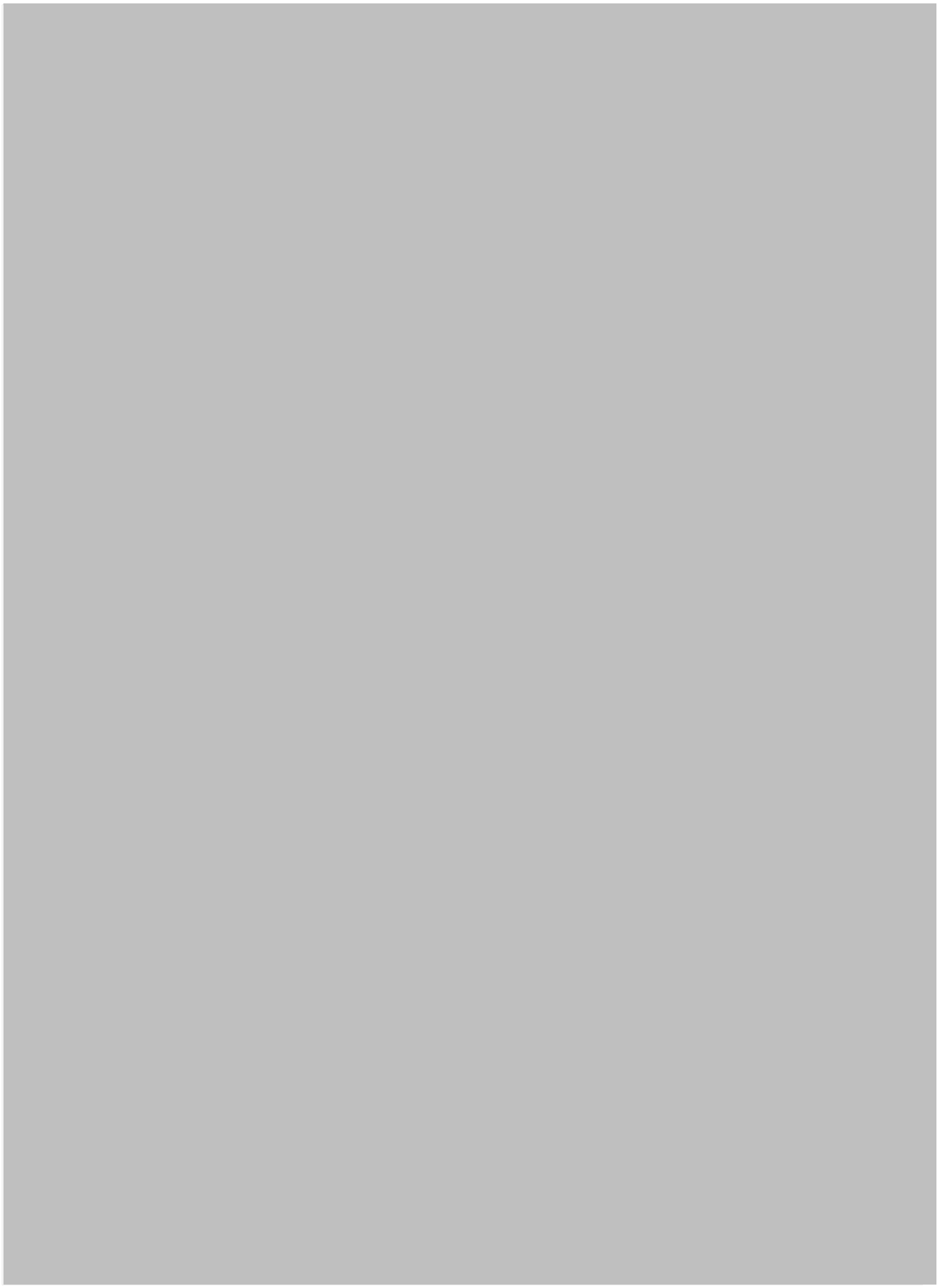
CircadianSense system components and sensors

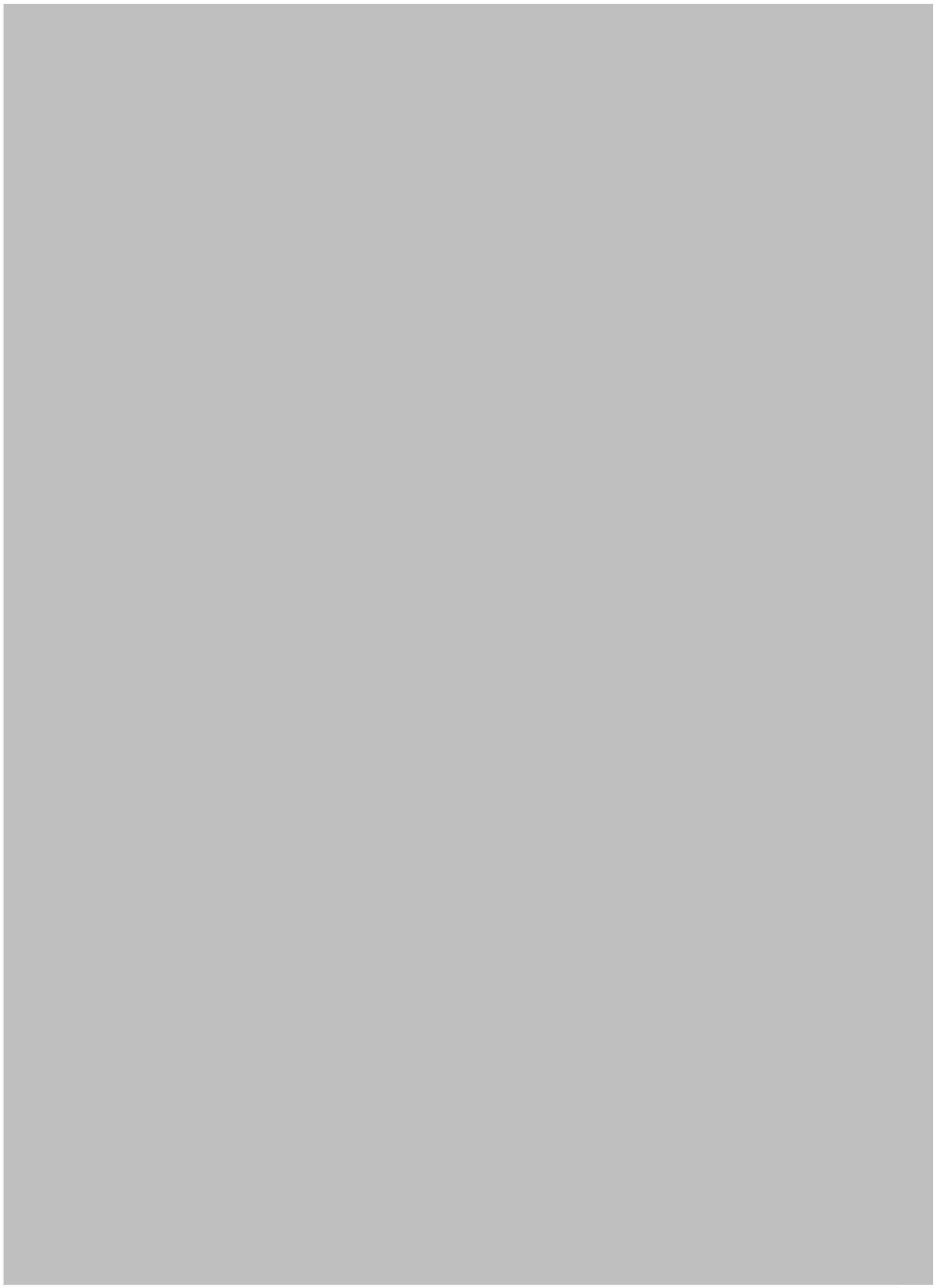
Antibacterial wipes will be used to clean cables and enclosures before system use and new electrodes will be provided for day. A patch test of the electrodes and sticking plasters will be recommended prior to use of the system. Small changes in the positioning of electrodes and sticking tape will be recommended to reduce skin irritation caused by prolonged application. A test fitting is also recommended to accomodate sensor adjustments for comfort. Participants will be required to first use the system away from normal working hours to ensure that it does not impede function or sleep. Only after this assurance would the system be used in the hospital environment. If abnormal normal physiological values are detected, GP referral will be advised.

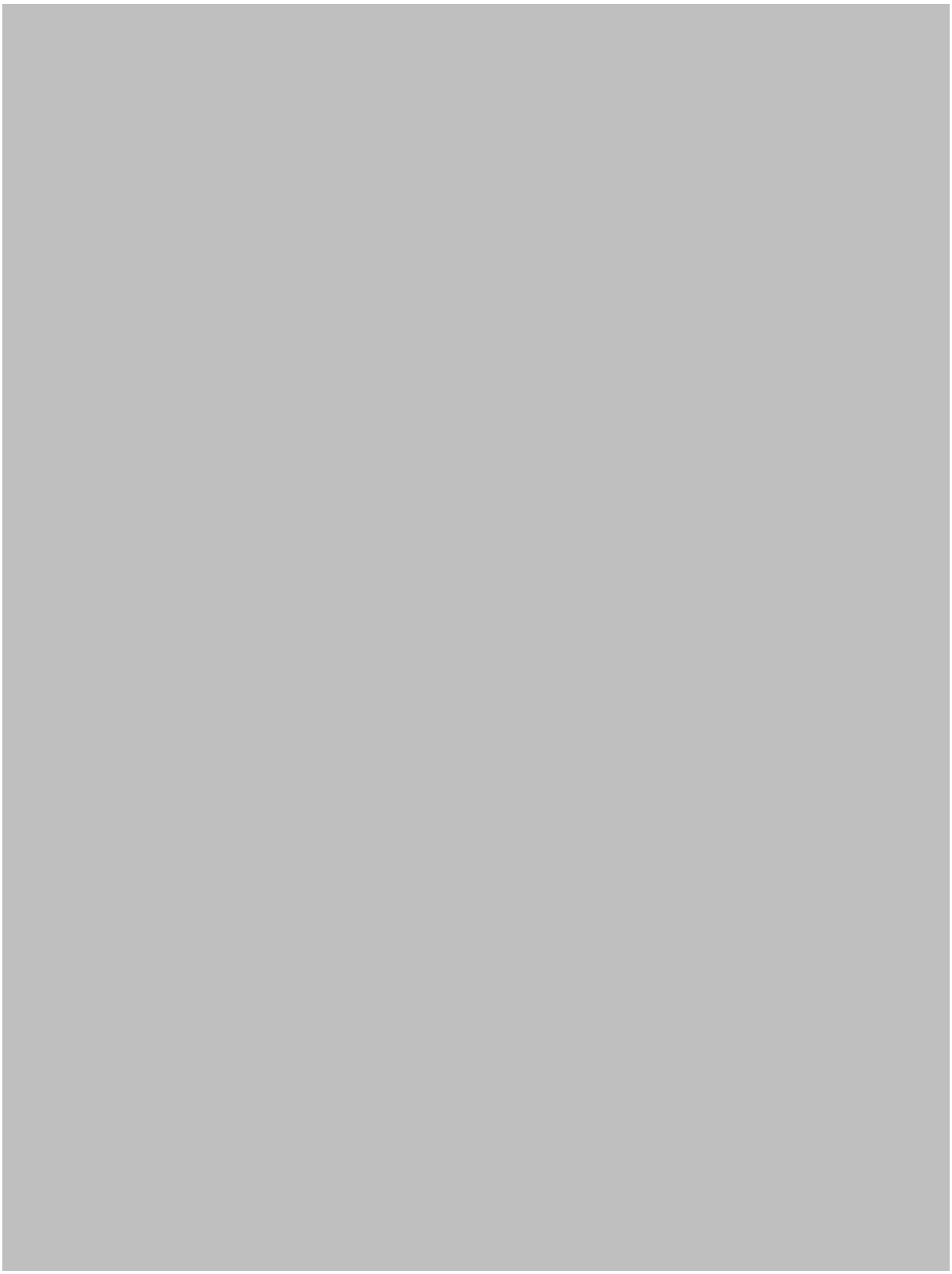


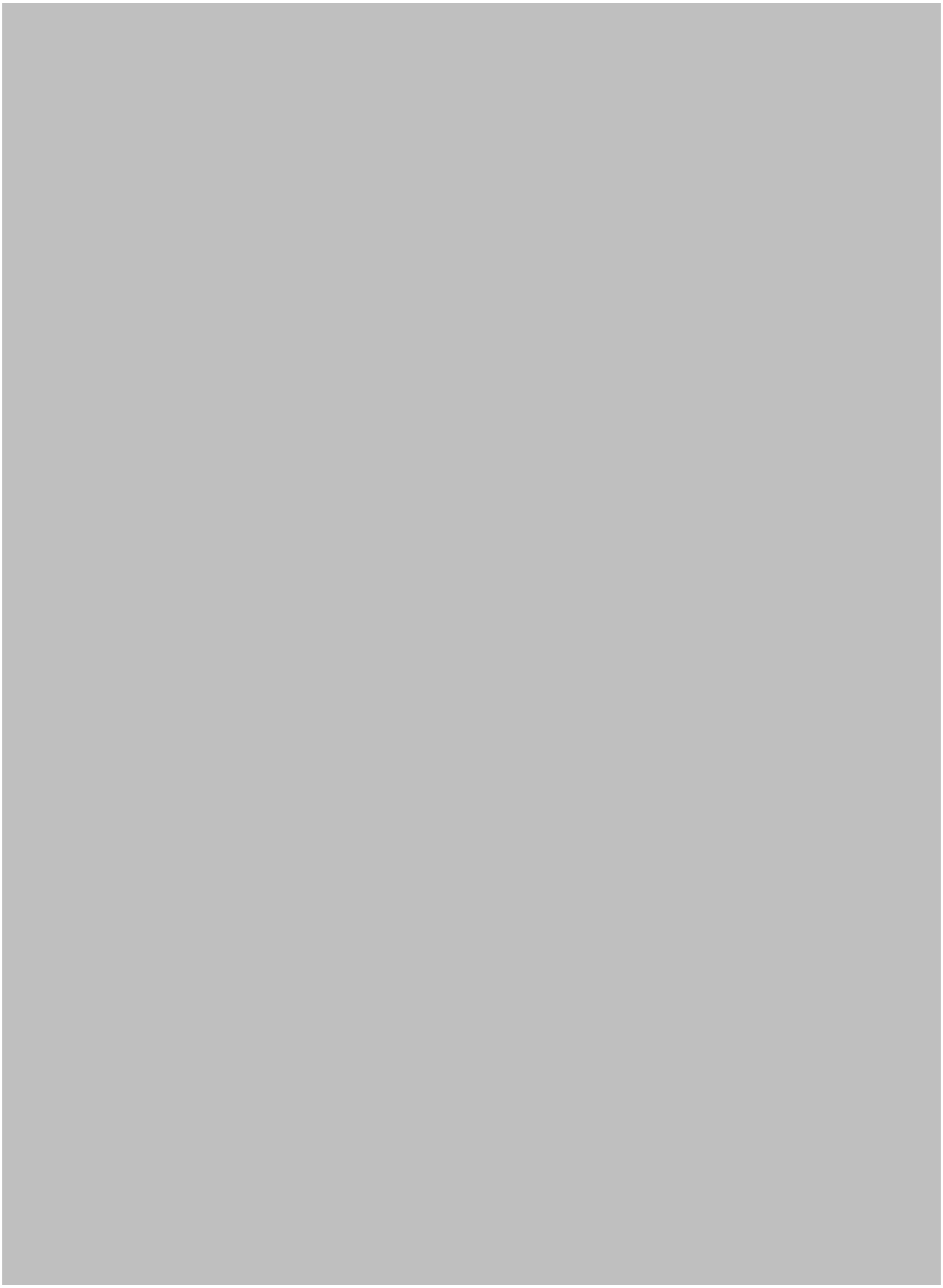
University of Birmingham Edgbaston Birmingham B15 2TT United Kingdom











Version 1: Date 28/3/14.

CONSENT FORM FOR PARTICIPANTS

CircadianSense – A proof-of-concept system for unobtrusive multi-sensing of circadian parameters in real environments.

- The nature and aims of the research have been explained to me and I understand what is expected of me. I have read and understood the Participant Information Sheet for the above study.
- I understand that I can contact the researchers if I have questions related to this study. The contact can be by phone, e-mail or in person. (Contact details are provided on the participant information sheet.)
- I understand that my participation is voluntary and that I am free to withdraw at any time up to two weeks after the last interview and that I can withdraw without having to give a reason for my withdrawal. I understand that if I withdraw within the specified period all my data will be removed and destroyed.
- I consent to the processing of my personal information for the purposes of this research study. I understand that such information will be treated as strictly confidential and handled in accordance with the provisions of the Data Protection Act 1998.
- I understand that recorded data will be stored in electronic format. All information relating to this study is to remain confidential and the use of such information will be used only for the purposes of the stated research. I also understand that the files will be preserved for 10 years to allow, if it is necessary, verification of data.
- I agree to volunteer as a participant for the study described in the information sheet and I give full consent for my participation in this study.
- This consent is specific to the study described in the Participant Information Sheet and shall not be taken to imply my consent to participate in any subsequent study or deviation from that detailed here.

Participant's Statement:

I agree that the research project named above has been explained to my satisfaction and I agree to take part in the study. I have read and understood both the notes written above and the Participant Information Sheet

Name of Participant	Date	Signature
Name of Person taking consent	Date	Signature

Participant Information Sheet

Title of Study: CircadianSense – A Proof-of-concept system for unobtrusive multi-sensing of circadian parameters in real environments.

We would like to invite you to participate in this study being undertaken by researchers at the University of Birmingham. You should only participate if you want to. Before you decide whether you want to take part, please take time to read the following information and please ask if there is anything that is not clear or if you would like more information.

CircadianSense is a system designed by the University of Birmingham's Human Interface Technology group for unobtrusive multi-sensing of circadian parameters in real environments. It was designed with the aim of contributing toward the clinical needs expressed for improved recording of patient data over longer terms and in the normal activities and real environments of everyday life. It has been successfully piloted in real use by the research team throughout the development period.

CircadianSense consists of three component systems: a sensing system worn during waking-hours and two sensing systems for sleeping; one worn and one proximal to the sleeper, for example, placed on a bedside table. Each component system comprises a processor box which contains a processing unit, data storage unit and battery, and, an interface to a set of sensors. The figure below shows the component systems and location of the sensors.

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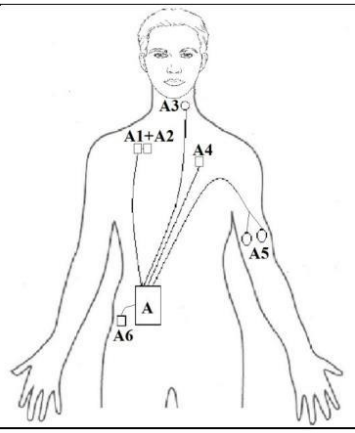
<td> 
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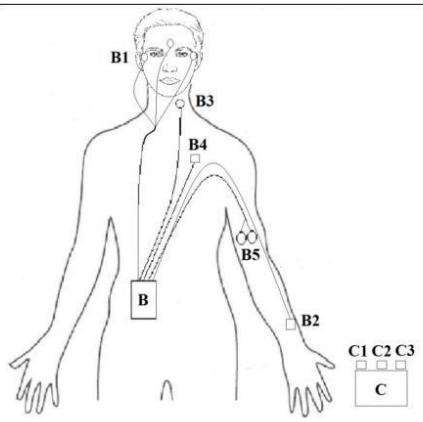
<td> 
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<tr>
<td>Waking-Hours System:
A. On-Body Waking-Hours Processor
A1. Ambient temperature sensor
A2. Ambient light sensor
A3. Optical pulse sensor
A4. Body temperature sensor
A5. Galvanic skin response electrodes
A6. Accelerometer</td>
<td>Sleeping System:
B. On-Body Sleeping Processor
B1. Electrooculography electrodes
B2. Accelerometer
B3. Optical pulse sensor
B4. Body temperature sensor
B5. Galvanic skin response electrodes
C. Ambient Sleeping Processor
C1. Ambient temperature sensor
C2. Ambient light sensor
C3. Ambient noise meter</td>
</tr>
</table>

Proposed Procedure

Participation in this study will involve wearing the CircadianSense system for 3 days and 3 nights, completing activity logs and sleep questionnaires, and participating in two structured interviews to provide feedback regarding the system and the recorded data.

