Monitoring Circadian Rhythm and Sleep Patterns Using Wrist-worn Temperature and 3-axis Accelerometer Sensors: A Study with Healthy Younger Adults, Healthy Older Adults, and People Living with Dementia

by

Jing Wei

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Author's Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Abstract

Sleep plays an important role in our life; monitoring and understanding our sleep can support better sleep habits and therefore health and quality of life. Research has shown that sleep is mainly regulated by people's internal circadian rhythms. The traditional way to infer circadian rhythm is to measure dim light melatonin or core body temperature, both of which are impractical to monitor on a day-to-day basis. Recently, wrist temperature has been shown to be a good alternative as it has a closer association with sleep patterns. Wrist temperature increases when people fall asleep and decreases after people wake up. However, there has been virtually no research on whether and how this trend will change as people get older or have dementia. Revealing differences in wrist temperature rhythms among healthy younger adults, healthy older adults and Older Adults with Dementia (OAWD) could help to support a better sleep for each population.

The goal of this research is to explore the wrist temperature patterns and their underlying implications for both circadian rhythms and sleep patterns for people of different ages and cognition. Healthy younger adults (n=10), healthy older adults (n=10), and OAWD (n=8) wore a customized wristband with a temperature sensor and a three-axis accelerometer sensor along with a commercial wristband (Mi Band 2) for 14 days. Their wrist temperature rhythms were analyzed and compared for the three groups and differences in daytime temperature value and variation are found. An evaluation of the Mi Band 2 is showed decreasing accuracy for the older adult populations, especially OAWD. Accelerometer data showed one older participant and all OAWD had frequent body movements during sleep, which is pinpointed as the main cause for the poor performance of the Mi Band 2. Four case studies are presented to show these body movements together with their wrist temperature rhythms. As wrist temperature rhythms were not affected by participants' movements, this supports the usefulness of wrist temperature in more comprehensive and accurate sleep analysis. Lastly, novel two sleep detection algorithms are proposed; one is built solely on wrist temperature, while the other uses features from both wrist temperature and accelerometry. While the wrist temperature alone algorithm performed better than the Mi Band for OAWD, using both data sources showed increases in sleep detection accuracy for all participants it was tested with. Preliminary results show that the wrist temperature has the potential to play a valuable role in better identification and understanding or sleep, including for people with movement-related sleep disorders.

Acknowledgements

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I want to thank all my participants and the working staff in the Schlegel Village. All my participants had been diligently recorded the sleep journal and wore the wristbands correctly. They contributed a lot to this research and this thesis. And a special thank to Karen Norris, who drove me from Waterloo to Guelph for data collection multiple times. Without her, I could never get sleep data from people living with dementia.

I'm also thankful for the companionship of my labmates: Ahmed, Karan, Mehdi (ranked alphabetically) and other people, who helped me to overcome my social anxiety and I had a memorable time with all of them.

I want to thank Dr. Jonathan Kofman and Dr. Plinio Morita for taking the time to read my thesis.

Finally, I'd like to thank all the little people who made this thesis possible.

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Dedication

This thesis is dedicated to my parents; their endless love and support make me become who I am now.

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Abbreviations

CBT Core Body Temperature 2

DLMO Dim Light Melatonin Onset 2

ESS Epworth Sleepiness Scale 14

MEQ Morningness-eveningness questionnaire 14

MMSE Mini-Mental State Examination 15

OAWD Older Adults with Dementia iii, 8

PD Parkinson's Diseases 18

PSG Polysomnography 9

PSQI Pittsburgh Sleep Quality Index 14

PSW Personal Support Workers 15

REM Rapid Eye Movement 2

SCN Suprachiasmatic Nucleus 2, 6

SWTD Sleep/wake Temperature Difference 28

Chapter 1

Introduction

1.1 Motivation

Sleep is a substantial process for all human beings; however, lack of sleep and having low sleep quality have become a worldwide epidemic. It has been shown that people with compromised and insufficient sleep suffer from a decline in cognitive performance and daytime neurobehavioral functions, such as decision making and memory loss [1, 2, 3]. In modern society, increasing awareness of sleep health and new technology developments have made daily sleep tracking accessible to the public. One of the most affordable and convenient systems is smart wristband or smartwatch. Wearing a device on the wrist can help people track when they sleep and even their daily sleep quality. These wristbands and smartwatches can send the collected data to a smartphone via Bluetooth and then to the cloud so that people can easily access their sleep data as they wish.

Being able to monitor sleep every day can be useful for people to keep track of their sleep health; however, only measuring the ”external performance” of sleep is not enough. A common notion of good sleep is well stated by the famous old saying ”Early to bed and early to rise makes a man healthy, wealthy and wise.” However, it should be noted that not everyone is naturally predisposed to sleeping and waking up earlier. The optimal sleep time and length of sleep varies considerably for different people [4].

From a modern biology perspective, sleep is a complicated biological process. [5] It is not solely controlled by people’s willpower; people’s sleepiness is dictated by their internal biological clock under normal conditions. Even without sleeping, the human body still secretes melatonin and runs different biological processes that follow a 24-hour cycle. This cycle is called circadian rhythm, and a small region called Suprachiasmatic Nucleus (SCN) in our brain is the main controller of the circadian rhythm. [6] Each individual has different circadian rhythms. Interfering factors including increased stress, illness, stimulants such as caffeine, or willpower can lead to delayed or interrupted sleep and eventually result in a misalignment between sleep patterns and circadian rhythms.

While commercially available smart wristbands such as *Fitbit Alta HR* [1] can provide detailed sleep monitoring and analysis, including sleep duration and estimation of deep/light (even Rapid Eye Movement (REM)) sleep, all the commercial devices fail to monitor people's sleep from an internal perspective; they cannot directly measure one's circadian rhythms. Obtaining circadian rhythm information and detecting whether there is a misalignment between daily sleep patterns and the internal rhythms could provide a more comprehensive and individualized understanding of sleep and constitute a new, more comprehensive way of performing sleep monitoring.

Based on different circadian rhythms and chronotypes (i.e., the propensity to sleep earlier or later), people can be categorized into "night owl" for people tend to sleep late or "morning lark" for people tend to sleep early [7]. If a "night owl" sleeps earlier than their natural diurnal rhythm, they might not get optimized sleep. The circadian rhythms are partly controlled by genes, but they also change across the lifespan. For example, older adults generally have earlier sleep onset and offset than younger adults do, which has much to do with the phase advancement of older adults' internal rhythms. Changes in circadian rhythms are shown to be correlated to poor sleep performance of the older population [8]. In some special cases like shift workers, research has also shown that sleep pattern shifts or sleep deficiency can lead to a higher probability of depression [9]. Furthermore, the misalignment between internal biological process and real sleep patterns are shown to be highly correlated to smoking, obesity and other negative effects [10, 11].

Many factors bring disruptions to people's circadian rhythms and can eventually lead to irregular sleep patterns. While maintaining the rhythmicity of the circadian system is important, the circadian rhythm is a less-known concept to the public. This is partly due to the difficulty of measuring gold standards of circadian phase markers, which are Dim Light Melatonin Onset (DLMO) [12] and Core Body Temperature (CBT) [13]. DLMO requires testing melatonin levels in people's saliva or urine, while CBT refers to people's rectal temperature. Both measurements are obtrusive and costly in time and money. Recently, wrist temperature has been proposed to be a good alternative to measure circadian rhythms [14]. With the development of sensor technology, wrist temperature can be easily measured with a small-sized temperature sensor worn on the inside of a wristband. Unlike CBT,

[1] https://www.fitbit.com/en-ca/shop/inspire

which drops at night and reaches the lowest value during sleep, wrist temperature has an opposite trend. Before sleep occurs, wrist temperature starts to increase, remains at a relatively higher value during sleep, then drops drastically right after the sleep offset [14] (an example is shown in Figure 1.1). Furthermore, the time when wrist temperature starts to increase before the sleep onset has shown a high correlation to DLMO[15, 16]. As research has shown that wrist temperature can be a phase marker for circadian rhythm and wrist temperature sensor can be easily integrated into a wristband, the addition of temperature sensor to a wrist-worn band is a good candidate for improving day-to-day monitoring sleep monitoring. The knowledge of individual circadian rhythms could enable a deeper understanding of sleep timing and point out the potential in improving and supporting better sleep schedules.

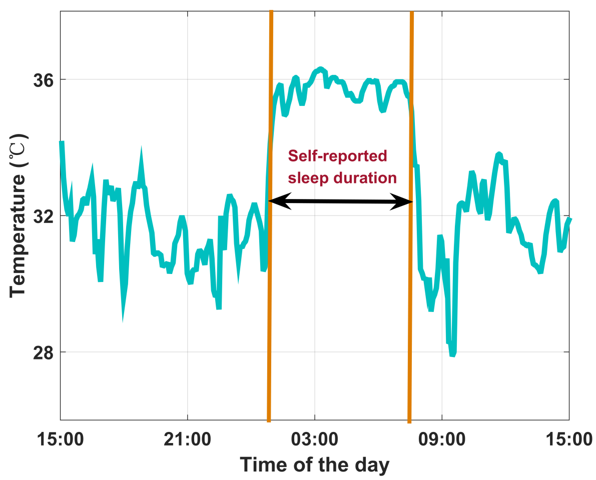


Figure 1.1: An example of wrist temperature pattern of one participant (Y004) from this research over a 24 hour period.

The length of sleep duration has dropped drastically, and the incidence of nighttime insomnia has increased 42% from 2007 to 2015 in Canada [17]. Moreover, sleep disorders are more common in older adult and dementia populations, both of whom can experience sleep disturbances caused by morbidity such as sleep apnea, chronic pain, and disrupted circadian rhythms [18]. This can result in excessive daytime sleepiness as well as symptoms associated with lack of sleep, including decreased cognitive performance, irritability, and feelings of exhaustion [19, 20, 21]. Therefore, measuring the circadian rhythms as well as sleep patterns of the aged and dementia populations could support better sleep management, which in turn could benefit overall quality of life.

1.1.1 Research objective and questions

The overreaching objective of the research presented in this thesis is to investigate how aging and dementia influence sleep patterns detected by wrist temperature and accelerometry (actigraphy).

The research questions that guided this thesis are listed below and outlined in more detail in Chapter 3:

- How do circadian wrist temperature patterns differ between healthy younger adults, healthy older adults, and older adults living with dementia?
- What variables can be used to identify peoples sleep quality from their wrist temperature?
- What advantages does wrist temperature have compared to monitoring sleep using actigraphy?

1.2 Thesis Organization

The remainder of the thesis is structured as follows:

Chapter 2 provides an overview of the literature, with a focus on two aspects related to the topic of sleep monitoring. First, the mechanism of sleep and circadian rhythm system inside the human body are explained. Second, existing approaches to sleep monitoring that are based on wearable sensors are be summarized.

In Chapter 3, the objectives of this study are defined and the study experiment protocol is outlined. The demographics as well as the sleep patterns collected during experiment are presented and discussed.

In Chapter 4 parameters extracted from wrist temperature measurements are compared between the three groups.