Antibacterial wipes will be used to clean cables and enclosures before system use and new electrodes will be provided for each day. A patch test of the electrodes and sticking plasters will be recommended prior to use of the system. Small changes in the positioning of electrodes and sticking tape are recommended to reduce skin irritation caused by prolonged application. A test fitting is also recommended to accommodate sensor adjustments for comfort and wearability, for example, the system can be attached to the belt or can be contained in a small shoulder bag under clothes. The system was designed to be unobtrusive. With only the exception of a small sticking plaster and clip, it is completely covered by a short sleeved shirt or hospital scrubs.

Potential participants will be asked to wear the system on a day/night cycle when they will not be working, and, after which, they would be asked to confirm that the system did not impede their activity or deteriorate their sleep. Only with this confirmation would participants be invited to continue use into the working week. Participants could then wear the system for two further day/night cycles, but, of course, being free to remove the system at any time.

Daily assistance with CircadianSense will be provided. The researcher will remove captured data and reset the system ready for further use. The participants need only switch CircadianSense on each day.

Participants will be asked to complete an activity log, sleep questionnaire, and assist with feedback regarding the CircadianSense system and the recorded data. At the end of the testing we will invite you to attend two semi-structured interviews to ask you about different examples of visualisations of captured data.

Any information obtained during the tests will remain confidential. All data will be anonymised in publication. You may ask for copies of all papers, reports and other published or presented material. Interested participants will be invited to co-author a journal paper submission summarising the system and results. Experimental records of physiological and environmental signals, including paper records and computer files, will be held securely for a minimum of 10 years in conditions appropriate for the storage of personal information.

You may withdraw from the study at any point up to two weeks after the final interview. Withdrawal within this time will ensure the removal and destruction of all your data from the study records.

Principal Investigator
Dr. Sandra I. Woolley
School of Electronic, Electrical & Computer Engineering
University of Birmingham
[redacted]

PhD Researcher
David Infante Sanchez,
School of Electronic, Electrical & Computer Engineering
University of Birmingham

Academic supervisors and clinical collaborator
Prof. Robert Stone
[redacted]

Dr. Tim Collins
[redacted]

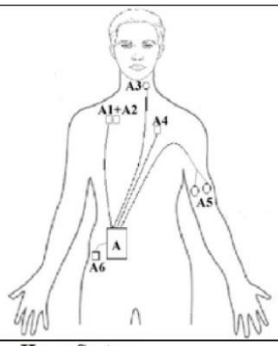
Dr Charlotte Small
Queen Elizabeth Hospital Birmingham (QEHB)

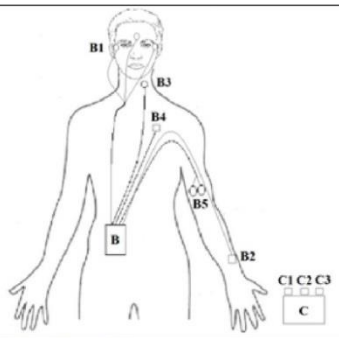
Assessment of CircadianSense

Please assign a weights and ratings from 1 to 5 as patient/wearer, clinician and/or engineer/system designer.

Feature	Feature Importance 1: not at all - 5: very high			Feature Description (and rating scale)	Feature Rating for CircadianSense Prototype			Feature Rating for CircadianSense's Potential		
	Wearer/ Patient	Clinician	Engineer		Wearer/ Patient	Clinician	Engineer	Wearer/ Patient	Clinician	Engineer
Wearability (F1)				E.g., system comfort, weight and size. Rating: 1:very poor ... 5:very good						
Intrusion (F2)				E.g., interference with patient movement, behaviour or daily activity. Rating: 1:very poor ... 5:very good						
Aesthetic issues (F3)				Affecting the patient's appearance. Rating: 1:very much ... 5:not at all						
Potential for security alert (N19)				Could the system be construed as a security threat, e.g., at an airport? Rating: 1:very much ... 5:not at all						
Data security (F4)				Encryption and protection of patient data. Rating: 1:very poor ... 5:very good						
Ease of use (F9)				E.g., ease of putting on and taking off, and switching on and off. Rating: 1:very poor ... 5:very good						
Access to data (N20)				Ability to access recorded data. Rating: 1:very poor ... 5:very good						
Maintenance (F5)				Recharging batteries and any servicing while in use. Rating: 1:very poor ... 5:very good						
Real-life application (F6)				Applicability to real-life and real health conditions. Rating: 1:very little ... 5:very much						
Performance in real-world use (F10)				Rating: 1:very poor ... 5:very good						
Availability of results (F7)				Timeliness of data and results. Rating: 1:very poor ... 5:very good						
Reliability (F11+F14)				Rating: 1:very poor ... 5:very good						
Cost (F12)				Rating: 1:very poor ... 5:very good						
Scalability (F15)				E.g., potential to add sensors. Rating: 1:very poor ... 5:very good						
Decision Support (F16)				Support for data interpretation Rating: 1:very poor ... 5:very good						
Clinical hygiene (N17)				E.g., Disposable electrodes. Rating: 1:very poor ... 5:very good						
Data presentation (N18)				Presentation of data for both clinician and user. Rating: 1:very poor ... 5:very good						

Please rate each of the worn sensors and units below from 1-5
(1=very uncomfortable 2=uncomfortable 3=OK 4=comfortable 5=didn't notice)





Waking-Hours System:
A. On-Body Waking-Hours Processor
A1. Ambient temperature sensor
A2. Ambient light sensor
A3. Optical pulse sensor
A4. Body temperature sensor
A5. Galvanic skin response electrodes
A6. Accelerometer

Sleeping-hours System:
B. On-Body Sleeping Processor
B1. Electrooculography electrodes
B2. Accelerometer
B3. Optical pulse sensor
B4. Body temperature sensor
B5. Galvanic skin response electrodes
C. Ambient Sleeping Processor
C1. Ambient temperature sensor
C2. Ambient light sensor
C3. Ambient noise meter

System Components	Comfort Rating (1-5) 1=very uncomfortable 2=uncomfortable 3=OK 4=comfortable 5=didn't notice
The On-Body Waking-Hours System:	
A. Processor Box	
A1+A2. Ambient temperature and light sensors (clip on)	
A3. Optical pulse sensor	
A4. Body temperature sensor	
A5. Galvanic skin response electrodes	
The On-Body Sleeping System:	
B. Processor Box	
B1. Electrooculography electrodes	
B2. Accelerometer	
B3. Optical pulse sensor	
B4. Body temperature sensor	
B5. Galvanic skin response electrodes	

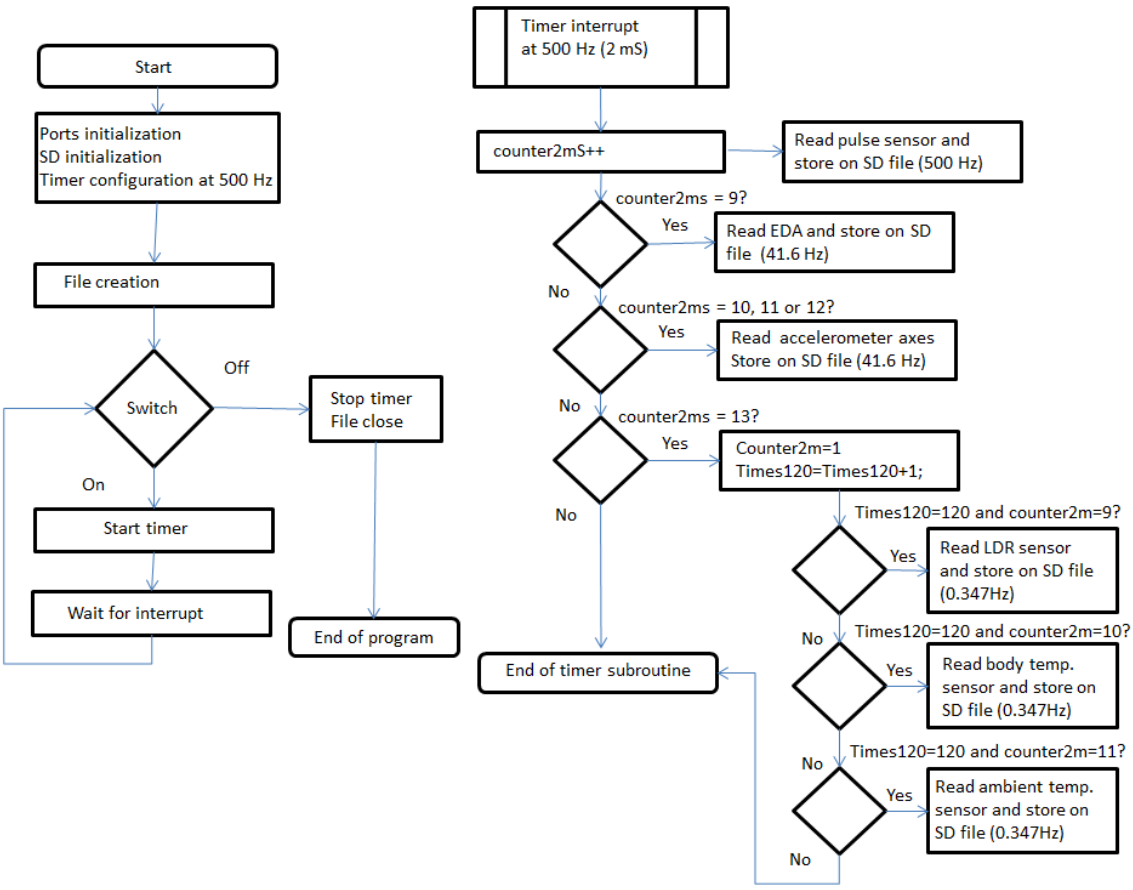
Did you notice any change in comfortability over time? What if anything became less noticeable or more uncomfortable?

Any other comments?

Thank you *very* much for your time! It is appreciated.

APPENDIX B CIRCADIANSENSE ARDUINO FIRMWARE

Waking-hours firmware



Waking-hours Arduino flowchart

```
#include <SdFat.h>
#include <SdFatUtil.h>
#include <FlexiTimer2.h>

// SD chip select pin const uint8_t chipSelect = SS;
// number of blocks in the contiguous file // 1.24 block per second
const uint32_t BLOCK_COUNT =64960;        // 14.5 hours
// time to produce a block of data
//const uint32_t MICROS_PER_BLOCK = 10000;
// file system
SdFat sd;
// test file
SdFile file;
// file extent
uint32_t bgnBlock, endBlock;
uint32_t bn=0;
uint8_t pCachet[522];
uint8_t Times120;
const int sd_switch=2;
const int power_sd=3;
const int power_sensors=4;
const int led=6;

unsigned int counter2m=0, index=0,full=0,var=0,pulse,EDR,ax,ay,az,light,excess;
unsigned int value1,bcd_switch=0,body,amb;
unsigned int interrupt_detected=0;
byte value2;

char filename[13];
int fileNumber = 0;
//------------------------------------------------------------------------
// store error strings in flash to save RAM
#define error(s) sd.errorHalt_P(PSTR(s))
//------------------------------------------------------------------------




//------------------------------------------------------------------------
void setup(void)
{
pinMode(sd_switch, INPUT);
digitalWrite(sd_switch, HIGH);      // turn on pullup resistors
pinMode(5, OUTPUT);
pinMode(power_sensors, OUTPUT);
pinMode(power_sd, OUTPUT);
pinMode(led, OUTPUT);
delay(2000);
FlexiTimer2::set(1, 1.0/500, read_sensors); // call every 500 1ms "ticks"
}
```

```
void loop(void) {

  digitalWrite(power_sensors,LOW); // Turn off sensor
  digitalWrite(power_sd,LOW);     // Turn off transistor SD
  digitalWrite(led,LOW);          // Turn off led

while(digitalRead(sd_switch)==HIGH); //Stop recordings
  digitalWrite(power_sensors,HIGH);  // Turn on sensors
  digitalWrite(power_sd,HIGH);      // Turn on transistor SD
  digitalWrite(led,HIGH);           // Turn on led
  delay(4000);

// initialize the SD card at SPI_FULL_SPEED for best performance.
// try SPI_HALF_SPEED if bus errors occur.
  if (!sd.begin(chipSelect, SPI_FULL_SPEED)) sd.initErrorHalt();
// Keep creating filenames until we get to one that does not exist
do {
   sprintf(filename,"Day2D%03d.TXT",fileNumber++);
   } while(sd.exists(filename));


  // create a contiguous file
  if (!file.createContiguous(sd.vwd(), filename, 512UL*BLOCK_COUNT)) {
    error("createContiguous failed");
  }
  // get the location of the file's blocks
  if (!file.contiguousRange(&bgnBlock, &endBlock)) {
    error("contiguousRange failed");
  }
 // file.close();

 //**********************NOTE*****************************************
 // NO SdFile calls are allowed while cache is used for raw writes
 //*************************************************************


 // clear the cache and use it as a 512 byte buffer
  uint8_t* pCache = (uint8_t*)sd.vol()->cacheClear();

  // tell card to setup for multiple block write with pre-erase
  if (!sd.card()->erase(bgnBlock, endBlock))
error("card.erase failed");

  // start multiple block write
  if (!sd.card()->writeStart(bgnBlock, BLOCK_COUNT)) {
    error("writeStart failed");
  }

FlexiTimer2::start();  //Timer on
```

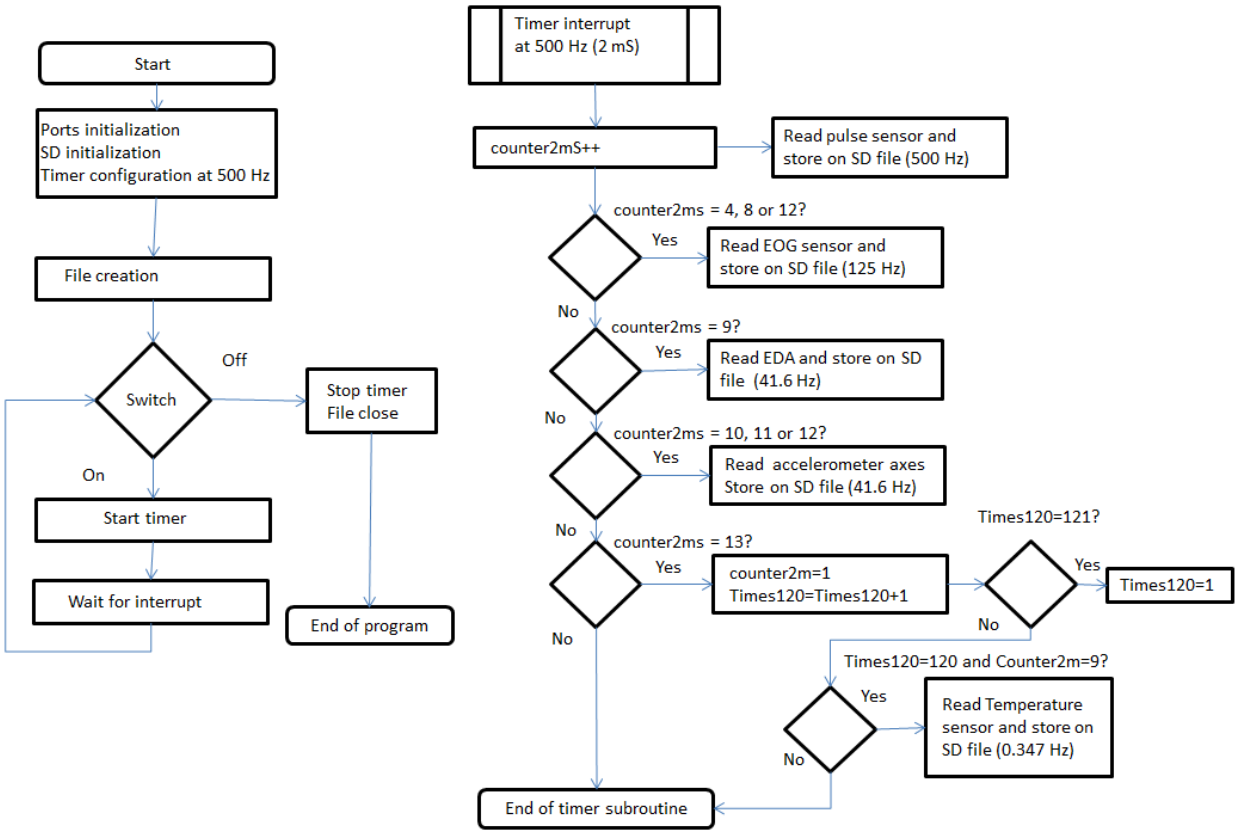
```
while (bn<BLOCK_COUNT)
{

//Stop the writing data on the SD card with the switch

if (digitalRead(sd_switch)==HIGH)
 {
  FlexiTimer2::stop();  //Interrupts off, no more interrupts
  memcpy(pCache,pCachet,512);
  while (bn<BLOCK_COUNT)
    {
     bn++;
     if (!sd.card()->writeData(pCache)) error("writeData failed");
     }
     digitalWrite(led, LOW);  //system is not storing data
     // close file for next pass of loop
     file.close();
     asm volatile ("jmp 0");
     for(;;);
  }
//Code for stopping the SD card with the switch


if (full==1)
   {
     full=0;
     bn++;
      memcpy(pCache,pCachet,512);

    if (!sd.card()->writeData(pCache)) error("writeData failed");
      }
 }

 FlexiTimer2::stop();
  // end multiple block write mode

  if (!sd.card()->writeStop()) error("writeStop failed");

//This procedure is necessary  in case the recording stopped early

  if (bn != BLOCK_COUNT) {
    file.open(filename, O_WRITE);
    file.truncate(512L * bn);
    file.close();

  asm volatile ("jmp 0");
  for(;;);
 }
//This procedure is necessary  in case the recordings stopped early
```

```
// close file for next pass of loop
  file.close();
  asm volatile ("jmp 0");
  for(;;);
 }


void read_sensors()
{
if (excess!=0)
{
  if (excess==1)
     {
     pCachet[0]=pCachet[512];
     index=1;
     }
  if (excess==2)
     {
     pCachet[0]=pCachet[512];
     pCachet[1]=pCachet[513];
     index=2;
     }
      excess=0;
}

pulse=analogRead(2);
value1=pulse>>(2);     //Storing the 8 MSb
value2=byte (value1);  //Casting to 8 bits
pCachet[index]=value2;
index++;

if (counter2m==9)     // Frequency=41 Hz
    {
    EDR=analogRead(4);
    value1=EDR>>(2);      //Storing the 8 MSb
    value2=byte (value1);  //Casting to 8 bits
    pCachet[index]=value2;   //It was storing "G"
    index++;
   }

if (counter2m==10) // Frequency=41 Hz
    {
    ax=analogRead(5);   //AX
    value1=ax>>(2);     //Storing the 8 MSb
    value2=byte (value1);  //Casting to 8 bits
    //value2=88;
    pCachet[index]=value2;
    index++;
    }
```

```
if (counter2m==11)
   {
   ay=analogRead(3);     //AY
   value1=ay>>(2);       //Storing the 8 MSb
   value2=byte (value1);  //Casting to 8 bits
   //value2=89;
   pCachet[index]=value2;
   index++;
  }

if (counter2m==12)
   {
   az=analogRead(0);     //AZ
   value1=az>>(2);      //Storing the 8 MSb
   value2=byte (value1);  //Casting to 8 bits
   //value2=90;
   pCachet[index]=value2;
   index++;
   }

if ((counter2m==9)&&(Times120==120))   //Read every 3 seconds
   {
   light=analogRead(6);    //Light
   value1=light>>(2);     //Storing the 8 MSb
   value2=byte (value1);   //Casting to 8 bits
   pCachet[index]=value2;
   index++;
   }

if ((counter2m==10)&&(Times120==120))
   {
   body=analogRead(1);     //Body Temperature
   value1=body>>(2);      //Storing the 8 MSb
   value2=byte (value1);   //Casting to 8 bits
   pCachet[index]=value2;
   index++;
   }

if ((counter2m==11)&&(Times120==120))
   {
   amb=analogRead(7);      //Ambient Temperature
   value1=amb>>(2);        //Storing the 8 MSb
   value2=byte (value1);    //Casting to 8 bits
   pCachet[index]=value2;
   index++;
   }
  counter2m++;
```

```
if (index==512)
{
full=1;         //Buffer is full
index=0;
excess=0;
}

if (index>512)
{
excess=index-512;
full=1;         //Buffer is full
}

if (counter2m==13)
  {
  counter2m=1;
  Times120++;
   if (Times120==121)
      Times120=0;
  }
}
```