Chapter 5 focuses on sleep data obtained from Mi Band 2, including some case studies to illustrate how the addition of temperature could improve sleep monitoring accuracy.

In Chapter 6, two sleep detection algorithms are proposed and tested. In particular, the unsupervised sleep detection algorithm that uses features of both wrist temperature and accelerometer data is shown to be more effective in detecting sleep for people with body movements during sleep.

Chapter 7 includes a general discussion of this study, including insights into why wrist temperature rhythm and sleep patterns are different for different populations, why Mi Band 2 failed to detect OAWD's sleep and how wrist temperature can be utilized to build a better sleep monitoring system in the future.

Chapter 8 summarizes the key findings and conclusions as well as provides insights regarding future work related to sleep monitoring.

Chapter 2

Background

2.1 Sleep and Circadian Rhythms

The SCN is located inside the brain and is what coordinates the circadian system [5]. In daily life, environmental cues such as sunlight and mealtimes influences the SCN; the SCN uses these cues to "learn" external time then uses this to send temporal information via neural signals to the body so that different biological processes can keep running. The schematic of circadian rhythm system and its link to sleep and aging is shown in Figure 2.1. Among these biological processes, the sleep-wake cycle is the center of interest in this study.

Circadian system coordinates the sleep-wake cycle by two means:(1) regulating the secretion of melatonin and cortisol, (2) thermoregulation. [22] After the sun goes down and the environment becomes darker, the photoreceptors in our eyes receive less light. A signal is then sent to the SCN to let it know it is night outside. Once the SCN receives the temporal information from photoreceptors, it signals the pineal gland to secrete melatonin. With the amount of melatonin secreted increasing, people will gradually feel sleepier and less alert. [23] The secretion of melatonin is stopped by the SCN in the morning as the photoreceptors receive more light. Instead of melatonin, more cortisol is secreted so that people become more active and alert. As for the thermoregulation, the SCN controls the oscillation of CBT. As the night progresses, people feel sleepier when the CBT drops [24]. As a result of decreasing CBT, the heat loss through distal skin surfaces is more prominent, which leads to an increase in wrist temperature. For most people, CBT will reach its lowest point (nadir) at around 5 AM, which also happens to be the time when sleep tendency reaches its highest point. In the morning, CBT gradually increases thus causing distal skin temperature to decrease. These two processes together regulate the sleep-wake cycle.

As the SCN directly coordinates the melatonin secretion and CBT oscillation, two gold standards are commonly used in the medical fields to infer internal circadian phase: (1) DLMO, (2) CBT nadir. [12, 25] While accurate, it is not convenient and cost-effective to measure either DLMO or CBT. DLMO measurement requires blood, urine, or saliva samples from people, and the analysis of melatonin can only be done in specific sleep laboratories in hospitals. CBT usually refers to rectal temperature; its measurement in the past requires participants to retain a constant posture and, even with the newest technology (e.g., ingestible telemetric temperature sensor [26]), the measuring process is considered to be unpleasant for most people. When it comes to building an ongoing sleep and circadian rhythm monitoring system, both methods are complicated, costly, and obtrusive; hence they are not practical for day-to-day measurements.

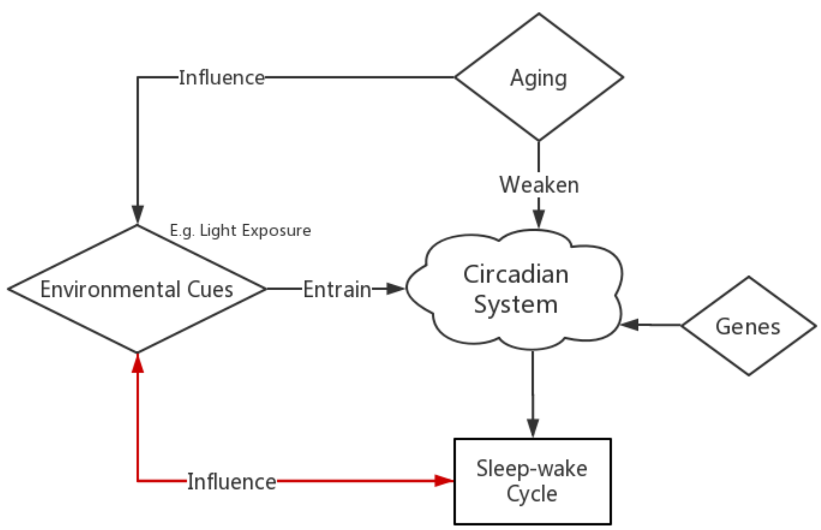


Figure 2.1: Schematic of the Circadian System. The circadian system influences the sleep-wake cycle and is influenced by internal factors, such as genes, aging, as well as by external factors, such as environmental cues.

2.2 Prevalence of Sleep Disturbances and Problems

As people get older, they tend to have lower sleep efficiency and more fragmented sleep according to several studies [27, 28, 29]. Compared to the younger population, older adults have longer *sleep latency* and wake more often during the night. While the sleep duration between the younger population and the older population might be comparable, the sleep quality of older adults is reported as worse [28, 30]. Also, diagnosable sleep disorders, such as apnea, are more common in the aged population, which can bring excessive daytime sleepiness and eventually lead to more disturbed sleep patterns [31, 32]. As for the sleep time preference, many people will change from a "night owl" into a "morning bird" as they age [33]. As there is a tight tie between sleep and circadian rhythms, the decreasing function of the circadian system is considered to be a key cause of the worsening of sleep patterns and quality in the aged population [34, 35].