Sleeping-hours firmware



Sleeping-hours Arduino firmware flowchart

```
#include <SdFat.h>
//#include <SdFatUtil.h>
#include <FlexiTimer2.h>

// SD chip select pin
const uint8_t chipSelect = SS;
// number of blocks in the contiguous file

//Factor=1.5332 blocks per second, 11.92 Hours of data
const uint32_t BLOCK_COUNT = 66000;
// time to produce a block of data
//const uint32_t MICROS_PER_BLOCK = 10000;
// file system
SdFat sd;
// test file
SdFile file;
// file extent
uint32_t bgnBlock, endBlock;
uint32_t bn=0;
uint8_t pCachet[522];
uint8_t Times120;

const int sd_switch=2;
const int power_sensors=4;
const int power_sd=9;
const int led=6;


unsigned int counter2m=1,index=0,full=0,var=0,pulse,ax,ay,az,EDR,EOG,excess;
unsigned int value1,body,amb;
byte value2;

char filename[13];
int fileNumber = 0;
//------------------------------------------------------------------------------
// store error strings in flash to save RAM
#define error(s) sd.errorHalt_P(PSTR(s))
//------------------------------------------------------------------------------



//------------------------------------------------------------------------------
void setup(void)
{
pinMode(sd_switch, INPUT);
digitalWrite(sd_switch, HIGH);      // turn on pullup resistors

pinMode(power_sensors, OUTPUT);
pinMode(power_sd, OUTPUT);
pinMode(led, OUTPUT);
```

```
delay(2000);
FlexiTimer2::set(1, 1.0/500, read_sensors); // call every 500 1ms "ticks"
}
//-------------------------------------------------------------------------


void loop(void) {
 digitalWrite(power_sensors,LOW); // Turn off pulse
 digitalWrite(power_sd,LOW);    // Turn off transistor SD
 digitalWrite(led,LOW);         // Turn off led

while(digitalRead(sd_switch)==HIGH);
 digitalWrite(power_sensors,HIGH); // Turn on sensors
 digitalWrite(power_sd,HIGH);    // Turn on transistor SD
 digitalWrite(led,HIGH);         // Turn on led

 delay(4000);

 // initialize the SD card at SPI_FULL_SPEED for best performance.
 // try SPI_HALF_SPEED if bus errors occur.
 if (!sd.begin(chipSelect, SPI_FULL_SPEED)) sd.initErrorHalt();
 // Keep creating filenames until we get to one that does not exist
do {
  sprintf(filename,"Slp2N%03d.TXT",fileNumber++);
  } while(sd.exists(filename));


 // create a contiguous file
 if (!file.createContiguous(sd.vwd(), filename, 512UL*BLOCK_COUNT)) {
  error("createContiguous failed");
 }
 // get the location of the file's blocks
 if (!file.contiguousRange(&bgnBlock, &endBlock)) {
  error("contiguousRange failed");
 }

 //**********************NOTE*****************************************
 // NO SdFile calls are allowed while cache is used for raw writes
 //*************************************************************

 // clear the cache and use it as a 512 byte buffer
 uint8_t* pCache = (uint8_t*)sd.vol()->cacheClear();

 // tell card to setup for multiple block write with pre-erase
 if (!sd.card()->erase(bgnBlock, endBlock)) error("card.erase failed");

 // start multiple block write
 if (!sd.card()->writeStart(bgnBlock, BLOCK_COUNT)) {
  error("writeStart failed");
 }
```

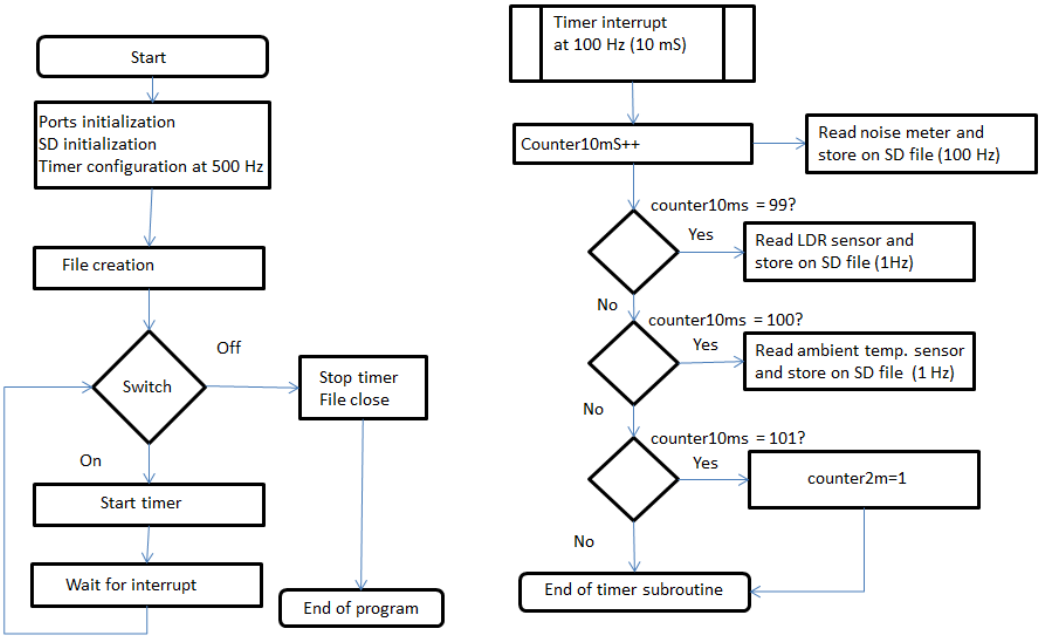
```
FlexiTimer2::start();

while (bn<BLOCK_COUNT)
{
//SD starts recordings when switch is closed
if (digitalRead(sd_switch)==HIGH)
 {
  FlexiTimer2::stop();  //no more interrupts
  memcpy(pCache,pCachet,512);
  while (bn<BLOCK_COUNT)
    {
     bn++;
     if (!sd.card()->writeData(pCache)) error("writeData failed");
     }
     digitalWrite(led, LOW);  //To know that microcontrolers is powered up
     // close file for next pass of loop
     file.close();
     asm volatile ("jmp 0");
     for(;;);
  }
//SD starts recordings when switch is closed


if (full==1)
   {
     full=0;
     bn++;

    memcpy(pCache,pCachet,512);

    if (!sd.card()->writeData(pCache)) error("writeData failed");
      }
  }

 FlexiTimer2::stop();
  // end multiple block write mode

  if (!sd.card()->writeStop()) error("writeStop failed");

 // truncate file if recording stoped early
  if (bn != BLOCK_COUNT) {
    file.open(filename, O_WRITE);
    file.truncate(512L * bn);
    file.close();

   asm volatile ("jmp 0");
   for(;;);
  }
// truncate file if recording stoped early
```

```
 // close file for next pass of loop
 file.close();
 asm volatile ("jmp 0");
 for(;;);
}


void read_sensors()
{
if (excess!=0)
{
 if (excess==1)
    {
    pCachet[0]=pCachet[512];
    index=1;
    }
 if (excess==2)
    {
    pCachet[0]=pCachet[512];
    pCachet[1]=pCachet[513];
    index=2;
    }
     excess=0;
}

pulse=analogRead(0);   //Channel 0 for pulse
value1=pulse>>(2);     //Storing the 8 MSb
value2=byte (value1);  //Casting to 8 bits
pCachet[index]=value2;
index++;

if ((counter2m==4)||(counter2m==8)||(counter2m==12))
   {
   EOG=analogRead(2);     //EOG
   value1=EOG>>(2);       //Storing the 8 MSb
   value2=byte (value1);  //Casting to 8 bits
   pCachet[index]=value2;
   index++;
   }

if (counter2m==9)
   {
   EDR=analogRead(5);     //Channel 5 for EDR
   value1=EDR>>(2);       //Storing the 8 MSb
   value2=byte (value1);  //Casting to 8 bits
   pCachet[index]=value2;
   index++;
  }
```

```
if (counter2m==10)       // Frequency=41 Hz
   {
   ax=analogRead(1);     //AX
   value1=ax>>(2);         //Storing the 8 MSb
   value2=byte (value1);   //Casting to 8 bits
   pCachet[index]=value2;
   index++;
   }

if (counter2m==11)
   {
   ay=analogRead(4);       //AY
   value1=ay>>(2);          //Storing the 8 MSb
   value2=byte (value1);   //Casting to 8 bits
   pCachet[index]=value2;
   index++;
   }

if (counter2m==12)
   {
   az=analogRead(6);     //AZ
   value1=az>>(2);         //Storing the 8 MSb
   value2=byte (value1);  //Casting to 8 bits
   pCachet[index]=value2;
   index++;
   }


if ((counter2m==9)&&(Times120==120))
   {
   body=analogRead(3);    //Channel 3 for temperature
   value1=body>>(2);     //Storing the 8 MSb
   value2=byte (value1);  //Casting to 8 bits
   pCachet[index]=value2;
   index++;
    }


  counter2m++;

 if (index==512)
 {
 full=1;         //Buffer is full
 index=0;
 excess=0;
 }

 if (index>512)
 {
 excess=index-512;
```

```
 full=1;          //Buffer is full
 }



 if (counter2m==13)
   {
   counter2m=1;
   Times120++;
    if (Times120==121)
       Times120=0;
   }
}
```

Ambient variables sleeping-hours firmware



Ambient sleeping hours Arduino firmware flowchart

```
#include <SdFat.h>
#include <SdFatUtil.h>
#include <FlexiTimer2.h>

// SD chip select pin
const uint8_t chipSelect = SS;
// number of blocks in the contiguous file

//Factor=0.1953 blocks per second, 14.93 hours per file
const uint32_t BLOCK_COUNT = 10500;
// time to produce a block of data
//const uint32_t MICROS_PER_BLOCK = 10000;
// file system
SdFat sd;
// test file
SdFile file;
// file extent
uint32_t bgnBlock, endBlock;
uint32_t bn=0;
uint8_t pCachet[522];
//uint8_t times_120;

const int sd_switch=2;
const int LED=4;
const int power_sd=6;
const int power_circuits=9;

unsigned int counter10m=1,index=0,full=0,var=0,noise,light,temp,excess;
unsigned int value1;
byte value2;

char filename[13];
int fileNumber = 0;
//------------------------------------------------------------
// store error strings in flash to save RAM
#define error(s) sd.errorHalt_P(PSTR(s))
//------------------------------------------------------------


//------------------------------------------------------------
void setup(void)
{
pinMode(sd_switch, INPUT);
digitalWrite(sd_switch, HIGH);      // turn on pullup resistors

pinMode(5, OUTPUT);
pinMode(LED, OUTPUT);
pinMode(power_sd, OUTPUT);
pinMode(power_circuits, OUTPUT);
delay(2000);
```

```
FlexiTimer2::set(10, read_sensors); // call 100 times a second or every 0.10ms "ticks"
}
//------------------------------------------------------------


void loop(void) {
//Led blinks once to indicate system is on
digitalWrite(LED, HIGH);
delay(2000);
digitalWrite(LED, LOW);
digitalWrite(power_sd,LOW);
digitalWrite(power_circuits,LOW);
while(digitalRead(sd_switch)==HIGH);    //Stop recordings
digitalWrite(power_sd,HIGH);       // Turn SD card on
digitalWrite(power_circuits,HIGH);  // Turn sensors on
digitalWrite(LED, HIGH);
delay(2000);

// initialize the SD card at SPI_FULL_SPEED for best //performance.
// try SPI_HALF_SPEED if bus errors occur.
  if (!sd.begin(chipSelect, SPI_FULL_SPEED)) sd.initErrorHalt();
// Keep creating filenames until we get to one that does not //exist
do {
   sprintf(filename,"AMB2N%03d.TXT",fileNumber++);
   } while(sd.exists(filename));

// create a contiguous file
  if (!file.createContiguous(sd.vwd(), filename, 512UL*BLOCK_COUNT)) {
    error("createContiguous failed");
  }
  // get the location of the file's blocks
  if (!file.contiguousRange(&bgnBlock, &endBlock)) {
    error("contiguousRange failed");
  }

  digitalWrite(LED, LOW);

 // file.close();
 //**********************NOTE*************************************
  // NO SdFile calls are allowed while cache is used for raw writes
  //*************************************************************

  // clear the cache and use it as a 512 byte buffer
  uint8_t* pCache = (uint8_t*)sd.vol()->cacheClear();

  // tell card to setup for multiple block write with pre-erase
  if (!sd.card()->erase(bgnBlock, endBlock)) error("card.erase failed");

  // start multiple block write
  if (!sd.card()->writeStart(bgnBlock, BLOCK_COUNT)) {
```

```
   error("writeStart failed");
  }

digitalWrite(5,LOW);
FlexiTimer2::start();

while (bn<BLOCK_COUNT)
{
if (digitalRead(sd_switch)==HIGH)
 {
  FlexiTimer2::stop();  //no more interrupts
  memcpy(pCache,pCachet,512);
  while (bn<BLOCK_COUNT)
    {
     bn++;
     if (!sd.card()->writeData(pCache)) error("writeData failed");
     }
      // close file for next pass of loop
     file.close();
      asm volatile ("jmp 0");
     for(;;);
  }


if (full==1)
   {
     full=0;
     bn++;
        memcpy(pCache,pCachet,512);
    if (!sd.card()->writeData(pCache)) error("writeData failed");
      }
  }

 FlexiTimer2::stop();
  // end multiple block write mode

  if (!sd.card()->writeStop()) error("writeStop failed");

 // truncate file if recording stoped early
  if (bn != BLOCK_COUNT) {
    file.open(filename, O_WRITE);
    file.truncate(512L * bn);
    file.close();

    asm volatile ("jmp 0");
    for(;;);
  }


  // close file for next pass of loop
```

```
 file.close();
 asm volatile ("jmp 0");
 for(;;);
}



void read_sensors()
{
//  digitalWrite(3,!digitalRead(3));   //Toggle every 2mS

if (excess!=0)
{
 if (excess==1)
    {
    pCachet[0]=pCachet[512];
    index=1;
    }
 if (excess==2)
    {
    pCachet[0]=pCachet[512];
    pCachet[1]=pCachet[513];
    index=2;
    }
     excess=0;
}

noise=analogRead(1);   //Channel 1 for noise
value1=noise>>(2);     //Storing the 8 MSb
value2=byte (value1); //Casting to 8 bits
pCachet[index]=value2;
index++;

if (counter10m==99)
   {
   light=analogRead(0);    //Channel 0 for Light
   value1=light>>(2);        //Storing the 8 MSb
   value2=byte (value1);   //Casting to 8 bits
   pCachet[index]=value2;
   index++;
   }

if (counter10m==100)
   {
   temp=analogRead(2);      //Channel 2 for temperature
   value1=temp>>(2);        //Storing the 8 MSb
   value2=byte (value1);     //Casting to 8 bits
   pCachet[index]=value2;
   index++;
    }
```

```
 counter10m++;

 if (index==512)
 {
 full=1;         //Buffer is full
 index=0;
 excess=0;
 }

 if (index>512)
 {
 excess=index-512;
 full=1;         //Buffer is full
 }



 if (counter10m==101)
   {
   counter10m=1;
   }
}
```