OAWD have overall sleep patterns that are more uneven than for normal/healthy older adults and their sleep patterns tend to be more disturbed with more fragmented sleep during the night and more naps or short-period sleep during the day [18, 36]. Evidence has shown deteriorated SCN and impaired circadian systems in the OAWD population compared to healthy older adults [37, 34]. With the progression of dementia, many OAWD have a more sedentary lifestyle [38]. This relative lack of movement may exacerbate a deficit in environmental cues that can promote healthy sleep. For example, light is the most potent cue that helps to synchronize SCN. Campbell et al. have reported the bright light exposure for community-dwelling older adults was, on average, less than 30-minute per day [39]. Lacking enough environmental cues will weaken the functioning of the circadian system, which will cause a deterioration in sleep. Furthermore, sleeping during the daytime, in turn, can lower the effective light exposure.

2.3 Commercially Available Wearable Sleep Monitoring Systems

Recent technological advances have made wearable sleep monitoring devices much more available and accessible to the public. Commercial smart wearable devices that can track sleep are popular in the current market. Both high-end products like Apple Watch, Fitbit, and lower-end ones like **Mi Band 2** (used in this study) have a sleep monitoring feature. All their sleep monitoring algorithms are based on the use of actigraphy, which estimates sleep using data from accelerometers and gyroscopes that detect wrist movements. In order to achieve more accurate sleep detection, some more expensive smartwatches can also measure the heart rate during the night and use its variability as a feature [40, 41]. Other than actimetry sensors (i.e., 3-axis accelerometers and gyroscopes) and an optical heart-rate sensor, light sensors in some wristbands and smartwatches are also used for sleep detection as most people sleep in relative darkness [42, 43].

All these smart wearable devices can be paired with smartphones via Bluetooth; the sleep-related data will be automatically transmitted to smartphones. The data can then be processed and stored on the device and in the cloud. While the advanced digital media has become a convenient way for people to store and access their sleep data as well as allows for sleep quality trends to be assessed over a long period, the sleep detection accuracy of different devices varies, and these sleep trackers' accuracy is still questionable [44].

Due to the popularity of commercial wristbands and their low-cost, several programmable Android Wear OS wristbands have been proposed by Samsung and Huawei. Researchers built more advanced sleep monitoring systems based on these Android Wear smart wristbands [42, 43] by using sensors such as microphones and light sensors to fuse data and determine light/deep sleep stages. While these systems show promise for more accurate sleep monitoring, none of their algorithms are commercially available yet.

Some bands, such as the Microsoft Band 2, have a skin temperature sensor that is used to determine whether the user is wearing the wristband. There are also a few research-grade devices that include a temperature sensor, such as Empatica E4 [1] and GENEActiv Sleep [2]. However, none of these wristbands measure skin temperature for the sake of sleep monitoring. Therefore, to the author's knowledge, there is no available product in the market that integrates wrist temperature measurement into sleep monitoring.

2.4 Justification of Wrist Temperature Monitoring

Actigraphy (i.e., measurements using accelerometer sensors) has been the most established method to detect sleep as well as to infer the circadian rhythm [45, 46] since the last century. It has been used in the monitoring of sleep for different populations (e.g., children [47], adolescents [48], older adults [49]) due to its convenience for long-term continuous monitoring compared to the traditional gold standard Polysomnography (PSG) (i.e., a multi-parametric diagnostic tool in sleep medicine). While its convenience and accuracy in sleep monitoring have been recognized by American Academy of Sleep Medicine [50],

[1] https://www.empatica.com/en-int/research/e4/
[2] https://www.activinsights.com/actigraphy/geneactiv-sleep/

actigraphy for circadian rhythm related study has an obvious drawback - it does not measure circadian rhythm directly and is highly dependent on the physical health of users. As actigraphy is based on movement, people who have impaired or irregular movement patterns may not have accurate sleep detection using this method. For example, compared to the normal healthy population, a significant decline can be seen in the activity level for people who are using walkers or sitting on a wheelchair. More contrast day/night activity can promote the circadian system health [51]; however, this activity difference might be too small to precisely infer the circadian rhythms for people who need walking aids or have mobility impairments.

There is a significant portion of older adults, especially people living with dementia, who are frail and have living and moving patterns that are different from younger adults. For example, frail older adults tend to walk or exercise much less than normal younger or older adults. Due to changes in physical abilities, merely measuring the physical movement rest/activity rhythms to infer their circadian system health might not be an appropriate or accurate approach. Compared to the activity level, body temperature is less subject to the general physical health and more directly influenced by biological circadian rhythm. As the SCN controls the thermoregulation and the oscillation of CBT, the resulting heat loss or gains over the skin is reflected by the variations of skin temperature [52, 14]. In this sense, wrist temperature rhythms are intrinsically more of a direct correlation to the circadian rhythms in the body.

While wrist temperature rhythms of older adults have been measured in the past, there is a lack of research investigating the wrist temperature rhythms of OAWD. This literature review only found one study that measured the proximal skin temperature and sleepiness level of OAWD [53]. Considering OAWD have more difficulties related to sleep and that lack of sleep can exacerbate the symptoms associated with dementia (e.g., poor memory, irritability, disorientation, etc.), understanding their circadian rhythm and sleep better could help support better sleep management. For all populations, better sleep management can result in better rest, which in turn can have a positive impact on the quality of life.

Chapter 3

Sleep Monitoring Using Wrist Temperature Study

3.1 Objectives

As highlighted in Section 2.4, there is a lack of research regarding how wrist temperature may be impacted by age and dementia. In addition, the accuracy of commercial wristbands may be influenced by factors such as aging and dementia. Therefore, this thesis research focused on two parts: (1) measuring and analyzing the wrist temperature patterns of younger healthy adults, older healthy adults, and older adults with dementia, and (2) exploring whether wrist temperature can augment accemetry-based sleep monitoring data to improve sleep detection for these populations.

This thesis is guided by the following *Research Questions* and related sub-questions:

- Question 1: How do circadian wrist temperature patterns differ between healthy younger adults, healthy older adults, and older adults living with dementia?

  - 1.1 How does age influence wrist temperature patterns?

  - 1.2 How are wrist temperature patterns different for people living with dementia compared to healthy younger and older adults?

  - 1.3 What associations can be made between wrist temperature patterns and sleep patterns obtained from a self-reported sleep journal?

- Question 2: What variables can be used to identify people's sleep quality from their wrist temperature?
- Question 3: What advantages does wrist temperature have compared to monitoring sleep using actigraphy?

  - 3.1 How does age impact usefulness of temperature versus actigraphy?

  - 3.2 How does cognition (i.e., healthy versus dementia diagnosis) impact the usefulness of temperature versus actigraphy?
- Question 4: How can wrist temperature be used to develop a better sleep detection algorithm?

  - 4.1 Can wrist temperature and accelerometer data be used together to more accurately detect sleep?

For each research question, the respective hypothesis as well as methods to test the hypothesis are listed in Table 3.1. Note several of the methods were identified and developed as the research progressed, as is described in subsequent chapters.

Table 3.1: Research questions, hypotheses and methods that guided this research. WT represents wrist temperature.

Questions	Hypotheses	Methods
Question 1.1	1. Older adults wrist temperature rhythms are flatter and have more fluctuations during sleep and at daytime. 2.The peak of WT patterns of older adults will be earlier in the day than that of younger adults.	1. Extract metrics from WT (i.e., s/w temperature difference (SWTD), quartile deviation, IS, IV). 2. Use t-test to detect any significant differences between the WT of the healthy younger and older groups.
Question 1.2	1. OAWD have a more fragmented sleep/wake cycle (i.e., they wake up multiple times at night and sleep multiple times at the day), which makes their WT more variable.	1. Extract metrics from WT using (i.e., s/w temperature difference (SWTD), quartile deviation, IS, IV). 2. Use t-test to detect any significant differences between the WT of the healthy older and OAWD groups. (use multiple regression to rule out the influence of WT) 3. Use case studies from each group to compare and contrast differences in WT patterns.
Question 2	1. People who report less regular sleep patterns in their sleep journal will have a less regular WT rhythm. 2. People who have more awakenings during the night will have more irregular nighttime WT temperature.	1. Employ a qualitative visual analysis of averaged WT rhythms for participants from each group. 2. Use simulations to show how averaged WT is influenced by regular/irregular sleep patterns.
Question 3.1	1. Aging results in less accurate actigraphy-based estimates of sleep from a commercially available band.	1. Compare sleep data collected from Mi Band to custom-built research band. 2. Analyze case studies from the different populations
Question 3.2	1. Dementia results in less accurate actigraphy-based estimates of sleep from a commercially available band.	1. Compare sleep data collected from Mi Band to custom-built research band. 2. Analyze case studies from the different populations
Question 4.1	1. Wrist temperature can be used to measure sleep. 2. Combine WT and accelerometry data, sleep detection can be more accurate.	1. Build machine learning algorithms to detect sleep. 2. Test the validity of proposed algorithms.

3.2 Methods

3.2.1 Participants

Participants of this study were recruited from three groups: (1) younger adults (20 - 30 years old), (2) healthy older adults (at least 65 years old who self-identified as healthy), and (3) older adults living with dementia (at least 65 years old, have early to middle staged dementia). All participants had to fluently understand English and individuals who were diagnosed with severe sleep disorders were excluded. This study was granted ethics clearance (ORE # 31860 and ORE # 40459) through the University of Waterloo Office of Research Ethics and was conducted as stated in the approved protocols.

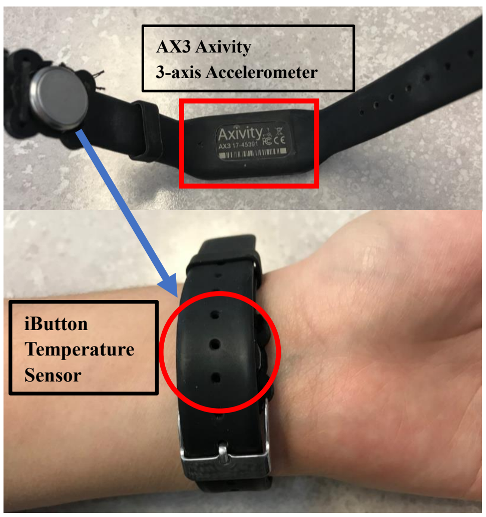
3.2.2 Protocol

All participants had an individual one-on-one orientation session. After providing informed consent, younger and healthy older participants were asked to complete four questionnaires see (Appendix A):

- (1) a demographic questionnaire
- (2) Morningness-eveningness questionnaire (MEQ) [7]
- (3) Pittsburgh Sleep Quality Index (PSQI) [54]
- (4) Epworth Sleepiness Scale (ESS) [55]

The demographic form captured the participants gender, age, height, and weight as well as sleep-related disorders (e.g., insomnia, daytime sleepiness). MEQ is a validated measure that determines morningness-eveningness in human circadian rhythms; PSQI is an established subjective measurement of sleep quality; ESS is commonly used to measure daytime sleepiness.