APPENDIX C SCILAB CODE

Waking-hours Scilab code

```
//W is a vector, w(1) contains the file size
//Data stored on the SD card is decoded and organised
clear;  //Clear all variables
clc;
file2read='C:\Analysis\Participant1\Day1.txt'
file2write='C:\Analysis\Particpant1\Participant1.sod'
file2write2='C:\Analysis\Participants\Participant1Pulse.sod'

stacksize(180000000);
w=fileinfo(file2read);
fd_r = mopen(file2read, 'rb')  //rt

numberofbytes=0;
block=0;
block1=0;
block_index=1;
bytes_file=w(1);  //This is the number of bytes stored in the file
number_of_blocks=(bytes_file *121/2060);
disp(number_of_blocks,"that is the size of blocks");
number_of_blocks=number_of_blocks;
pulse = zeros(number_of_blocks*13,1);
EDR = zeros(number_of_blocks,1);
ax = zeros(number_of_blocks,1);
ay = zeros(number_of_blocks,1);
az = zeros(number_of_blocks,1);
light1 = zeros(ceil(number_of_blocks/121),1);
body = zeros(ceil(number_of_blocks/121),1);
amb = zeros(ceil(number_of_blocks/121),1);

while (block<number_of_blocks-2)

  if (block_index<=120) then
  v=mget(17,'uc')';          //13 data per block
  pulse(block*13+(1:13)) = v([(1:10) 12 14 16]);
  EDR(block+1)=v(11);
  ax(block+1)=v(13);
  ay(block+1)=v(15);
  az(block+1)=v(17);

  else
  v=mget(20,'uc')';          //20 data per block
  pulse(block*13+(1:13)) = v([(1:10) 13 16 19]);
  EDR(block+1)=v(11);
  ax(block+1)=v(14);
  ay(block+1)=v(17);
  az(block+1)=v(20);
  light1(block1+1)=v(12);
  body(block1+1)=v(15);
  amb(block1+1)=v(18);
  block1=block1+1;
```

```
  end

  block=block+1;     //Calculates data in the next block
    block_index=block_index+1;  //Identify the block where EDR, Temperature are stored
  if (block_index==122) then
     block_index=1;
   end
end
mclose(fd_r);
save(file2write,'EDR','ax','ay','az','light1','body','amb');
k1=length(ax);
k2=length(ay);
k3=length(az);
k4=length(EDR);
k5=length(light1);
k6=length(body);
k7=length(amb);
k8=length(pulse);
save(file2write2,"pulse");

// Close all opened figures and clear workspace
xdel(winsid());
clear;  //Delete all variables
clc;    //clean screen
chunk=15;   //Chunk of 15 minutes
chunkmin=1;

stacksize(100000000);

// Data separated is processed and stored in a excel file

file2read='C:\Backup\Analysis\Participants\Participant1.sod'
file2Write='C:\Backup\Analysis\Participants\Participant1.csv'
st=9:30;                //Time when recordings started

load(file2read,"EDR","ax","ay","az","light1","body","amb");//
m=stacksize();
disp(m(1)/m(2))

scf(8);
plot(EDR)
///Characterisation of the accelerometer and offset
axoffset=1.6165;
ayoffset=1.6255;
azoffset=1.67;

//Sensitivity in volts per m/s2
axs=0.0345174;
ays=0.0339056;
azs=0.0331408;

axv=ax*3.3/255;
ayv=ay*3.3/255;
azv=az*3.3/255;
axv=(axv-axoffset)/axs;
ayv=(ayv-ayoffset)/ays;
azv=(azv-azoffset)/azs;

ax=axv;
ay=ayv;
az=azv;
//Eliminating gravity factor with a high pass filter
//Eliminating gravity factor with a high pass filter
x=ax';
```

```
Fs=1/(12*0.002);
hz=iir(5,'hp','butt',[0.1/Fs],[]);//,[.8 .01]);
mx = flts(x,hz);

x=ay';
hz=iir(5,'hp','butt',[0.1/Fs],[]);//,[.8 .01]);
my = flts(x,hz);

x=az';
hz=iir(5,'hp','butt',[0.1/Fs],[]);//,[.8 .01]);
mz = flts(x,hz);

//Eliminating gravity factor with a high pass filter
//Eliminating gravity factor with a high pass filter

//Calculating chunks of data of Energy Expenditure Calculating chunks of data of Energy Expenditure

vx=zeros(length(mx));
vy=zeros(length(my));
vz=zeros(length(mz));

vx=cumsum(mx)*(12*0.002); //Calculating velocity in each axis
vy=cumsum(my)*(12*0.002); //Calculating velocity in each axis
vz=cumsum(mz)*(12*0.002); //Calculating velocity in each axis
p=abs(vx.*mx+vy.*my+vz.*mz)/1.2;  //Power per unit of mass

e=(1/(12*0.002))*60*chunkmin;
number_of_blocks=(length(p)/e);          //Blocks of P of 1 minute
time=linspace(0,60,floor(e));

block=0;
while (block<number_of_blocks-1),
   MET1min(block+1)=inttrap(time,p(block*e+1:block*e+e))  //Integration in 1 minute
   block=block+1;
end
MET1min=MET1min*1.68/60+1.06;     //Integration period
//Calculating chunks of data of Energy Expenditure Calculating chunks of data of Energy Expenditure

//Computes blocks of 1 minute Computes blocks of 1 minute Computes blocks of 1 minute Computes blocks of 1 minute
number_of_blocks=(length(MET1min)/15);
block=0;
while (block<number_of_blocks-1),
 METmean(block+1)=sum(MET1min(block*15+1:block*15+15)); //Sums data in chunks of 15 minutes
 temporal=MET1min(block*15+1:block*15+15);
 METmax1min(block+1)=max(temporal);
 METmin1min(block+1)=min(temporal);
 block=block+1;
end
METmean=METmean/15;        //Averaging the signal to obtain the mean

hrMET=length(METmean)/(4);
timeMET=linspace(st,hrMET+st,length(METmean));

//Computes blocks of 1 minute Computes blocks of 1 minute Computes blocks of 1 minute Computes blocks of 1 minute

scf(1);
plot2d2(timeMET,[METmean METmin1min METmax1min])
xlabel("Time in Hours","fontsize",3,"color","black");
ylabel("MET","fontsize",3,"color","black");
title("METABOLIC EQUIVALENT OF TASK (MET)/15Min for clinician 1","fontsize",3,"color","black");
xgrid(12);

//Calculating chunks of data of EDR Calculating chunks of data of EDR Calculating chunks of data of EDR
```

```
EDR=EDR';                          //Calculating tonic component
Fs=1/(12*0.002);
hz=iir(6,'lp','butt',[3/Fs],[]);

Rfiltered1 = flts(EDR,hz);
Rfiltered1(find(Rfiltered1<=1))=255;

 Rfiltered1=(Rfiltered1*3.3)/255;      //Converts EDR to voltage
EDR1=((3.3*100000)-Rfiltered1*100000)./Rfiltered1; //Calculating the resistance in Ohms

hz=iir(6,'hp','butt',[0.2/Fs],[]);             //Phasic eliminated
Rfiltered = flts(EDR1,hz);
EDR=Rfiltered;

Rfiltered=abs(Rfiltered);
Rfiltered(find(Rfiltered>=800000))=800000;                //Limiting the tonic component

e=(1/0.024)*60*chunk;                                  //Data in 15 minutes= 40*60sec*15min;
number_of_blocks=(length(Rfiltered)/e);
block=0;
while (block<number_of_blocks-1),
 EDRmean(block+1)=sum(Rfiltered(block*e+1:block*e+e)); //Sums data in chunks of 15 minutes
 temporal=Rfiltered(block*e+1:block*e+e);
 EDRmax(block+1)=max(temporal);
 EDRmin(block+1)=min(temporal);
 block=block+1;
end

EDRmean=EDRmean./floor(e);        //Averaging the signal to obtain the mean

e=(1/0.024)*60*chunkmin;                                  //Data in 15 minutes= 40*60sec*15min;
number_of_blocks=(length(Rfiltered)/e);
block=0;
while (block<number_of_blocks-1),
 EDRmean1min(block+1)=sum(Rfiltered(block*e+1:block*e+e)); //Sums data in chunks of 15 minutes
 block=block+1;
end
EDRmean1min=EDRmean1min./floor(e);        //Averaging the signal to obtain the mean

block=0;
k=floor(length(EDRmean1min)/15);
while (block<=k-1),
EDRmax1min(block+1)=max(EDRmean1min(block*15+1:block*15+15));
EDRmin1min(block+1)=min(EDRmean1min(block*15+1:block*15+15));
block=block+1;
end

//Computes blocks of 1 minute Computes blocks of 1 minute Computes blocks of 1 minute Computes blocks of 1 minute
hrTonic=length(EDRmean)/(4);            //4 blocks of 15 minutes in 1 hour
timeTonic=linspace(st,hrTonic+st,length(EDRmean));

scf(2);
plot2d2(timeTonic,[EDRmean EDRmin1min EDRmax1min])
xlabel("Time in Hours","fontsize",3,"color","black");
ylabel("Tonic Component in Ohms","fontsize",3,"color","black");
title("Mean, Maximum, and minimum Tonic value for clinician 1","fontsize",3,"color","black");
xgrid(12);

//Calculating chunks of data of body temperature Calculating chunks of data of body temperature

//bodyreal=body.*0.40441176-50;            //For system2 with sensor 2
bodyreal=body.*0.23109243-8.92857156

e=(0.3178640*60*chunk);                                  //Data in 15 minutes= 40*60sec*15min;
```

```
number_of_blocks=(length(bodyreal)/e);
block=0;
while (block<number_of_blocks-1),
 bodymean(block+1)=sum(bodyreal(block*e+1:block*e+e)); //Sums data in chunks of 15 minutes
 temporal=bodyreal(block*e+1:block*e+e);
 block=block+1;
end

bodymean=bodymean./floor(e);    //Averaging the signal

hrbody=length(bodymean)/(4);            //4 blocks of 15 minutes in 1 hour
timebody=linspace(st,hrbody+st,length(bodymean));

//Calculating chunks of data of body temperature Calculating chunks of data of body temperature

e=(0.3178640*60*chunkmin);                              //Data in 15 minutes= 40*60sec*15min;
number_of_blocks=(length(bodyreal)/e);
block=0;
while (block<number_of_blocks-1),
 bodymean1min(block+1)=sum(bodyreal(block*e+1:block*e+e)); //Sums data in chunks of 15 minutes
 block=block+1;
end
bodymean1min=bodymean1min./floor(e);        //Averaging the signal to obtain the mean

block=0;
k=floor(length(bodymean1min)/15);
while (block<=k-1),
bodymax1min(block+1)=max(bodymean1min(block*15+1:block*15+15));
bodymin1min(block+1)=min(bodymean1min(block*15+1:block*15+15));
block=block+1;
end
//Computes blocks of 1 minute Computes blocks of 1 minute Computes blocks of 1 minute Computes blocks of 1 minute
scf(3);
plot2d2(timebody,[bodymean bodymin1min bodymax1min])
xlabel("Time in Hours","fontsize",3,"color","black");
ylabel("Temperature in C","fontsize",3,"color","black");
title("Mean, maximum, and minimum body Temperature for clinician 1","fontsize",3,"color","black");
xgrid(12);

//Calculating chunks of data of ambient temperature Calculating chunks of data of ambient temperature

ambreal=amb.*0.4621849-8.92857142;
/ambreal=1.2941176*amb-50;
e=0.3178640*60*chunk;                               //Data in 15 minutes= 40*60sec*15min;
number_of_blocks=(length(ambreal)/e);
block=0;
while (block<number_of_blocks-1),
 ambmean(block+1)=sum(ambreal(block*e+1:block*e+e)); //Sums data in chunks of 15 minutes
 temporal=ambreal(block*e+1:block*e+e);
 block=block+1;
end

ambmean=ambmean./floor(e);    //Averaging the signal

//Calculating chunks of data of ambient temperature Calculating chunks of data of ambient temperature

e=0.3178640*60*chunkmin;
number_of_blocks=(length(ambreal)/e);
block=0;
while (block<number_of_blocks-1),
 ambmean1min(block+1)=sum(ambreal(block*e+1:block*e+e)); //Sums data in chunks of 15 minutes
 block=block+1;
end
ambmean1min=ambmean1min./floor(e);        //Averaging the signal to obtain the mean
```

```
block=0;
k=floor(length(ambmean1min)/15);
while (block<=k-1),
ambmax1min(block+1)=max(ambmean1min(block*15+1:block*15+15));
ambmin1min(block+1)=min(ambmean1min(block*15+1:block*15+15));
block=block+1;
end

//Computes blocks of 1 minute Computes blocks of 1 minute Computes blocks of 1 minute Computes blocks of 1 minute

hramb=length(ambmean)/(4);              //4 blocks of 15 minutes in 1 hour
timeamb=linspace(st,hramb+st,length(ambmean));

scf(4);
plot2d2(timeamb,[ambmean ambmin1min ambmax1min])
xlabel("Time in Hours","fontsize",3,"color","black");
ylabel("Temperature in C","fontsize",3,"color","black");
title("Mean, maximum, and minimum ambient temperature for clinician 1","fontsize",3,"color","black");
xgrid(12);  //Seting axis on and line colour

//Calculating chunks of data of light Calculating chunks of data of light Calculating chunks of data of light
//sampling rate=1/3.024887 seconds=0.3305909
lightreal=light1*100/255;

e=0.3178640*60*chunk;  //Data in 15 minutes= 40*60sec*15min;
number_of_blocks=(length(lightreal)/e);
block=0;
while (block<number_of_blocks-1),
 lightmean(block+1)=sum(lightreal(block*e+1:block*e+e)); //Sums data in chunks of 15 minutes
 temporal=lightreal(block*e+1:block*e+e);
 block=block+1;
end

lightmean=lightmean./floor(e);    //Averaging the signal

//Calculating chunks of data of light Calculating chunks of data of light Calculating chunks of data of light

e=0.3178640*60*chunkmin;                    //Data in 15 minutes= 40*60sec*15min;
number_of_blocks=(length(lightreal)/e);
block=0;
while (block<number_of_blocks-1),
 lightmean1min(block+1)=sum(lightreal(block*e+1:block*e+e)); //Sums data in chunks of 15 minutes
 block=block+1;
end
lightmean1min=lightmean1min./floor(e);        //Averaging the signal to obtain the mean

block=0;
k=floor(length(lightmean1min)/15);
while (block<=k-1),
lightmax1min(block+1)=max(lightmean1min(block*15+1:block*15+15));
lightmin1min(block+1)=min(lightmean1min(block*15+1:block*15+15));
block=block+1;
end
//Computes blocks of 1 minute Computes blocks of 1 minute Computes blocks of 1 minute Computes blocks of 1 minute
hrlight=length(lightmean)/(4);              //4 blocks of 15 minutes in 1 hour
timelight=linspace(st,hrlight+st,length(lightmean));

scf(5);
plot2d2(timelight,[lightmean lightmin1min lightmax1min])
xlabel("Time in Hours","fontsize",3,"color","black");
ylabel("Light in","fontsize",3,"color","black");
title("Mean, maximum, and minimum ambient light for clinician 1","fontsize",3,"color","black");
xgrid(12);  //Seting axis on and line colour
```

```
//Time when the participant awake not the actual time
time=st;
k=length(bodymean1min)
thetime=linspace(1,k,k)';

k=length(METmean);
for i=1:k //blocks of 15 minutes
  time=time+0.25;
  thetime(i)=time;
end

METmean=METmean(1:k);
METmax1min=METmax1min(1:k);
METmin1min=METmin1min(1:k);

EDRmean=EDRmean(1:k);
EDRmax1min=EDRmax1min(1:k);
EDRmin1min=EDRmin1min(1:k);

bodymean=bodymean(1:k);
bodymax1min=bodymax1min(1:k);
bodymin1min=bodymin1min(1:k);

ambmean=ambmean(1:k);
ambmax1min=ambmax1min(1:k);
ambmin1min=ambmin1min(1:k);

lightmean=lightmean(1:k);
lightmax1min=lightmax1min(1:k);
lightmin1min=lightmin1min(1:k);

m=[thetime MET1min EDRmean1min bodymean1min ambmean1min lightmean1min];
csvWrite(m, file2visualise, ",", ".","%5.3f");

m=[METmean METmax1min METmin1min EDRmean EDRmax1min  EDRmin1min bodymean bodymax1min  bodymin1min
ambmean ambmax1min ambmin1min lightmean lightmax1min lightmin1min];
csvWrite(m, file2write, ",", ".","%5.3f");



//Pulse Data separated is processed and stored in a excel file
// Close all opened figures and clear workspace
xdel(winsid());
clear;  //Delete all variables
clc;    //clean screen

stacksize(200000000);

file2read='C:\Backup\Analysis\Participants\Participant1Pulse.sod'
file2Write='C:\Backup\Analysis\Participants\Participant1.csv'
load(file2read,'pulse');

pulse = pulse(1:500*60*30);       // Block of 1 hour
t = (1:length(pulse))/500/60;   // Used for plotting data
L = 3750;                    // Length of observation blocks in samples
M = floor(length(pulse)/L);
threshold = 0.5;               // Decision threshold for identifying bad blocks
Fs=500;

scf(1);
subplot(4,1,1);
plot(t,pulse');
title('Original pulse data')
```

```
hz=iir(10,'bp','butt',[0.5/Fs 20/Fs],[]); // Bandpass filter, f_lower = 0.5 Hz, f_upper = 20 Hz
p1=flts(pulse',hz);

//Calculate the auto-correlation function of each block
z=[matrix(p1(1:L*M),L,M);zeros(L,M)];  //Matrix with LxM dimension
y=z;  //How z looks like, function size(y) to see the shape of matrix
Z=abs(fft(z,-1,2,1)).^2;  //this is the equivalent in scilab
z=real(fft(Z,1,2,1));     //This is the equivalent in scilab

//Find the location of the first maximum of the autocorrelation function

i = zeros(M,1);
i1 = zeros(M,1);
for n = 1:M
   x=mtlb_diff(sign(mtlb_diff(z(:,n))));
   i(n) = find(x <-1,1);
   i1(n) = find(Z(1:100,n) == max(Z(1:100,n)),1);
end

// Convert position of maximum into a frequency [Hz]
pRate = 500/i;              // Estimate from autocorrelation function
pRate = pRate';
pRateFreq = (i1-1)*500/L/2;   // Estimate from power spectrum
pRate0 = pRate;

badSegments = abs(pRate-pRateFreq) > threshold;
badSegments1 = badSegments;

// Interpolate where only one or two isolated samples are corrupt
// Look for single bad samples
//badSegments'
//Interpotale where only one or two isolated samples are corrupt
//Look for single bad sample
for n = 2:(M-1)                 //index modified index is higher than the length of badSegments (the double)
   if isequal(badSegments((-1:1)+n),[0;1;0])
      pRate(n) = mean(pRate([n-1 n+1]));
      badSegments1(n) = 0;
   end
end

disp('step one done');
// Look for pairs of bad samples

for n = 2:(M-2) index is higher than the length of badSegments (the double)
   if isequal(badSegments((-1:2)+n),[0;1;1;0])
      pRate(n) = (2*pRate(n-1) + pRate(n+2))/3;
      pRate(n+1) = (pRate(n-1) + 2*pRate(n+2))/3;
      badSegments1(n+(0:1)) = 0;
   end
end

disp('step two done');

// Any remaining bad segments are in runs of three or more. I am marking
// these sections as missing.
pRate(badSegments1 > 0) = %nan; not valid for scila. I guess that the equivalent would be with –find" function?

subplot(4,1,2);
plot((1:M)*L/500/60,badSegments)
title('Bad segments detected');

subplot(4,1,3);
plot((1:M)*L/500/60,badSegments1)
title('Bad segments remaining');
```

```
minsToProc = 60;
bpm = pRate(1:8*minsToProc) * 60;
mins = 1:minsToProc;
bpmAv=median(matrix(bpm,8,minsToProc),'m')';

// Count the number of bad blocks in the minute.
confidence=8-sum(matrix(badsegments(1:8*minsToProc),8,minsToProc))';

scf(2);
//plot((1:8*minsToProc)*L/500/60,bpm,'-',mins-.5,bpmAv,'.',mins-.5,confidence*6,'-')
legend('bpm estimate','averaged bpm','confidence')

// Write bpmAv and confidence to a csv file for data mining
csvwrite([filename '_pulse.csv'], [bpmAv confidence]);
```

Sleeping-hours Scilab code

```
//W is a vector, w(1) contains the file size
clc;
clear;  //Clear all variables

file2read='C:\Analysis\Particiapnt1\sleep1.txt'
file2write1='C:\Analysis\Participan1\Participant1.sod'   //All variables
file2write2='C:\Analysis\Participan1\Participant1.sod'c  //Pulse

stacksize(100000000);
w=fileinfo(file2read);
fd_r = mopen(file2read, 'rb')  //rt

numberofbytes=0;
block=0;
block1=0;
block_index=1;
bytes_file=w(1);  //This is the number of bytes stored in the file
number_of_blocks=(bytes_file *121/2300);
//number_of_blocks=(bytes_file/17)-3;  //Calculates the number of blocks of 17 bytes
disp(number_of_blocks)
disp('that is the size of blocks')
//Data is in the same order in one block of 17 bytes
//One block of 17 bytes is read and split into different vectors

pulse = zeros(number_of_blocks*13,1);
eog = zeros(number_of_blocks*3,1);
EDR = zeros(number_of_blocks,1);
ax = zeros(number_of_blocks,1);
ay = zeros(number_of_blocks,1);
az = zeros(number_of_blocks,1);
body = zeros(ceil(number_of_blocks/121),1);
//Eliminating gravity factor with a high pass filter
//Eliminating gravity factor with a high pass filter
x=ax';
Fs=1/(12*0.002);
hz=iir(5,'hp','butt',[0.1/Fs],[]);//,[.8 .01]);
mx = flts(x,hz);

x=ay';
hz=iir(5,'hp','butt',[0.1/Fs],[]);//,[.8 .01]);
my = flts(x,hz);

x=az';
hz=iir(5,'hp','butt',[0.1/Fs],[]);//,[.8 .01]);
mz = flts(x,hz);

//Eliminating gravity factor with a high pass filter
//Eliminating gravity factor with a high pass filter
ax=x;
ay=y;
az=z;


while (block<number_of_blocks-2)
  if (block_index<=120) then
  v=mget(19,'uc')';          //17 data per block
  pulse(block*12+(1:12)) = v([(1:4) (6:9) 11 13 15 17]);
  eog(block*3+(1:3))= v([5 10 18]);
  EDR(block+1)=v(12);
  ax(block+1)=v(14);
  ay(block+1)=v(16);
```

```
  az(block+1)=v(19);

  else
  v=mget(20,'uc')';          //20 data per block
  pulse(block*12+(1:12)) = v([(1:4) (6:9) 11 14 16 18]);
  eog(block*3+(1:3))= v([5 10 19]);
  EDR(block+1)=v(12);
  ax(block+1)=v(15);
  ay(block+1)=v(17);
  az(block+1)=v(20);  //it was 20
  body(block1+1)=v(13);
  block1=block1+1;
  end

  block=block+1;                    //Calculates data in the next block
    block_index=block_index+1;  //Identify the block where EDR, Temperature are stored
  if (block_index==122) then
     block_index=1;
   end
end
mclose(fd_r);
k1=length(pulse);
k2=length(EDR);
k3=length(ax);
k4=length(ay);
k5=length(az);
k6=length(body);
k7=length(eog);
save(file2write2,'pulse'); //Raw data stored on the file
clear pulse;
save(file2write,'EDR','eog','ax','ay','az','body'); //Raw data stored on the file


//Data decoded from the SD card is processed and stored in a Excel file
xdel(winsid());

clear;  //Delete all variables
clc;    //clean screen
stacksize(100000000);

file2read='C:\Backup\Analysis\Particiapnt1\Participant1Night1.sod'
file2write='C:\Backup\Analysis\Participant1\Participant1Night1.csv'

load(file2read,'EDR','eog','ax','ay','az','body');

st=0;
sh=1/0.024;        //Sampling rate for EDR,ax,ay,az 1/(12*0.002)=38.4615 Hz
seog=1/(4*0.002);   //Sampling rate for eog=125Hz,
sbody=sh/121;       //sampling rate for body temp;
chunk=15;
chunkmin=1;

hrh=length(EDR)/(60*60*sh);          //Calculating hours
hrbody=length(body)/(60*60*sbody);   //Calculating hours
hreog=length(eog)/(60*60*seog);      //Calculating hours

timeh=linspace(0,hrh,length(EDR));
timel=linspace(0,hrbody,length(body));
timeeog=linspace(0,hreog,length(eog));

//Calculating "counts" per 15 minutes during the sleep
//The threshold must be calculated for every participant

A=real(sqrt((ax(2:$)-ax(1:$-1)).^2+(ay(2:$)-ay(1:$-1)).^2+(az(2:$)-az(1:$-1)).^2));
```

```
Ath=zeros(A);
Ath(find(A>=10))=gequivalent;      //Threshold g equivalent set to 0.1modify this depending on the accelerometer
x=diff(Ath);     // Computes Ath(2:$)-Ath(1:$-1) to detect edges that are going to be counted
x(find(x<=0))=0;
Ath=x;

e=(1/0.024)*60*chunk;       //Data in 15 minutes= 40*60sec*15min;
number_of_blocks=(length(Ath)/e);
block=0;
while (block<number_of_blocks-1),
 Acount(block+1)=sum(Ath(block*e+1:block*e+e)); //Sums data in chunks of 15 minutes
 block=block+1;
end

//Computes blocks of 1 minute Computes blocks of 1 minute Computes blocks of 1 minute Computes blocks of 1 minute

e=((1/0.024)*60*chunkmin);                    //Data in 15 minutes= 40*60sec*15min;
number_of_blocks=(length(Ath)/e);
block=0;
while (block<number_of_blocks-1),
 Acount1min(block+1)=sum(Ath(block*e+1:block*e+e)); //Sums data in chunks of 15 minutes
 block=block+1;
end

block=0;
k=floor(length(Acount1min)/15);
while (block<=k-1),
Acountmax1min(block+1)=max(Acount1min(block*15+1:block*15+15));
Acountmin1min(block+1)=min(Acount1min(block*15+1:block*15+15));
block=block+1;
end
//Computes blocks of 1 minute Computes blocks of 1 minute Computes blocks of 1 minute Computes blocks of 1 minute

hrAcount=length(Acount)/(4);            //4 blocks of 15 minutes in 1 hour
timeAcount=linspace(st,hrAcount+st,length(Acount));

scf(1);
plot2d2(timeAcount,[Acount Acountmin1min Acountmax1min])
xlabel("Time in Hours","fontsize",3,"color","black");
ylabel("Light in","fontsize",3,"color","black");
title("Counts in 15 minutes, maximum, and minimum in 1 minute during sleep for clinician 1","fontsize",3,"color","black");
xgrid(12);  //Seting axis on and line colour

//Calculating chunks of data of EDR Calculating chunks of data of EDR Calculating chunks of data of EDR

EDR=EDR';                    //Calculating tonic component
Fs=1/(12*0.002);
hz=iir(6,'lp','butt',[3/Fs],[]);
Rfiltered1 = flts(EDR,hz);

Rfiltered1(find(Rfiltered1<=1))=255;   //Avoid divison by 0
Rfiltered1=(Rfiltered1*3.3)/255;      //Converts EDR to voltage
EDR1=((3.3*100000)-Rfiltered1*100000)./Rfiltered1; //Calculating the resistance in Ohms

hz=iir(6,'hp','butt',[0.2/Fs],[]);
Rfiltered = flts(EDR1,hz);
EDR=Rfiltered;

Rfiltered=abs(Rfiltered);
Rfiltered(find(Rfiltered>=800000))=800000;          //Limiting the tonic component

e=(1/0.024)*60*chunk;                    //Data in 15 minutes= 40*60sec*15min;
number_of_blocks=(length(Rfiltered)/e);
block=0;
```

```
while (block<number_of_blocks-1),
 EDRmean(block+1)=sum(Rfiltered(block*e+1:block*e+e)); //Sums data in chunks of 15 minutes
 temporal=Rfiltered(block*e+1:block*e+e);
 EDRmax(block+1)=max(temporal);
 EDRmin(block+1)=min(temporal);
 block=block+1;
end

EDRmean=EDRmean./floor(e);        //Averaging the signal to obtain the mean
//Calculating chunks of data of EDR Calculating chunks of data of EDR Calculating chunks of data of EDR

e=(1/0.024)*60*chunkmin;                              //Data in 15 minutes= 40*60sec*15min;
number_of_blocks=(length(Rfiltered)/e);
block=0;
while (block<number_of_blocks-1),
 EDRmean1min(block+1)=sum(Rfiltered(block*e+1:block*e+e)); //Sums data in chunks of 15 minutes
 block=block+1;
end
EDRmean1min=EDRmean1min./floor(e);        //Averaging the signal to obtain the mean

block=0;
k=floor(length(EDRmean1min)/15);
while (block<=k-1),
EDRmax1min(block+1)=max(EDRmean1min(block*15+1:block*15+15));
EDRmin1min(block+1)=min(EDRmean1min(block*15+1:block*15+15));
block=block+1;
end
//Computes blocks of 1 minute Computes blocks of 1 minute Computes blocks of 1 minute Computes blocks of 1 minute

hrTonic=length(EDRmean)/(4);              //4 blocks of 15 minutes in 1 hour
timeTonic=linspace(st,hrTonic+st,length(EDRmean));

scf(2);
plot2d2(timeTonic,[EDRmean EDRmin1min EDRmax1min])
xlabel("Time in Hours","fontsize",3,"color","black");
ylabel("Tonic Component in Ohms","fontsize",3,"color","black");
title("Mean in 15 minutes, Maximum, and minimum Tonic value in 1 minute during sleep for clinician
1","fontsize",3,"color","black");
xgrid(12);

//Calculating chunks of data of body temperature Calculating chunks of data of body temperature
//sampling rate=1/3.024887 seconds=0.3305909

bodyreal=0.23109243*body-8.92857156;
//bodyreal=body.*0.40441176-50;

e=(0.3178640*60*chunk);                               //Data in 15 minutes= 40*60sec*15min;
number_of_blocks=(length(bodyreal)/e);
block=0;
while (block<number_of_blocks-1),
 bodymean(block+1)=sum(bodyreal(block*e+1:block*e+e)); //Sums data in chunks of 15 minutes
 temporal=bodyreal(block*e+1:block*e+e);
 block=block+1;
end

bodymean=bodymean./floor(e);    //Averaging the signal

hrbody=length(bodymean)/(4);              //4 blocks of 15 minutes in 1 hour
timebody=linspace(st,hrbody+st,length(bodymean));

//Calculating chunks of data of body temperature Calculating chunks of data of body temperature
//Computes blocks of 1 minute Computes blocks of 1 minute Computes blocks of 1 minute Computes blocks of 1 minute

e=(0.3178640*60*chunkmin);                            //Data in 15 minutes= 40*60sec*15min;
```

```
number_of_blocks=(length(bodyreal)/e);
block=0;
while (block<number_of_blocks-1),
 bodymean1min(block+1)=sum(bodyreal(block*e+1:block*e+e)); //Sums data in chunks of 15 minutes
 block=block+1;
end
bodymean1min=bodymean1min./floor(e);        //Averaging the signal to obtain the mean

block=0;
k=floor(length(bodymean1min)/15);
while (block<=k-1),
bodymax1min(block+1)=max(bodymean1min(block*15+1:block*15+15));
bodymin1min(block+1)=min(bodymean1min(block*15+1:block*15+15));
block=block+1;
end
//Computes blocks of 1 minute Computes blocks of 1 minute Computes blocks of 1 minute Computes blocks of 1 minute

scf(3);
plot2d2(timebody,[bodymean bodymin1min bodymax1min])
xlabel("Time in Hours","fontsize",3,"color","black");
ylabel("Temperature in C","fontsize",3,"color","black");
title("Mean in 15 minutes, maximum, and minimum body Temperature in 1 minute during sleep for clinician
1","fontsize",3,"color","black");
xgrid(12);

//Time when the participant awake not the actual time
time=st;
k=length(Acount1min)
thetime=linspace(1,k,k)';
Acount1min=Acount1min(1:k);
EDRmean1min=EDRmean1min(1:k);
bodymean1min=bodymean1min(1:k);

//m=[thetime Acount1min EDRmean1min bodymean1min];
//csvWrite(m, file2visualise, ",", ".","%5.3f");

k1=length(Acount);
Acount=Acount(1:k1);
Acount=Acount/15;
Acountmin1min=Acountmin1min(1:k1);
Acountmax1min=Acountmax1min(1:k1);
EDRmean=EDRmean(1:k1);
EDRmin1min=EDRmin1min(1:k1);
EDRmax1min=EDRmax1min(1:k1);
bodymean=bodymean(1:k1);
bodymin1min=bodymin1min(1:k1);
bodymax1min=bodymax1min(1:k1);
//Pulse is processed with the code used for waking-hours
m=[Acount Acountmin1min Acountmax1min EDRmean EDRmin1min EDRmax1min bodymean bodymin1min bodymax1min];
csvWrite(m, file2write, ",", ".","%5.3f");


stacksize(100000000);
xdel(winsid());
clear;  //Delete all variables
clc;    //clean screen
file2read='P4Night1'
load(file2read+'.sod','eog','ax','ay','az');
k1=round(0.7788*length(eog));
k2=round(0.7788*length(ax));
eog=eog(1:k1);
ax=ax(1:k2);
ay=ay(1:k2);
az=az(1:k2);
```

```
eog=eog'-117; //Eliminating offset of EOG
Fs=125;
//hz = iir(8,'lp','butt',50/Fs,[]);
hz=iir(10,'bp','butt',[8/Fs 12/Fs],[ ]);
[hzm,fr]=frmag(hz,256);
fr2 = fr.*Fs;
//scf(1);
plot(fr2,hzm)
Sa = flts(eog,hz);

disp("Filter A")
Fs=125;
hz=iir(12,'bp','butt',[18/Fs 30/Fs],[ ]);
[hzm,fr]=frmag(hz,256);
fr2 = fr.*Fs;
plot(fr2,hzm)
Sb = flts(eog,hz);
disp("Filter B")
//8 to 12 Hz 8 to 12 Hz 8 to 12 Hz 8 to 12 Hz 8 to 12 Hz 8 to 12 Hz
block=0;
n = 7500;   // One-minute block size
number_of_blocks=length(Sa)/n;
Sa=abs(Sa);
Sa=Sa.^2;
eog_averagedSa=zeros(number_of_blocks);
while (block<number_of_blocks-1),
 eog_averagedSa(block+1)=sqrt(sum(Sa(block*n+1:block*n+n))/n);
  block=block+1;
end
block=0;
number_of_blocks=length(Sb)/n;
Sb=abs(Sb);
Sb=Sb.^2;

eog_averagedSb=zeros(number_of_blocks);
while (block<number_of_blocks-1),
 eog_averagedSb(block+1)=sqrt(sum(Sb(block*n+1:block*n+n))/n);
  block=block+1;
end

sh=1/0.024;
seog=3*sh;

hrh=length(ax)/(60*60*sh);
hreog=length(eog)/(60*60*seog);

timeh=linspace(0,hrh,length(ax));
timeeog=linspace(0,hreog,length(eog));
timepower=linspace(0,hreog,length(eog_averagedSa));;

 // Export to spreadsheet
 headings = ["Time" "RMS EOG (8-12)" "RMS EOG (18-30)" "RMS Accel"];
 write_csv([headings;string([timepower' eog_averagedSa eog_averagedSb acc_averaged])],file2read+".csv");
```

Ambient variables Scilab code

```
//W is a vector, w(1) contains the file size
clc;
clear;  //Clear all variables

file2read='C:\Temp\Amb1n000.txt'
file2write='C:\Temp\Amb3IvCut.sod'

stacksize(100000000);
w=fileinfo(file2read);
fd_r = mopen(file2read, 'rb')  //rt

numberofbytes=0;
block=0;
bytes_file=w(1);  //This is the number of bytes stored in the file
number_of_blocks=(bytes_file/102)/24;
disp(number_of_blocks,'that is the size of blocks');

//Data is in the same order in one block of 17 bytes
//One block of 17 bytes is read and splited into different vectors

noise = zeros(number_of_blocks*100,1);
light = zeros(number_of_blocks,1);
temp = zeros(number_of_blocks,1);

while (block<number_of_blocks-1)
  v=mget(102,'uc')';          //13 data per block
  noise(block*100+(1:100)) = v([(1:99) 101]);
  light(block+1)=v(100);
  temp(block+1)=v(102);
  block=block+1;     //Calculates data in the next block
end

mclose(fd_r);

sh=1/0.010;  //Samplin rate for sound 1/(0.010)=100Hz
sl=1/1;      //sampling rate for light, ambient temperature =1 Hz

hrh=length(noise)/(60*60*sh);   //Sampling rate of 38.4 Hz, EDR,ax,ay, and az
hrl=length(light)/(60*60*sl);   //Sampling rate of 0.325Hz, ligth,body,and amb

timeh=linspace(0,hrh,length(noise));
timel=linspace(0,hrl,length(light));

subplot(2,1,1);
plot(timeh,noise);
xtitle( 'Sound', 'Time in hours', 'ADC results' ) ;

subplot(2,1,2);
plot(timel,temp,'r')
plot(timel,light,'b')
xtitle( 'Ambient Temp (red) and Light (black)','Time in hours', 'ADC results') ;

cutat=10;   //Depending on the data recorded this number is modified to save only valid data, this numbes is given in hours
cuth=round(cutat*60*60*(1/(0.01)));
cutl=round(cutat*60*60*1);
a=1;
tempc=temp(1:cutl);
light=light(1:cutl);
noise=noise(1:cuth);
tempc=tempc*1.29-50;
//noisedB=20*log10(noise);
```

```
//noisedB=0.984836885*noisedB+34.586759;
noise=20*log10(noise);
noise=0.984836885*noise+34.586759;
m=[tempc light noisewrite];
csvWrite(m, file2write, ",", ".","%5.3f");
```

APPENDIX D PATIENTSENSE DOCUMENTS

Version 1: Date 04/2/17.

CONSENT FORM FOR PARTICIPANTS

PatientSense – A proof-of-concept system for unobtrusive multi-sensing of physiological and environmental parameters in real environments.

- The nature and aims of the research have been explained to me and I understand what is expected of me. I have read and understood the Participant Information Sheet for the above study.

- I understand that I can contact the researcher if I have questions related to this study. The contact can be by phone, e-mail or in person. (Contact details are provided on the participant information sheet.)

- I understand that my participation is voluntary and that I am free to withdraw at any time without having to give a reason for my withdrawal and all my data will be removed and destroyed.

- I consent to the processing of my personal information for the purposes of this research study. I understand that such information will be treated as strictly confidential and handled in accordance with the provisions of the Data Protection Act 1998.

- I understand that recorded data will be stored in electronic format. All information relating to this study is to remain confidential and the use of such information will be used only for the purposes of the stated research. I also understand that the files will be preserved for 10 years to allow, if it is necessary, verification of data.

- I agree to volunteer as a participant for the study described in the information sheet and I give full consent for my participation in this study.

- This consent is specific to the study described in the Participant Information Sheet and shall not be taken to imply my consent to participate in any subsequent study or deviation from that detailed here.

Participant's Statement:

I agree that the research project named above has been explained to my satisfaction and I agree to take part in the study. I have read and understood both the notes written above and the Participant Information Sheet

_____	_____	_____
Name of Participant	Date	Signature
_____	_____	_____
Name of Person taking consent	Date	Signature

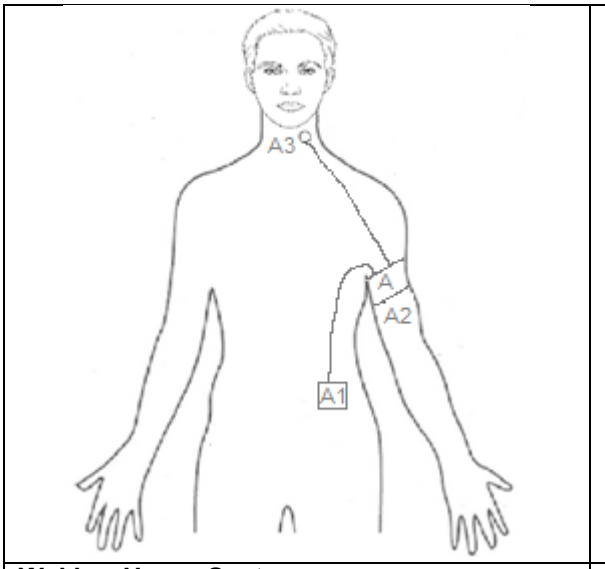
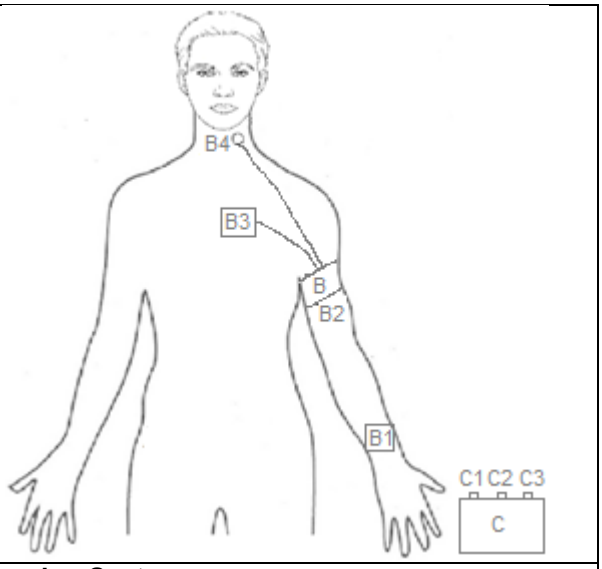
Participant Information Sheet

Title of Study: PatientSense – A Proof-of-concept system for unobtrusive multi-sensing of circadian parameters in real environments.