Participants from the dementia group were identified by the staff in the Schlegel Village of Riverside Glen (i.e., the long-term care facility partnered with for this study). These participants were mainly identified based on their Cognitive Performance Scale (out of 6, higher scores indicate more severe cognitive impairment), their daily behaviors (i.e., people who are less likely to lose the wristband during the experiment) and their sleep habits (residents with very irregular sleep patterns were excluded). As dementia can profoundly impact free-recall, participants' assent in the continuing study was obtained every visit session. OAWD were not able to reliably self-report their sleep quality and fill out the questionnaires. Therefore Schlegel Village staff who were familiar with the resident filled out the demographic form on the OAWD's behalf; the MEQ, PSQI, and ESS could not be captured for this group. In addition, the Mini-Mental State Examination (MMSE) for the dementia group [56] was conducted to approximate level of cognition.



(a) The prototype wristband.

(b) The Mi Band 2.

Figure 3.1: Two wristbands used in the study.

After completing the forms, all participants were introduced to the study wristbands: (1) the custom-built wristband and (2) Mi Band 2. As seen in Figure 3.1, the custom wristband contains an iButton DS1922L temperature sensor (Maxim, Dallas, US) and an off-the-shelf accelerometer data logger Axivity AX3 sensor (Axivity, York, UK; 100 Hz, $\pm$ 8 g, weight: 9 g). Mi Band 2 is used for reference as a comparison of a commercial wristbands sleep monitoring. Participants were asked to wear both wristbands on the left wrist for 14 days and only take them off when showering.

Younger and healthy older adults were given instructions on how to operate both wristbands; for the older adults living with dementia, their Personal Support Workers (PSW) were given instructions. Healthy adult groups kept a daily sleep journal that asked when they went to sleep, when they woke up, and subjective sleep quality (adapted from [57]). Sleep journals for the dementia group were completed by PSW who were familiar with them and their routines. In addition, as many OWAD exhibit excessive daytime sleepiness, working staff were asked to observe participants' status and write down either '1 - awake' or '2 - sleeping' on a created sheet for every half an hour. This sheet was used as supplementary material to the sleep journal.

3.2.3 Analysis of Sleep Onset and Offset

Sleep patterns were extracted from the self-reported sleep journals of both healthy younger and older participants. Sleep onset and offset, waking-up times, and sleep quality score were obtained from the sleep journals for each day. Based on reported sleep onset and offset, the sleep duration and midsleep point (i.e., the halfway point between the onset and offset) were calculated.

While OAWD were not required to fill out a sleep journal, staff were asked to report participants' sleep based on their observations. In the long-term care facility worked with, there are three shifts each day: (1) morning (6:00 to 14:00), (2) afternoon (14:00 to 22:00), (3) evening (22:00 to 6:00). All three teams could observe the sleep of OAWD. However, the sheet and sleep journals had significant missing data due to bad communications and shift changes between different teams. The night team reported more detailed sleep observations of some participants while the afternoon team reported more detailed observations for other participants. For most participants, either their sleep onset data was missing, or their sleep offset data were missing; often, there were no data recorded for either. It is estimated that more than 60% of sleep onset/offset data was missing for OAWD.

In order to make up for the missing reported OAWD sleep onset/offset data, the awake/sleeping status (only nighttime sleep was labeled) was manually labeled by looking into the actigraphy data recorded by the wristband sensor AX3. Since accelerometer data during sleep are characterized with a still and static signal, sleep duration was identified by finding data periods with the least variations. The longest sleep duration was extracted if there were multiple static data periods more than 30 minutes apart. The sleep onset, offset, and duration were estimated using the onset, offset, and duration of the longest data period. If static data periods were almost equally long (i.e., 22:00 to 3:00 and 4:00 to 8:00), the sleep onset and offset were estimated using the onset of the first period and the offset of the last period (i.e., 22:00 as onset and 8:00 as offset). Sleep duration was calculated by adding the duration of all the data periods (see Case study D002 in Section 5.3, Figure 5.4). The naps during the daytime were not included due to the difficulty of reliably identifying whether a nap occurs or not. Furthermore, a short interview (questions are listed in Appendix B) was conducted asking staff for their overall observations about each participant's sleep patterns. Together with sleep journals, sheet, manual labels, and answers in this interview, the sleep onset, offset, duration, and mid-sleep point were calculated.

3.3 Results

3.3.1 Demographics

Data for the MEQ, PSQI, ESS for the healthy younger and older adults are summarized in Table 3.2. Comprehensive data can be found in Appendix C. Between the healthy younger group and healthy older group, MEQ scores of older participants were significantly larger than those of younger participants ($p = 0.0056$). For all 10 younger participants, their scores fall into the "intermediate" category, suggesting they are neither "morning" nor "evening" type. Among 10 older adults, six of them (five females and one male) appear to be the "moderate morning" type while the rest belong to the "intermediate" type. The older adult group also scored significantly higher in the PSQI than the young group ($p = 0.032$). Normally, a cut-off score indicating poor sleep quality is set to be 5 and $PSQI > 5$ indicates potential sleep disturbances [58]. Three younger participants in the young group scored over 5 (Y003, Y007 and Y008) while eight older participants scored higher than 7, with the oldest participant (age = 88) scoring 15 (see Appendix C).

Table 3.2: Participant demographics of healthy young and older adults, scores from three questionnaires (MEQ, PSQI, and ESS). BMI was calculated based on self-reported weight and height.

Demographics	Young Group (n = 10)	Older Adult Group (n = 10)
Age	24.1 ± 2.12	75 ± 6.99
Sex (% female)	60	60
BMI	23.69 ± 5.98	25.94 ± 2.95
MEQ	51.1 ± 4.09	59 ± 7.00
PSQI	5.2 ± 2.27	7.8 ± 3.19
ESS	6.8 ± 2.18	6.3 ± 2.76

The average score of ESS of the younger participants was slightly higher than that of the older participants; however, no significant difference was found between the two groups (p = 0.337). The average Body Mass Index (BMI) of the older adult group was higher than that of the younger group, however no significant difference was found (p = 0.162).

Each OAWD participant was contacted and introduced the study in private with the help of the long-term care staff. For OAWD participants, seven were able to give their own consent and sign the consent form; for the one participant who could not self-consent, his power of attorney signed the consent form and assent was obtained from the participant.

Average demographic characteristics of OAWD are listed in Table 3.3; more comprehensive data can be found in Appendix C. The average age of OAWD was more than eight years older than that of the healthy older adult group (83.25 yr vs 75 yr) and the average BMI of this group was much higher than that of the healthy older adult group (29.90 vs 25.94) with no significant difference found (p = 0.103).

Table 3.3: Participant demographics for OAWD. BMI was calculated based on data from Schlegel Village database.

Demographics	Dementia Group (n = 8)
Age	83.25 ± 9.71
Sex (% female)	50
BMI	29.90 ± 8.34
MMSE	20 ± 2.34

For the MMSE, based on the scoring scheme from [59], seven participants fell into the category of mild cognitive impairment (i.e., score between 18 and 23) and one participant scored 16, which is considered to be severe cognitive impairment. Two participants were diagnosed with obtrusive sleep apnea (D002 and D010), and one of them was diagnosed with insomnia (D002). Four participants (D001, D003, D009, and D010) needed to take medications that could influence their sleep (i.e., Citalopram and Dilantin). In addition, two of them (D009 and D010) have Parkinson's Diseases (PD) and had to be awakened at approximately 3 AM to take medications to treat their PD every day. Compared to the healthy older adult group, more participants from OAWD group reported sleep disorders (see Appendix A Table C.2) and took medications that could affect their sleep.

3.3.2 Sleep Patterns of Healthy Younger and Older Adults

As reported in Table 3.4 and Appendix D, on average the older participants have an earlier sleep onset (went to bed earlier) and have later sleep offset (got up later) than the younger participants. Thus, on average, older participants slept slightly longer (excluding the wakening during the night) than the younger participants and had earlier midsleep time. Also, the number of wake-ups during the night also differed between the two groups, with the older participants reported significantly more often wakening than the younger participants (tested with one-tailed t-test, p = 0.0007).

Self-reported sleep quality was captured using the sleep journal (see Appendix A) and is included in Table 3.4 and Appendix D. The sleep quality was calculated by adding the scale of three different components: sleep quality (0-8), mood (0-8), alertness (0-8). On average, the younger participants reported a slightly higher self-reported sleep quality; however, a t-test showed no significant differences (p = 0.196). In addition, sleep quality varied more in the older population than in the young population. The younger participants had generally good sleep quality; two older participants had extremely poor sleep while the others had much better sleep quality based on their self-reported sleep quality.

Table 3.4: Sleep parameters calculated from self-reported journals by young adults and older adults. Sleep onset, offset, duration, and midsleep are expressed in hours (hh:mm), while wake-up times and sleep quality score have no units. Values are expressed as the mean ± SEM. Sleep quality score ranges between 0 (low sleep quality, low alertness, low mood) to 24 (good sleep quality, high alertness, good mood).

Sleep Parameters	Young Group	Elderly Group
Sleep Onset	0:32 ± 0:50	23:49 ± 0:58
Sleep Offset	7:55 ± 0:51	7:31 ± 1:14
Sleep Duration	7:22 ± 0:08	7:42 ± 0:08
Midsleep	4:14 ± 0:49	3:41 ± 1:05
Wake-up Times	0.81 ± 0.56	2.57 ± 1.21*
Sleep Quality Score	18.39 ± 1.14	17.67 ± 2.07

Compared to self-reported sleep quality score, PSQI asks more objective questions about the sleep timing and wakening during the night (e.g., "how often have you had trouble sleeping because you wake up in the middle of the night or early morning?"). People who have lower sleep efficiency and frequent wake-ups score higher in the questionnaire. Sleep quality score from the sleep journal, on the other hand, is a more subjective measurement. Its range is highly dependent on how each participant feels and their subjective criteria for good sleep quality. While each measurement stresses different parts of sleep, a weak correlation was found between them using the Pearson correlation test (R = 0.57, p = 0.008, see Figure 3.2).

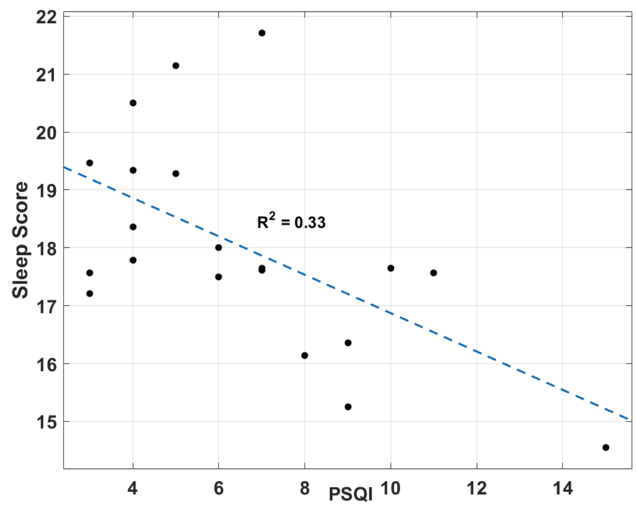


Figure 3.2: PSQI v.s averaged sleep quality score from sleep journal. Only healthy younger adults and older adults are included as PSQI could not be collected for OAWD.