We would like to invite you to participate in this study being undertaken by researchers at the University of Birmingham. You should only participate if you want to. Before you decide whether you want to take part, please take time to read the following information and please ask if there is anything that is not clear or if you would like more information.

PatientSense is a system designed by the University of Birmingham's Human Interface Technology group for unobtrusive multi-sensing of physiological and ambient parameters in real environments. It was designed with the aim of contributing toward the clinical needs expressed for improved recording of patient data over longer terms and in the normal activities and real environments of everyday life. It has been successfully piloted in real use by the research team throughout the development period.

PatientSense consists of three component systems: a sensing system worn during waking-hours and two sensing systems for sleeping; one worn and one proximal to the sleeper, for example, placed on a bedside table. Each component system comprises a processor box which contains a processing unit, data storage unit and battery, and, an interface to a set of sensors. The figure below shows the component systems and location of the sensors.

<table>
<tr>
<td> 
</td>
<td> 
</td>
</tr>
<tr>
<td>Waking-Hours System:
A. On-Body Waking-Hours Processor
A1. Accelerometer
A2. Electrodermal activity
A3. Optical pulse sensor</td>
<td>Sleeping System:
B. On-Body Sleeping Processor
B1. Accelerometer
B2. Electrodermal activity
B3. Body temperature sensor
B4. Optical pulse sensor
C. Ambient Sleeping Processor
C1. Ambient temperature sensor
C2. Ambient light sensor
C3. Ambient noise meter</td>
</tr>
</table>

Proposed Procedure

Participation in this study will involve wearing the PatientSense system for 36 hours (one night), completing activity logs and sleep questionnaires, and participating in a focus group to provide feedback regarding the system and assessment of the device.

Antibacterial wipes will be used to clean cables and enclosures before system use. Small changes in the positioning of electrodes and sticking tape are recommended to reduce skin irritation caused by prolonged application. A test fitting is also recommended to accommodate sensor adjustments for comfort and wearability. The system was designed to be unobtrusive.

Daily assistance with CircadianSense will be provided if needed. The researcher will remove captured data and reset the system ready for further use. The participants need only switch CircadianSense on each day. Participants will be asked to complete an activity log, sleep questionnaire, and assist with feedback regarding the CircadianSense system and the recorded data.

Any information obtained during the tests will remain confidential. All data will be anonymised in publication. Experimental records of physiological and environmental signals, including paper records and computer files, will be held securely for a minimum of 10 years in conditions appropriate for the storage of personal information.

You may withdraw from the study at any point during the testing and before the focus group. Withdrawal within this time will ensure the removal and destruction of all your data from the study records.

PhD Researcher
David Infante Sanchez,
School of Engineering
University of Birmingham

Version 1: Date 04/02/17.

Participant Information Sheet

Title of Study: PatientSense – A Proof-of-concept system for unobtrusive multi-sensing of circadian parameters in real environments.

We would like to invite you to participate in this study being undertaken by a researcher of the University of Birmingham. You should only participate if you want to. Before you decide whether you want to take part, please take time to read the following information and please ask if there is anything that is not clear or if you would like more information.

PatientSense is a system designed by the University of Birmingham's Human Interface Technology group for unobtrusive multi-sensing of physiological and environmental data in real environments. It was designed with the aim of contributing toward the clinical needs expressed for improved recording of patient data over longer terms and in the normal activities and real environments of everyday life. It has been successfully piloted in real use by the research team throughout the development period.

PatientSense consists of three component systems: a sensing system worn during waking-hours and two sensing systems for sleeping; one worn and one proximal to the sleeper, for example, placed on a bedside table.

Proposed Procedure

Participation in this study will involve participating in one or more focus groups with more clinicians. Each focus group will last around one hour. The objectives of focus group one is to gather limitation regarding to the information provided from clinicians. Objective of focus group 2 is to provide information related to features, characteristics and data collection relevant for a wearable health monitoring system for its clinical adoption. Objectives of focus group 3 is to provide feedback about visualisation of data collected. Objective focus group 4 is to assess a werable system designed called PatientSense to provide feedback for further improvement. During the focus groups the study will be audio recorded for further qualitative analysis of the responses. Depending on your time availability you can participate in one or more focus groups.

Any information obtained during the tests will remain confidential. All data will be anonymised in publication. Experimental records of physiological and environmental signals, including paper records and computer files, will be held securely for a minimum of 10 years in conditions appropriate for the storage of personal information. The access to data by people other than researcher will be under your permission.

You may withdraw from the study at any point up. Withdrawal within this time will ensure the removal and destruction of all your data from the study records.

Participant information

Name:

1. Years of experience:

2. Current place of practice:

3. Do you have any qualification, specialities?

4. Have you used wearable devices or mobile apps related to health or well-being?

   If yes list them

5. Do you use smartphones, desk top computer, laptops, tablets?

6. Do you use computers in your practice? If yes, what software applications do you use?

APPENDIX E PATIENTSENSE FIRMWARE

Waking-hours Feather M0 Firmware

```
// Day Time Body Data
// Creates a unique folder and records 10min data files
#include <SPI.h>
#include "SdFat.h"
#include <M0Timer.h>
#include <SparkFun_MMA8452Q.h>    //Accelerometer
#include <DS18B20.h>              //Temperature Sensor
#include <BH1790GLC.h>            //Heart Rate Monitor
#include <RTCZero.h>

// Pin labels
#define RLED 13
#define GLED 8
#define SW 5
#define POWER 11
#define VBATPIN A7
#define SDCardCS 4
#define USBPOWER 12
#define EDAPIN A1      ////////////////////////////EDA pin


// SD card defines
#define BLOCK_COUNT (300 * 2)  // Each 2s frame is 1024 bytes, 2
blocks. 300 frames = 10 mins
#define error(s) sd.errorHalt(F(s))

uint32_t bgnBlock, endBlock;          // file extent
uint32_t blocksDone = 0;

SdFat sd;
SdFile file;
DS18B20 tempSensor;
MMA8452Q accel;
M0Timer timer;
BH1790GLC pulse;
RTCZero rtc;
/*
struct nightBodyDataFrame {
  uint32_t timeStamp;
  uint16_t pulse[128];
  int16_t accel[288];
```

```
  float temp;
  float vbat;
};
*/

struct dayBodyDataFrame {
  uint32_t timeStamp;
  uint16_t pulse[128];
  int16_t accel[288];
  float temp;
  float vbat;
  float eda[96];
////////////////////////////////////////////////////////////////////
//////////////////////////////EDA readings
};




// dataFrame pads the nightBodyDataFrame structure to 1024 bytes
length
union dataFrame {
  dayBodyDataFrame d;
  uint8_t x[1024];
};

dataFrame buff[2];        // Double buffer memory allocation
unsigned int wBuff = 0;     // write buffer index
bool buffersSwapped = false;  // flags when buffer needs writing to SD
card
bool isRecording = false;
unsigned int sampleindex = 0;
char dirname[13];
char filename[13];
int dirNumber = 0;
int fileNumber = 0;
uint8_t ledCounter = 0;

void samplerCallback();     // Callback function used by sample timer
void startRecording();
void openNewFile();
void dateTime(uint16_t* date, uint16_t* time);  // SD card callback
for timestamping
void setRTC(String datetime);
void externalInterrupt(){};   // Dummy function needed to set
interrupts for waking system from sleep
void enterSleepMode(bool USBWakeUpOnly);

void setup() {
  Serial.begin(9600);
  pinMode(RLED,OUTPUT);
```

```
  pinMode(GLED,OUTPUT);
  pinMode(SW,INPUT_PULLUP);
  pinMode(POWER, OUTPUT);
  digitalWrite(GLED,LOW);
  digitalWrite(RLED,HIGH);
  memset(buff[0].x, 0, sizeof(dataFrame));
  memset(buff[1].x, 0, sizeof(dataFrame));

  SYSCTRL->DFLLCTRL.bit.RUNSTDBY = 1; // Keeps clock running during
standby
  attachInterrupt(USBPOWER, externalInterrupt, RISING);

  rtc.begin();
  SdFile::dateTimeCallback(dateTime);
  timer.init(&samplerCallback);
}

void loop() {
  if(isRecording)
  {
    while(!buffersSwapped)
      delay(5); // Wait until new data

    // Write 1024 byte data frame to SD card
    buff[1-wBuff].d.temp = (float)tempSensor.temperature() * 0.0625;
//Conversion to celsius

    digitalWrite(GLED,HIGH);
    if (!sd.card()->writeData(&buff[1-wBuff].x[0]))
        error("writeData failed");
    if (!sd.card()->writeData(&buff[1-wBuff].x[512]))
        error("writeData failed");
    buff[1-wBuff].d.timeStamp += 2; // +2: double buffering
    digitalWrite(GLED,LOW);
    buffersSwapped = false;
    tempSensor.startConversion();
    blocksDone += 2;

    // If switch turned off fill current file with zeros and stop
    if(!digitalRead(SW))
    {
      memset(buff[1-wBuff].x,0,512);     //Write zeros to buffer
      while(blocksDone < BLOCK_COUNT)
      {
        if (!sd.card()->writeData(buff[1-wBuff].x))
            error("writeData failed");
        blocksDone++;
      }
      isRecording = false;
      timer.stop();
      Serial.println("Stopping recording.");
      // Turn off peripherals
      digitalWrite(POWER, LOW);
```

```
    }

    // If file complete close and start a new one
    if(blocksDone >= BLOCK_COUNT){
      if (!sd.card()->writeStop()) {
        error("writeStop failed");
      }
      file.close();
      // If battery is low, pause recording and enter sleep mode
      if(buff[1-wBuff].d.vbat < 3.55) {
        timer.stop();
        enterSleepMode(true);
        isRecording = false;
      }
      else if(isRecording)
        openNewFile();
      else
        sd.chdir("/");
    }
  }
  else // If not recording
  {
    if(digitalRead(SW))
    {
      digitalWrite(GLED,HIGH);
      digitalWrite(RLED,HIGH);
      delay(500); // Debounce
      digitalWrite(GLED,LOW);
      digitalWrite(RLED,LOW);
      startRecording();
    }
    else
    {
      // If not recording and no USB power, enter sleep mode. If
battery is low, only wake up when
      // USB charging is detected.
      if(!digitalRead(USBPOWER))
        enterSleepMode((float)analogRead(VBATPIN) * 6.6 / 1024.0 <
3.55);

      if(ledCounter++ == 0)
        digitalWrite(RLED,HIGH);
      else
        digitalWrite(RLED,LOW);
      delayMicroseconds(7812);

      if(Serial.available() > 0)
        handleSerial();
    }
  }
}

void startRecording()
```

```
{
  digitalWrite(POWER, HIGH);
  delay(250); // Give peripherals time to power-up
  digitalWrite(GLED,HIGH);
  delay(250);
  digitalWrite(GLED,LOW);
  tempSensor.init();
  accel.init(SCALE_8G);
  pulse.init();

  buff[0].d.timeStamp = 0;
  buff[1].d.timeStamp = 1;

  tempSensor.startConversion();
  if (!sd.begin(SDCardCS, SD_SCK_MHZ(50)))
    sd.initErrorHalt();
  do {
    sprintf(dirname,"Day%03d",dirNumber++);
  } while(sd.exists(dirname));
  Serial.print("Creating directory: ");
  Serial.println(dirname);
  sd.mkdir(dirname);
  sd.chdir(dirname);
  fileNumber = 0;
  openNewFile();

  Serial.println("Starting recording.");
  timer.start(96);
  isRecording = true;
}

void openNewFile()
{
  sprintf(filename,"DayData%04d.dat",fileNumber++);

  if (!file.createContiguous(filename, 512UL*BLOCK_COUNT)) {
    error("createContiguous failed");
  }
  if (!file.contiguousRange(&bgnBlock, &endBlock)) {
    error("contiguousRange failed");
  }

  if (!sd.card()->writeStart(bgnBlock, BLOCK_COUNT)) {
    error("writeStart failed");
  }

  blocksDone = 0;
}

void samplerCallback()
{
  unsigned short pVal[2];
```

```
  if((sampleindex % 3) == 0) {  // 96/3 = 32 Hz
    pulse.get_val(pVal);
    buff[wBuff].d.pulse[2*sampleindex/3] = pVal[0];
    buff[wBuff].d.pulse[2*sampleindex/3 + 1] = pVal[1];
  }

  if(sampleindex == 1)
    buff[wBuff].d.vbat = (float)analogRead(VBATPIN) * 6.6 / 1024.0;

  if((sampleindex % 2) == 0) { // 96/2 = 48 Hz
    if (accel.available())
    {
      accel.read();
      buff[wBuff].d.accel[(sampleindex * 3) / 2] = accel.x;
      buff[wBuff].d.accel[(sampleindex * 3) / 2 + 1] = accel.y;
      buff[wBuff].d.accel[(sampleindex * 3) / 2 + 2] = accel.z;
       buff[wBuff].d.eda[(sampleindex / 2)] =
(float)analogRead(EDAPIN) * 3.3 / 1024.0;
////////////////////////////////////////////////////////////////////
     }

  }
  if(sampleindex < 10)
    digitalWrite(RLED,HIGH);
  else
    digitalWrite(RLED,LOW);

  sampleindex++;
  if(sampleindex > 191){
    wBuff = 1 - wBuff;
    sampleindex = 0;
    buffersSwapped = true;
  }
}

void dateTime(uint16_t* date, uint16_t* time)
{
  uint16_t t[3],d[3];
  t[2] = rtc.getSeconds();
  t[1] = rtc.getMinutes();
  t[0] = rtc.getHours();
  d[2] = rtc.getDay();
  d[1] = rtc.getMonth();
  d[0] = rtc.getYear();
  *date = FAT_DATE(d[0] + 2000,d[1],d[2]);
  *time = FAT_TIME(t[0],t[1],t[2]);
}

void handleSerial()
{
  char timeString[12];
  char formatTime[32];
  uint16_t t[3],d[3];
```

```
  if(!isRecording){
    while(Serial.available()){
      char inChar = (char)Serial.read();
      // Set clock by sending ASCII string in the form "#YYMMddhhmmss"
      if(inChar == '#'){ // Set clock
        Serial.readBytes(timeString, 12);
        setRTC(timeString);
      }
      else if(inChar == '?'){ // Query time and battery status
        t[2] = rtc.getSeconds();
        t[1] = rtc.getMinutes();
        t[0] = rtc.getHours();
        d[2] = rtc.getDay();
        d[1] = rtc.getMonth();
        d[0] = rtc.getYear();
        sprintf(formatTime,"%02d/%02d/%d - %02d:%02d:%02d",
d[2],d[1],d[0] + 2000,t[0],t[1],t[2]);
        Serial.print("Date/Time =");
        Serial.println(formatTime);
        Serial.println("Battery Voltage = " +
String((float)analogRead(VBATPIN) * 6.6 / 1024.0) + "V");
      }
    }
  }
}

void setRTC(String datetime)
{
    uint8_t dt[6];
    for(int n = 0; n < 6; n++)
      dt[n] = ((datetime[n*2]-'0') * 10) + (datetime[n*2+1]-'0');
    rtc.setTime(dt[3],dt[4],dt[5]);
    rtc.setDate(dt[2],dt[1],dt[0]);
}

void enterSleepMode(bool USBWakeUpOnly)
{
  Serial.end();
  USBDevice.detach();

  digitalWrite(GLED,LOW);
  digitalWrite(RLED,LOW);
  digitalWrite(POWER,LOW);
  if(USBWakeUpOnly)
    rtc.standbyMode();
  else
  {
    attachInterrupt(SW, externalInterrupt, RISING);
    rtc.standbyMode();
    detachInterrupt(SW);
  }
  USBDevice.attach();
  Serial.begin(9600); }
```

Sleeping-hours Feather M0 Firmware

```
// Night Time Body Data
// Creates a unique folder and records 10min data files
#include <SPI.h>
#include "SdFat.h"
#include <M0Timer.h>
#include <SparkFun_MMA8452Q.h>

#include <BH1790GLC.h>
#include <DS18B20.h>
#include <RTCZero.h>



// Pin labels
#define RLED 13
#define GLED 8
#define SW 5
#define POWER 11
#define VBATPIN A7
#define SDCardCS 4
#define USBPOWER 12

// SD card defines
#define BLOCK_COUNT (300 * 2)  // Each 2s frame is 1024 bytes, 2
blocks. 300 frames = 10 mins
#define error(s) sd.errorHalt(F(s))

uint32_t bgnBlock, endBlock;          // file extent
uint32_t blocksDone = 0;

SdFat sd;
SdFile file;
DS18B20 tempSensor;
MMA8452Q accel;
M0Timer timer;
BH1790GLC pulse;
RTCZero rtc;

struct nightBodyDataFrame {
  uint32_t timeStamp;
  uint16_t pulse[128];
  int16_t accel[288];
  float temp;
  float vbat;
};
// dataFrame pads the nightBodyDataFrame structure to 1024 bytes
length
union dataFrame {
  nightBodyDataFrame d;
  uint8_t x[1024];
};
```

```
dataFrame buff[2];        // Double buffer memory allocation
unsigned int wBuff = 0;     // write buffer index
bool buffersSwapped = false;  // flags when buffer needs writing to SD
card
bool isRecording = false;
unsigned int sampleindex = 0;
char dirname[13];
char filename[13];
int dirNumber = 0;
int fileNumber = 0;
uint8_t ledCounter = 0;

void samplerCallback();     // Callback function used by sample timer
void startRecording();
void openNewFile();
void dateTime(uint16_t* date, uint16_t* time);  // SD card callback
for timestamping
void setRTC(String datetime);
void externalInterrupt(){};   // Dummy function needed to set
interrupts for waking system from sleep
void enterSleepMode(bool USBWakeUpOnly);

void setup() {
  Serial.begin(9600);
  pinMode(RLED,OUTPUT);
  pinMode(GLED,OUTPUT);
  pinMode(SW,INPUT_PULLUP);
  pinMode(POWER, OUTPUT);
  digitalWrite(GLED,LOW);
  digitalWrite(RLED,HIGH);
  memset(buff[0].x, 0, sizeof(dataFrame));
  memset(buff[1].x, 0, sizeof(dataFrame));

  SYSCTRL->DFLLCTRL.bit.RUNSTDBY = 1; // Keeps clock running during
standby
  attachInterrupt(USBPOWER, externalInterrupt, RISING);

  rtc.begin();
  SdFile::dateTimeCallback(dateTime);
  timer.init(&samplerCallback);
}

void loop() {
  if(isRecording)
  {
    while(!buffersSwapped)
      delay(5); // Wait until new data

    // Write 1024 byte data frame to SD card
    buff[1-wBuff].d.temp = (float)tempSensor.temperature() * 0.0625;

    digitalWrite(GLED,HIGH);
```

```
  if (!sd.card()->writeData(&buff[1-wBuff].x[0]))
      error("writeData failed");
  if (!sd.card()->writeData(&buff[1-wBuff].x[512]))
      error("writeData failed");
  buff[1-wBuff].d.timeStamp += 2; // +2: double buffering
  digitalWrite(GLED,LOW);
  buffersSwapped = false;
  tempSensor.startConversion();
  blocksDone += 2;

  // If switch turned off fill current file with zeros and stop
  if(!digitalRead(SW))
  {
    memset(buff[1-wBuff].x,0,512);
    while(blocksDone < BLOCK_COUNT)
    {
      if (!sd.card()->writeData(buff[1-wBuff].x))
          error("writeData failed");
      blocksDone++;
    }
    isRecording = false;
    timer.stop();
    Serial.println("Stopping recording.");
    // Turn off peripherals
    digitalWrite(POWER, LOW);
  }

  // If file complete close and start a new one
  if(blocksDone >= BLOCK_COUNT){
    if (!sd.card()->writeStop()) {
      error("writeStop failed");
    }
    file.close();
    // If battery is low, pause recording and enter sleep mode
    if(buff[1-wBuff].d.vbat < 3.55) {
      timer.stop();
      enterSleepMode(true);
      isRecording = false;
    }
    else if(isRecording)
      openNewFile();
    else
      sd.chdir("/");
  }
}
else // If not recording
{
  if(digitalRead(SW))
  {
    digitalWrite(GLED,HIGH);
    digitalWrite(RLED,HIGH);
    delay(500); // Debounce
    digitalWrite(GLED,LOW);
```

```
      digitalWrite(RLED,LOW);
      startRecording();
    }
    else
    {
      // If not recording and no USB power, enter sleep mode. If
battery is low, only wake up when
      // USB charging is detected.
      if(!digitalRead(USBPOWER))
        enterSleepMode((float)analogRead(VBATPIN) * 6.6 / 1024.0 <
3.55);

      if(ledCounter++ == 0)
        digitalWrite(RLED,HIGH);
      else
        digitalWrite(RLED,LOW);
      delayMicroseconds(7812);

      if(Serial.available() > 0)
        handleSerial();
    }
  }
}

void startRecording()
{
  digitalWrite(POWER, HIGH);
  delay(250); // Give peripherals time to power-up
  digitalWrite(GLED,HIGH);
  delay(250);
  digitalWrite(GLED,LOW);
  tempSensor.init();
  accel.init(SCALE_8G);
  pulse.init();

  buff[0].d.timeStamp = 0;
  buff[1].d.timeStamp = 1;

  tempSensor.startConversion();
  if (!sd.begin(SDCardCS, SD_SCK_MHZ(50)))
    sd.initErrorHalt();
  do {
    sprintf(dirname,"Night%03d",dirNumber++);
  } while(sd.exists(dirname));
  Serial.print("Creating directory: ");
  Serial.println(dirname);
  sd.mkdir(dirname);
  sd.chdir(dirname);
  fileNumber = 0;
  openNewFile();

  Serial.println("Starting recording.");
  timer.start(96);
```

```
  isRecording = true;
}

void openNewFile()
{
  sprintf(filename,"Data%04d.dat",fileNumber++);

  if (!file.createContiguous(filename, 512UL*BLOCK_COUNT)) {
    error("createContiguous failed");
  }
  if (!file.contiguousRange(&bgnBlock, &endBlock)) {
    error("contiguousRange failed");
  }

  if (!sd.card()->writeStart(bgnBlock, BLOCK_COUNT)) {
    error("writeStart failed");
  }

  blocksDone = 0;
}

void samplerCallback()
{

  unsigned short pVal[2];

  if((sampleindex % 3) == 0) {  // 96/3 = 32 Hz
    pulse.get_val(pVal);
    buff[wBuff].d.pulse[2*sampleindex/3] = pVal[0];
    buff[wBuff].d.pulse[2*sampleindex/3 + 1] = pVal[1];
  }

  if(sampleindex == 1)
    buff[wBuff].d.vbat = (float)analogRead(VBATPIN) * 6.6 / 1024.0;

  if((sampleindex % 2) == 0) { // 96/2 = 48 Hz
    if (accel.available())
    {
      accel.read();
      buff[wBuff].d.accel[(sampleindex * 3) / 2] = accel.x;
      buff[wBuff].d.accel[(sampleindex * 3) / 2 + 1] = accel.y;
      buff[wBuff].d.accel[(sampleindex * 3) / 2 + 2] = accel.z;
    }
  }
  if(sampleindex < 10)
    digitalWrite(RLED,HIGH);
  else
    digitalWrite(RLED,LOW);

  sampleindex++;
  if(sampleindex > 191){
    wBuff = 1 - wBuff;
    sampleindex = 0;
```

```
    buffersSwapped = true;
  }
}

void dateTime(uint16_t* date, uint16_t* time)
{
  uint16_t t[3],d[3];
  t[2] = rtc.getSeconds();
  t[1] = rtc.getMinutes();
  t[0] = rtc.getHours();
  d[2] = rtc.getDay();
  d[1] = rtc.getMonth();
  d[0] = rtc.getYear();
  *date = FAT_DATE(d[0] + 2000,d[1],d[2]);
  *time = FAT_TIME(t[0],t[1],t[2]);
}

void handleSerial()
{
  char timeString[12];
  char formatTime[32];
  uint16_t t[3],d[3];
  if(!isRecording){
    while(Serial.available()){
      char inChar = (char)Serial.read();
      // Set clock by sending ASCII string in the form "#YYMMddhhmmss"
      if(inChar == '#'){ // Set clock
        Serial.readBytes(timeString, 12);
        setRTC(timeString);
      }
      else if(inChar == '?'){ // Query time and battery status
        t[2] = rtc.getSeconds();
        t[1] = rtc.getMinutes();
        t[0] = rtc.getHours();
        d[2] = rtc.getDay();
        d[1] = rtc.getMonth();
        d[0] = rtc.getYear();
        sprintf(formatTime,"%02d/%02d/%d - %02d:%02d:%02d",
d[2],d[1],d[0] + 2000,t[0],t[1],t[2]);
        Serial.print("Date/Time =");
        Serial.println(formatTime);
        Serial.println("Battery Voltage = " +
String((float)analogRead(VBATPIN) * 6.6 / 1024.0) + "V");
      }
    }
  }
}

void setRTC(String datetime)
{
    uint8_t dt[6];
    for(int n = 0; n < 6; n++)
      dt[n] = ((datetime[n*2]-'0') * 10) + (datetime[n*2+1]-'0');
```

```
    rtc.setTime(dt[3],dt[4],dt[5]);
    rtc.setDate(dt[2],dt[1],dt[0]);
}

void enterSleepMode(bool USBWakeUpOnly)
{
  Serial.end();
  USBDevice.detach();

  digitalWrite(GLED,LOW);
  digitalWrite(RLED,LOW);
  digitalWrite(POWER,LOW);
  if(USBWakeUpOnly)
    rtc.standbyMode();
  else
  {
    attachInterrupt(SW, externalInterrupt, RISING);
    rtc.standbyMode();
    detachInterrupt(SW);
  }
  USBDevice.attach();
  Serial.begin(9600);
}
```

Ambient sleeping-hours Feather M0 Firmware

```
#include <Adafruit_TSL2561_U.h>
#include <pgmspace.h>


//#include <Wire.h>
//#include "TSL2561.h"

// Night Time Bed Side Recorder
// Creates a unique folder and records 10min data files
//#include <Wire.h>
#include <Adafruit_Sensor.h>
//#include <Adafruit_TSL2561_U.h>    //Light Sensor
//#include <pgmspace.h>

#include <SPI.h>
#include "SdFat.h"            //SD Card
#include <M0Timer.h>          //Timer
#include <DS18B20.h>          //Temperature
#include <RTCZero.h>

// Pin labels
#define RLED 13
#define GLED 8
#define SW 5
#define POWER 11
#define VBATPIN A7
#define SDCardCS 4
#define USBPOWER 12
#define SOUNDPIN A1

// SD card defines
#define BLOCK_COUNT (300 * 2)  // Each 2s frame is 1024 bytes, 2
blocks. 300 frames = 10 mins
#define error(s) sd.errorHalt(F(s))

uint32_t bgnBlock, endBlock;          // file extent
uint32_t blocksDone = 0;

SdFat sd;
SdFile file;
DS18B20 tempSensor;
M0Timer timer;
RTCZero rtc;

// The address will be different depending on whether you leave
// the ADDR pin float (addr 0x39), or tie it to ground or vcc. In
those cases
// use TSL2561_ADDR_LOW (0x29) or TSL2561_ADDR_HIGH (0x49)
respectively
Adafruit_TSL2561_Unified tsl =
Adafruit_TSL2561_Unified(TSL2561_ADDR_FLOAT, 12345);
```

```
struct nightAmbDataFrame {
  uint32_t timeStamp;
  int16_t sound[400];
  float lightlux;
  float temp;
  float vbat;
};
/*
struct nightBodyDataFrame {
  uint32_t timeStamp;
  uint16_t pulse[128];
  int16_t accel[288];
  float temp;
  float vbat;
};
*/
// dataFrame pads the nightBodyDataFrame structure to 1024 bytes
length
union dataFrame {
  nightAmbDataFrame d;
  uint8_t x[1024];
};

dataFrame buff[2];        // Double buffer memory allocation
unsigned int wBuff = 0;     // write buffer index
bool buffersSwapped = false;  // flags when buffer needs writing to SD
card
bool isRecording = false;
unsigned int sampleindex = 0;
char dirname[13];
char filename[13];
int dirNumber = 0;
int fileNumber = 0;
uint8_t ledCounter = 0;

void samplerCallback();     // Callback function used by sample timer
void startRecording();
void openNewFile();
void dateTime(uint16_t* date, uint16_t* time);  // SD card callback
for timestamping
void setRTC(String datetime);
void externalInterrupt(){};   // Dummy function needed to set
interrupts for waking system from sleep
void enterSleepMode(bool USBWakeUpOnly);
void configureLightSensor(void);
////////////////////////////////

void setup() {
  configureLightSensor();
  Serial.begin(9600);
```

```
  pinMode(RLED,OUTPUT);
  pinMode(GLED,OUTPUT);
  pinMode(SW,INPUT_PULLUP);
  pinMode(POWER, OUTPUT);
  digitalWrite(GLED,LOW);
  digitalWrite(RLED,HIGH);
  memset(buff[0].x, 0, sizeof(dataFrame));
  memset(buff[1].x, 0, sizeof(dataFrame));

  SYSCTRL->DFLLCTRL.bit.RUNSTDBY = 1; // Keeps clock running during
standby
  attachInterrupt(USBPOWER, externalInterrupt, RISING);

  rtc.begin();
  SdFile::dateTimeCallback(dateTime);
  timer.init(&samplerCallback);
}


void configureLightSensor()
{
    // tsl.setGain(TSL2561_GAIN_1X);      /* No gain ... use in bright
light to avoid sensor saturation */
  // tsl.setGain(TSL2561_GAIN_16X);     /* 16x gain ... use in low
light to boost sensitivity */
  tsl.enableAutoRange(true);          /* Auto-gain ... switches
automatically between 1x and 16x */

  /* Changing the integration time gives you better sensor resolution
(402ms = 16-bit data) */
  tsl.setIntegrationTime(TSL2561_INTEGRATIONTIME_13MS);      /* fast
but low resolution */
  // tsl.setIntegrationTime(TSL2561_INTEGRATIONTIME_101MS);  /* medium
resolution and speed   */
  // tsl.setIntegrationTime(TSL2561_INTEGRATIONTIME_402MS);  /* 16-bit
data but slowest conversions */
}




void loop() {
  if(isRecording)
  {
    while(!buffersSwapped)
      delay(5); // Wait until new data

    // Write 1024 byte data frame to SD card
    buff[1-wBuff].d.temp = (float)tempSensor.temperature() * 0.0625;
//0.0625 resolution, 12 bits, 750mS Sampling Rate

    digitalWrite(GLED,HIGH);
```

```
  if (!sd.card()->writeData(&buff[1-wBuff].x[0]))
      error("writeData failed");
  if (!sd.card()->writeData(&buff[1-wBuff].x[512]))
      error("writeData failed");
  buff[1-wBuff].d.timeStamp += 2; // +2: double buffering
  digitalWrite(GLED,LOW);
  buffersSwapped = false;
  tempSensor.startConversion();
  blocksDone += 2;

  // If switch turned off fill current file with zeros and stop
  if(!digitalRead(SW))
  {
    memset(buff[1-wBuff].x,0,512);
    while(blocksDone < BLOCK_COUNT)
    {
      if (!sd.card()->writeData(buff[1-wBuff].x))
          error("writeData failed");
      blocksDone++;
    }
    isRecording = false;
    timer.stop();
    Serial.println("Stopping recording.");
    // Turn off peripherals
    digitalWrite(POWER, LOW);
  }

  // If file complete close and start a new one
  if(blocksDone >= BLOCK_COUNT){
    if (!sd.card()->writeStop()) {
      error("writeStop failed");
    }
    file.close();
    // If battery is low, pause recording and enter sleep mode
    if(buff[1-wBuff].d.vbat < 3.55) {
      timer.stop();
      enterSleepMode(true);
      isRecording = false;
    }
    else if(isRecording)
      openNewFile();
    else
      sd.chdir("/");
  }
}
else // If not recording
{
  if(digitalRead(SW))
  {
    digitalWrite(GLED,HIGH);
    digitalWrite(RLED,HIGH);
    delay(500); // Debounce
    digitalWrite(GLED,LOW);
```

```
      digitalWrite(RLED,LOW);
      startRecording();
    }
    else
    {
      // If not recording and no USB power, enter sleep mode. If
battery is low, only wake up when
      // USB charging is detected.
      if(!digitalRead(USBPOWER))
        enterSleepMode((float)analogRead(VBATPIN) * 6.6 / 1024.0 <
3.55);

      if(ledCounter++ == 0)
        digitalWrite(RLED,HIGH);
      else
        digitalWrite(RLED,LOW);
      delayMicroseconds(7812);

      if(Serial.available() > 0)
        handleSerial();
    }
  }
}

void startRecording()
{
  digitalWrite(POWER, HIGH);
  delay(250); // Give peripherals time to power-up
  digitalWrite(GLED,HIGH);
  delay(250);
  digitalWrite(GLED,LOW);
  tempSensor.init();


  buff[0].d.timeStamp = 0;
  buff[1].d.timeStamp = 1;

  tempSensor.startConversion();
  if (!sd.begin(SDCardCS, SD_SCK_MHZ(50)))
    sd.initErrorHalt();
  do {
    sprintf(dirname,"Ambient%03d",dirNumber++);
  } while(sd.exists(dirname));
  Serial.print("Creating directory: ");
  Serial.println(dirname);
  sd.mkdir(dirname);
  sd.chdir(dirname);
  fileNumber = 0;
  openNewFile();

  Serial.println("Starting recording.");
  timer.start(96);
  isRecording = true;
```

```
}

void openNewFile()
{
  sprintf(filename,"AmbData%04d.dat",fileNumber++);

  if (!file.createContiguous(filename, 512UL*BLOCK_COUNT)) {
    error("createContiguous failed");
  }
  if (!file.contiguousRange(&bgnBlock, &endBlock)) {
    error("contiguousRange failed");
  }

  if (!sd.card()->writeStart(bgnBlock, BLOCK_COUNT)) {
    error("writeStart failed");
  }

  blocksDone = 0;
}

void samplerCallback()
{


  if(sampleindex == 1)
  {
    buff[wBuff].d.vbat = (float)analogRead(VBATPIN) * 6.6 / 1024.0;


//  if((sampleindex % 2) == 0) { // 96/2 = 48 Hz
//    if (accel.available())
//    {
//      accel.read();
//      buff[wBuff].d.accel[(sampleindex * 3) / 2] = accel.x;
//      buff[wBuff].d.accel[(sampleindex * 3) / 2 + 1] = accel.y;
//      buff[wBuff].d.accel[(sampleindex * 3) / 2 + 2] = accel.z;
//    }
//  }
  }

buff[wBuff].d.sound[sampleindex]  = (float)analogRead(SOUNDPIN) * 3.3
/ 1024.0;

sensors_event_t event;    //Sensor readings can take several mS
tsl.getEvent(&event);     //Sensor reagings can take several mS

if (sampleindex==100)
{
 buff[wBuff].d.lightlux = (float)event.light;   //Read sensor in lux
after 1 second
}

//buff[1-wBuff].d.temp = (float)tempSensor.temperature() * 0.0625;
```

```
  if(sampleindex < 10)
    digitalWrite(RLED,HIGH);
  else
    digitalWrite(RLED,LOW);

  sampleindex++;
  if(sampleindex > 399){
    wBuff = 1 - wBuff;
    sampleindex = 0;
    buffersSwapped = true;
  }
}

void dateTime(uint16_t* date, uint16_t* time)
{
  uint16_t t[3],d[3];
  t[2] = rtc.getSeconds();
  t[1] = rtc.getMinutes();
  t[0] = rtc.getHours();
  d[2] = rtc.getDay();
  d[1] = rtc.getMonth();
  d[0] = rtc.getYear();
  *date = FAT_DATE(d[0] + 2000,d[1],d[2]);
  *time = FAT_TIME(t[0],t[1],t[2]);
}

void handleSerial()
{
  char timeString[12];
  char formatTime[32];
  uint16_t t[3],d[3];
  if(!isRecording){
    while(Serial.available()){
      char inChar = (char)Serial.read();
      // Set clock by sending ASCII string in the form "#YYMMddhhmmss"
      if(inChar == '#'){ // Set clock
        Serial.readBytes(timeString, 12);
        setRTC(timeString);
      }
      else if(inChar == '?'){ // Query time and battery status
        t[2] = rtc.getSeconds();
        t[1] = rtc.getMinutes();
        t[0] = rtc.getHours();
        d[2] = rtc.getDay();
        d[1] = rtc.getMonth();
        d[0] = rtc.getYear();
        sprintf(formatTime,"%02d/%02d/%d - %02d:%02d:%02d",
d[2],d[1],d[0] + 2000,t[0],t[1],t[2]);
        Serial.print("Date/Time =");
        Serial.println(formatTime);
        Serial.println("Battery Voltage = " +
String((float)analogRead(VBATPIN) * 6.6 / 1024.0) + "V");
```

```
      }
    }
  }
}

void setRTC(String datetime)
{
    uint8_t dt[6];
    for(int n = 0; n < 6; n++)
      dt[n] = ((datetime[n*2]-'0') * 10) + (datetime[n*2+1]-'0');
    rtc.setTime(dt[3],dt[4],dt[5]);
    rtc.setDate(dt[2],dt[1],dt[0]);
}

void enterSleepMode(bool USBWakeUpOnly)
{
  Serial.end();
  USBDevice.detach();

  digitalWrite(GLED,LOW);
  digitalWrite(RLED,LOW);
  digitalWrite(POWER,LOW);
  if(USBWakeUpOnly)
    rtc.standbyMode();
  else
  {
    attachInterrupt(SW, externalInterrupt, RISING);
    rtc.standbyMode();
    detachInterrupt(SW);
  }
  USBDevice.attach();
  Serial.begin(9600);
}
```

APPENDIX F ANALYSIS OF FOCUS GROUPS

Category (Focus Group 1)	Group 1	Group 2	Group 3	Frequency
Clinical assessment	anamnesis	anamnesis	anamnesis	3
Time for clinical assessment	15-20 minutes Depends on the problem No much time if there are more patients waiting	 5 to 40 minutes First time 15 to 20 minutes to create the clinical history	 10 to 30 Ideally 20 to 25	1 1 1 1 1 1 1
Type of patients	Low-income patients People who avoid the public health service	 People who live near the office	Low-income patients People who live near the office First level care patients to terminal patients	2 1 2 1
Issues, limitations and problems of information provided by patient	Problems of communication of patient : Low-academic level, doctor has to ask many questions, patient gives the diagnose and treatment, elderly are close-minded, don't tell all the symptoms, patient hides important information Perception of pain varies from patient to patient More continuous measurements and laboratory tests to see behaviours of patterns Patient wants a magic pill that cures everything.	Problems of communication of patient : Answers given by patient are short, we have to ask many questions Patient comes with a diagnose and treatment found on Internet Subjective assessment of pain by patient. Symptoms said by patient and signs observed by clinician do not match Some patients think that a lot of medicine is better	 Patient expects medicine they think is better for their disease	2 2 1 3

	More information of the patient about stress, anxiety	More information of the environment of the patients	More information about stress, sleep, environment of patient	3
How to improve the issues	Improve attention and more time	Good relationship between doctor and patient	Improve attention and more time	3
	More training and expertise in cardiology, immunology and psychology			1
	More information from patient antecedents, hereditary diseases, their environment, more laboratory and pathological tests	We need to know habits, risk factors	More information of patient and clinical test,	3
Physiological information during the day	Pulse	Pulse	Pulse	3
	Respiration rate	Respiration rate	Respiration rate	3
	Body temperature	Body temperature	Body temperature	3
	Oxygen saturation		Oxygen saturation	2
	Glucose	Glucose		2
	Insulin			1
	Blood pressure	Blood pressure	Blood pressure	3
	Adrenaline			1
	PH of skin for stress			1
		Cholesterol		1
Environmental during the day	Temperature,	Temperature	Temperature	3
	Altitude (affects haemoglobin and blood pressure)			1
	Pollution for the asthmatic	Oxygen quality (respiration problems)	Pollution	3
		Noise		1
			Humidity (asthmatic)	1
	Naps			1
Activity-related and behavioural during the day	Quantity of food		Quantity of food	2
	Quality of food	Quality of food	Quality of food	3

	Number of cigarettes		Number of cigarettes	2
	Alcohol drank			1
	Calories burnt	Physical activities performed	Physical activities performed	3
	Drugs		Drugs	2
	Amount of water drank			1
	Times went to toilet			1
	Hours worked		Hours worked	2
	Environment of the place of work			1
	Personality (anger tests, anxiety tests) and targeted tests for specific groups	Stress	Depression, anxiety , stress , relax	3
		Pain assessment	Pain assessment	2
Physiological at night	Glucose levels			1
	Cortisol levels			1
	Oxygen saturation			1
	Seratonin and melatonin for sleep			1
	Sleep efficiency	Sleep efficiency	Sleep efficiency	3
		Pulse rate	Pulse rate	2
		Respiration rate	Respiration rate	2
		Body temperature	Body temperature	2
		Blood pressure	Blood pressure	2
Environmental at night	Light	Light	Light	3
	Temperature	Temperature	Temperature	3
	Noise	Noise	Noise	3
Benefits of data recorded	Tailor treatments to patient	Better disease control		2
	More complete treatment			1
		Assess general well-being of patient		1
			Correct diagnosis	1
			Dismiss diseases with similar symptoms	1
Physical appearance of the wearable recording device	T-shirt			1
	Vest	Vest with a wristband	Vest	3
	Watch			1
	Sensors connected by cables		Connected to several electrodes	2

		A mobile phone		1
		A belt		1
			Something covering the chest and upper arm	1
Features of the device	Reliable	Reliable		2
	Comfortable	Comfortable		2
	Data standardised			1
	Ergonomic			1
	Shock resistant			1
	Easy-to-use by patients	Easy-to-use by patients		2
	Does not interfere with other devices			1
	Water resistant			1
		Adaptable for different patients	Adaptable for different people	2
			Something not visible	1
			Personal use for hygiene reasons	1
			Easy to take it off	1
			Cheap	1
Features that would stop prescribing the use of the device	Uncomfortable			1
	Wrong measurements		Inaccurate	2
	Not calibrated			1
	Difficult to use	Difficult to use		2
	Put patient's life in risk with cables or pacemaker		Dangerous for patients	2
	Causes interference		Causes interferences	2
		Painful for the patient	Produce skin reactions, painful	2
		Costly		1
When to access data	At the end of prescribed use	At the end of prescribed use	At the end of prescribed use	3
	Every hour to see alterations			1
		Every 8 hours		1
			Any time for severe conditions	1
Format of the data	Printed in paper	Printed in paper	Printed in paper	3
	In a database			1
Reasons for the patient to access data	Legally they have the right to access their own data		They have the right to see their data	2
	They can have a second opinion of their data			1

recorded	Patients can use their data to modify behaviour	Patient can understand their condition and have a better control Good for diseases that do not show symptoms but they are developing	Better control of disease	3 1

Category (Focus Group 2)	Group 1	Group 2	Group 3	Frequency
Physiological variables to add in addition to: Pulse rate, respiration rate, body temperature, blood pressure, oxygen saturation, glucose and cholesterol	Nothing	Nothing	Nothing	
Environmental variables to add in addition to: Light level, noise level, temperature, pollen, altitude, pollution	Humidity, CO2. Recommended remove pollen	Nothing	Nothing	
Activity-related variables to add in addition to: Energy expenditure in MET, objective and subjective assessment of sleep quality, stress assessment	Nothing	Nothing	Nothing	
Subjective reports added in addition to: Pain, mood, anxiety, stress, tests for the elderly such as memory and functioning, time of medication and food, food quality, symptoms and time when they occurred, amount of food	Drug addiction	Socioeconomic status, education level, job, hours of work and rest Naps during the day	Drugs	
Connection of sensors	Wirelessly	Wirelessly	Wirelessly Wires	3 1

Where report activity-related and behavioural information (mobile phone or printed daily log)	Printed	Printed	Printed	3
When to report information of stress	Mood and depression just once a month, Once a day	 3 times a day	 3 times a day When they change	1 1 2 1
Period of time to wear the system	One week until disease is under control Disease under control one day a month To diagnose one day a month To diagnose twice a week	One week until disease is under control Disease under control one day a month To diagnose one week	One week To diagnose twice a week Disease under control twice a week	3 2 1 2 1 1

APPENDIX G WORKS PRESENTED

Wearable Patient and Health Worker Monitoring: Opportunities for Improved Outcomes and Open Source Sensing

S. Woolley — Keele University, UK

T. Collins — Manchester Metropolitan University, UK

D. Infante Sanchez — University of Birmingham, UK

P. Pemberton, T. Veenith, D. Hume, K. Laver, C. Small — University Hospitals Birmingham, UK

L. Lapão — Universidade Nova de Lisboa, Portugal

Introduction

Monitoring systems have wide clinical application in health service provisions, for example, in rehabilitation, pre- and post-surgical assessment, monitoring of the acute medical patient and management of chronic conditions [1-3]. They also provide new opportunities for insights into the workplace activities, processes and stressors of clinical staff and health workers [4]. In prior work of The Quantified Outpatient Project (http://quantifiedoutpatient.com), a prototype 24-hour wearable and ambient monitoring system was developed, and opportunities and challenges identified [1]. A **new "Sense247" wearable and ambient monitoring system** is now presented. The underpinning vision is for a generic and expandable "core" sensing system to provide objective sensed recordings that are combined with quantified subjective reports, with the potential for beneficial **insights for both patients and health workers**.

Method - Clinical Prototyping and a Health Worker Design

A clinical prototyping methodology, with healthy participants and clinicians, was used to evolve the Sense247 wearable and ambient sensing system. The original on-body prototype [1] was **designed to be worn under short-sleeved hospital scrubs and health worker uniforms.** Participating clinicians were able to wear the system at work in the hospital (with all necessary permissions and following appropriate processes) as well as outside work.

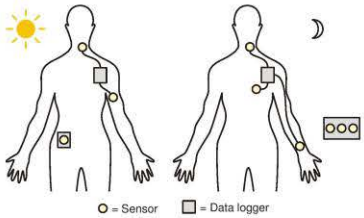
The Sense247 sensing system comprises:

- **Daytime wearable sensing unit**: on-body accelerometry for Metabolic Equivalent Task, pulse, skin temperature and electro-dermal activity.
- **Night-time sensing units**: on-body unit as per daytime but with wrist accelerometry, and bedside unit for ambient light, temperature and sound-level.

For ease of deployment [5], the original prototype was designed for continuous 72-hr operation. Continuous recordings generate averages, minima and maxima in 1-minute, 15-minute, 1-hour and 4-hour intervals.

The Sense247 prototype is enhanced with USB rechargeable Lithium-Polymer batteries and Feather Cortex-M0 Adalogger data loggers with built-in charging circuitry and micro-SD data storage. Additional circuitry detects critical battery levels and automatically closes files to prevent data corruptions. Importantly, unlike many commercial monitors.

Pilot Prototype Use (by clinician), University Hospitals Birmingham, UK



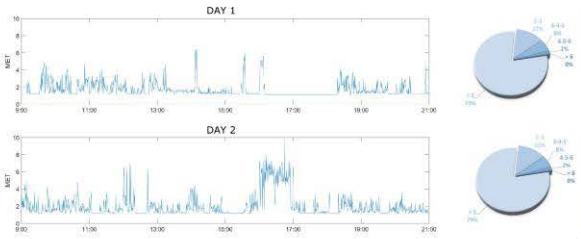
Sense247
- On-body daytime, night and ambient sensing

Compact Sense247 Data Logger
– Inside the on-body daytime logger
(processor, SD card, battery and accelerometer.)

Results

Assessments of system features and wearability, together with feedback from users and clinicians, informed improvements to the Sense247 design, benefiting wearability, usability and system performance, Improvements include the repositioning of sensors, **enhanced data integrity and more compact data loggers**,

As shown below, Sense247 enables **continuous Metabolic Equivalent Task (MET) monitoring down to sedentary levels**



Sense247 Daily Activity (MET) Recordings with Pie Chart Summaries

Conclusions

Whilst there are challenges in achieving robust, secure, ambulatory, multi-modal recordings from user-applied, hygienically-compliant systems, these challenges are not insurmountable, and the potential benefits are considerable, both in terms of improved insights and improved outcomes.

Discussion

24hr outpatient sensing has wide clinical application in rehabilitation, in the management of chronic conditions and, in pre- and post-surgical assessment. However, better detection of both low level activity and sleep is required than currently available in commercial activity monitoring devices.

Further Work

In addition to further use and testing, future research will focus on robust and compliant information security and clinical hygiene, and the potential for **open source delivery**.

The work of the Quantified Outpatient project can be found on-line at; http://quantifiedoutpatient.com.

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[1] D. Infante Sanchez, S. Woolley, T. Collins, P. Pemberton, T Veenith, D. Hume, K. Laver and C. Small The Quantified Outpatient - Challenges and Opportunities in 24hr Patient Monitoring, Informatics for Health, 24(1) (2017), 163-4.

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Medical Informatics Europe 2018: 24th–26th April 2018, Gothenburg, Sweden

Wearable Patient and Health Worker Monitoring: Opportunities for Improved Outcomes and Open Source Sensing

T. COLLINS [a], S. WOOLLEY [b], D. INFANTE SANCHEZ [c], P. PEMBERTON [d], T. VEENITH [d], D. HUME [d], K. LAVER [d], C. SMALL [d], L. LAPÃO [e]
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1. Introduction

Wearable multi-modal monitoring systems, capable of robust real-world recording during the activities of daily life, have the potential to provide rich objective experiential and well-being accounts. Sensing systems have wide clinical application in rehabilitation, pre- and post-surgical assessment, monitoring of the acute medical patient [1] and management of chronic conditions [2] [3], among others. They also provide new opportunities for insights into the workplace activities, processes and stressors of clinical staff and health workers [4] [5]. In prior work [6] of The Quantified Outpatient Project (http://quantifiedoutpatient.com), a prototype 24-hour wearable and ambient monitoring system was developed, and opportunities and challenges identified. A new and evolved "Sense247" design is now presented that addresses data and usability challenges identified in interview feedback and participant assessments. The underpinning vision is for a generic and expandable "core" sensing system to provide objective sensed recordings that supplement, not supplant, subjective reports. To this end, continuously-sensed physiological, environmental and actigraphy recordings are combined with quantified subjective reports.

2. Method

A clinical prototyping methodology, with clinician and healthy user participation, was employed to evolve the new Sense247 design. It employs digital sensors for on-body day/night measurement of pulse rate, actigraphy, body temperature, and night-time ambient light and temperature; and analogue sensors for day/night electro-dermal activity and night-time ambient sound level. Importantly, unlike many commercial monitors, the system provides continuous, high-precision Metabolic Equivalent Task (MET) monitoring down to sedentary levels. For ease of deployment [7], the original prototype was designed for continuous 72-hr operation. Sense247 is enhanced with USB rechargeable Lithium-Polymer batteries and Feather Cortex-M0 Adalogger data loggers with built-in charging circuitry and micro-SD data storage. Additional circuitry detects critical battery levels and automatically closes files to prevent SD card corruptions. The

design maintains the original use of continuous recordings to generate averages, minima and maxima at 1-min, 15-min, 1-hr and 4-hr intervals for physiological, environmental and actigraphy recordings. These are combined with quantified subjective user reports for data mining and visual analytics.

3. Results

Assessments of system features and wearability, together with feedback from users and clinicians, informed improvements to the Sense247 design, including the repositioning of pulse and actigraphy sensors. The new data loggers have enhanced data integrity and are half the size of the original units, making them smaller and lighter than a typical smartphone. The improvements benefit wearability, usability and system performance outcomes.

4. Discussion

In addition to further use and testing, future research will focus on robust and compliant information security and clinical hygiene, and open source delivery.

5. Conclusion

Whilst there are challenges in achieving robust, secure, ambulatory, multi-modal recordings from user-applied, hygienically-compliant systems, these challenges are not insurmountable, and the potential benefits are considerable, both in terms of improved insights and improved outcomes.

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[4] L.V Lapão and G. Dussault, The Contribution of eHealth and mHealth to Improving the Performance of the Health Workforce: A Review, *WHO Public Health Panorama*, (2017), 463-471.

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The Quantified Outpatient-Challenges and Opportunities in 24hr Patient Monitoring. Infante Sanchez, D., **Woolley, S.I.**, Collins, T., Pemberton, P., Veenith, T., Hume, D., Laver, K. & Small, C., Informatics for Health 2017, Journal of Innovation in Health Informatics, 24(1), 2017, pp. 163-4
Full Text: https://www.researchgate.net/publication/313861434_The_Quantified_Outpatient_-_Challenges_and_Opportunities_in_24hr_Patient_Monitoring

UNIVERSITY OF BIRMINGHAM

Keele UNIVERSITY

Manchester Metropolitan University

The Quantified Outpatient
Challenges and Opportunities in 24hr Patient Monitoring

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Introduction

Patient monitoring systems capable of accurate recording in the real-world, during activities of everyday living, can provide rich objective accounts of patient well-being that have broad application in clinical decision support. **Combining physiological, environmental and actigraphy sensing together with a quantified subjective patient report and activity log**, provides **new opportunities and new challenges in big data analysis, data mining and visual analytics**.

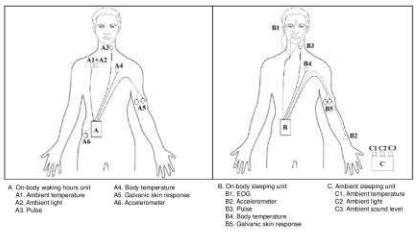
Method

An iterative prototyping approach together with clinical collaboration informed the design and development of a novel **24hr sensing system with broad application relevant to sleep assessment**. The system design, sensor selection and visual analytic strategies were informed by literature review and pilot studies with i) clinical staff and ii) healthy participants.

The sensing system comprised:

- **Daytime wearable sensing unit**: on-body accelerometry for Metabolic Equivalent Task, pulse, skin temperature and resistivity
- **Night-time sensing units**: on-body unit as per daytime but with wrist accelerometry, and bedside unit for ambient light, temperature and sound-level

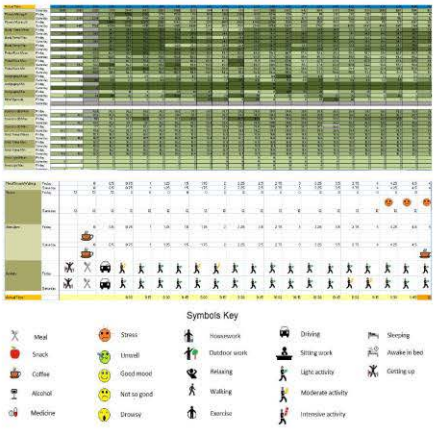
Continuous recordings were used to generate averages, minima and maxima in 1-minute, 15-minute, 1-hour and 4-hour intervals. For data mining and visual analytics, these records were combined with quantified accounts of subjective user reports and activity logs. Ten subjects (including three clinicians) tested the system for up to three consecutive days and nights and provided assessments of use and comfortability. Five clinicians were interviewed regarding system applications, barriers to use, data use and visual analytics.



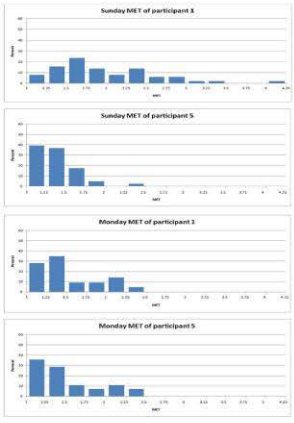
CircadianSense Prototype

CircadianSense Prototype: Pilot Testing

CircadianSense Motion Chart Example



CircadianSense Heat Map and Activity Visualizations



CircadianSense Examples of Daily Metabolic Equivalent Task Summaries

Results

Data acquisition was successful across a wide range of MET levels. System comfortability was good but with some discomfort and skin irritation arising from prolonged use of a carotid pulse sensor (selected for its robust performance compared with wristband alternatives). Electrooculography sensing for REM sleep detection was attempted but was uncomfortable and performance was unsatisfactory. Usability of the system benefitted from prolonged battery operation. Few data losses resulted from user-administration of sensors, but more resulted from a lack of prototype ruggedisation. Attempts at intuitive multivariate data visualizations, including heat maps, motion charts and clustered views, had limited success. However, the system and approach was assessed as very good for real-life application and decision support.

Conclusions

Multi-modal outpatient monitoring can perform robustly and with acceptable comfortability across a spectrum of activity types and levels, however, system robustness and ease-of-use are paramount to reliability, and users' self-application of sensors requires careful attention.

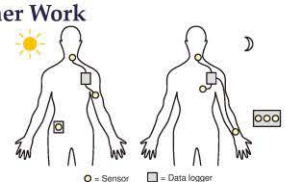
The new big un-delineated, multi-modal, multi-dimensional, data spaces created are unfamiliar, uncharted territories that require new understandings, guidance and training. Data mining and visual analytics provide new research insights but there are many challenges regarding their translation into clinical practice.

Discussion

24hr outpatient sensing has wide clinical application in rehabilitation, in the management of chronic conditions and, in pre- and post-surgical assessment. However, better detection of both low level activity and sleep is required than currently available in commercial activity monitoring devices.

Further Work

PatientSense is a new 24hr patient monitoring prototype design evolving from the CircadianSense prototype and from participatory design inputs from community physicians.



Related Publications

Hernandez-Munoz, L.U., Woolley, S.I., Luyt, D., Stiefel, G., Kirk, K., Makwana, N., Melchior, C., Dawson, T.C., Wong, G., Collins, T. and Diwakar, L., 2017. Evaluation of AllergiSense Smartphone tools for Adrenaline Injection Training. IEEE Journal of Biomedical and Health Informatics, 21(1), pp.272-282.
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Hernandez-Munoz, L., Woolley, S. and Diwakar, L., 2015. Pilot evaluation of smartphone technology for adrenaline injection training. Clinical and Experimental Allergy, 45(2), pp.507-507.

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