3.3.3 Sleep Patterns of OAWD

Table 3.5 and Table 3.6 demonstrate that the sleep patterns of OAWD are different from those of both healthy younger and older populations. Sleep timing of OAWD is very early with an average onset as early as 21:37 and midsleep at 2:21. Sleep duration was on average much longer than that of healthy younger and healthy older adults; this is especially true for D001, D003, and D005 whose average night sleep duration was longer than 11 hours during the experiment period. Furthermore, OAWD were reported to spend a longer time in bed and have more daytime sleepiness and naps. According to PSW, all participants took naps after breakfast and lunch.

Sleep quality of OAWD varied among the participants. According to PSWs, while some participants were reported to sleep well, two participants (D002 and D004) were reported to have poor sleep. Specifically, D002 had extremely bad sleep quality with score 1 out of 8. According to the PSW and D002's self-report, the participant would not fall asleep at all and stay up all night on some days (two sample days of D002's data will be presented in Section 5.3). D004 was observed to be awake multiple times during the experiment period, and D004's PSW thought the participant's sleep quality was 5 out of 8.

Table 3.5: Sleep onset, offset, midsleep and duration of older adults living with dementia.Values are expressed in hours (hh:mm).

ID	Sleep Onset	Sleep Offset	Midsleep	Duration
D001	18:26 ± 0:14	6:52 ± 0:33	0:39 ± 0:18	12:25 ± 0:36
D002	23:36 ± 1:13	7:15 ± 1:22	3:25 ± 1:03	7:38 ± 2:02
D003	20:15 ± 0:33	7:49 ± 1:42	2:02 ± 0:54	11:34 ± 1:46
D004	22:49 ± 2:19	6:57 ± 0:50	2:53 ± 1:09	7:59 ± 2:37
D005	20:35 ± 0:43	7:41 ± 0:22	2:09 ± 0:26	11:03 ± 0:48
D006	22:10 ± 0:47	5:37 ± 0:59	1:54 ± 0:35	6:56 ± 1:31
D009	23:17 ± 1:53	7:20 ± 0:35	3:19 ± 0:59	8:03 ± 1:58
D010	21:48 ± 0:55	7:09 ± 0:31	2:29 ± 0:36	9:20 ± 0:53
Mean ± SEM	21:37 ± 0:34	7:05 ± 0:13	2:21 ± 0:17	9:22 ± 0:40

Table 3.6: Observed qualitative sleep patterns and sleep quality of OAWD from their personal support workers (PSWs). A sleep quality score of 1 = worst sleep and 8 = best sleep.

ID	Sleep Patterns	Sleep Timing	Sleep Quality (1 ∼ 8)	Naps
D001	No trouble falling asleep and waking up in the morning.	Go to bed: 6:00 ∼ 6:30 Wake up: 6:00 ∼ 6:30	8	Other than Mon/Wed/Fri, he would take naps after breakfast and lunch.
D002	No trouble falling asleep. Sometimes have trouble waking up in the morning. Would wake up at night frequently and sometimes cannot falls asleep at all.	Go to bed: Not provided. Wake up: 7 ∼ 8	1	Nap after breakfast and lunch. Sometimes she goes to her room for napping.

D003	No trouble falling asleep. Likes to sleep in the morning.	Go to bed: 7 ∼ 9. Wake up: 7.	6	Nap after breakfast and lunch.
D004	Has trouble falling asleep. Usually is awake when the morning team checks him. One PSW reported he seemed to be awake all the time when she checked.	Go to bed: 9 ∼ 9:30. Wake up: 6:30 ∼ 7:30.	5	Nap after breakfast and lunch. He dozes on and off throughout the day, but he is easy to be awaken.
D005	No trouble falling asleep and waking up in the morning.	Go to bed: 8. Wake up: 7 ∼ 8.	7/8	Nap after breakfast and lunch.
D006	No trouble falling asleep and waking up in the morning.	Go to bed: 9:30 ∼ 10:00. Wake up: 6:00	7	Nap and doze a lot in the afternoon. One PSW thinks that she does not wake up multiple times during the night.
D009	Has no trouble falling asleep and waking up.	Go to bed: 9:30 ∼ 10:00. Wake up: 8.	6	Nap both after breakfast and lunch. At night, she takes medications for Parkinsons Disease at between 2 to 3 AM.
D010	Has trouble falling asleep and waking up in the morning.	Go to bed: 9 ∼ 10. Wake up: 8.	6	Nap both after breakfast and lunch. At night, he does not wake up a lot.

3.4 Discussion

According to [7], circadian types can be determined by the MEQ score. MEQ measures subjective self-reported morning-person or evening-person tendency, with a higher score representing a person's circadian rhythm (biological clock) tends to peak earlier in the morning. Healthy older participants in this study averagely scored higher in MEQ than younger participants, which means the older group reported having an earlier diurnal preference (more "morning-person").

With regard to the accuracy of self-reported sleep, most people did not report how long they stayed awake after they woke up at night due to a certain level of difficulty in accurately self-reporting sleep. Therefore, the real sleep duration for healthy younger adults and older adults might be slightly shorter than the calculated duration for the older adults since they wake up more often at night.

As for OAWD, obtaining the sleep patterns of them was challenging. Even though staff in the LTC helped in data collection by using a DOS sheet and filling out the sleep journal for each participant, the quality of DOS sheet completion was not good (and not consistent across participants), and the sleep journal had substantial missing data. Moreover, it is difficult to tell whether someone is sleeping soundly merely by checking in every 30 minutes; participants can stay in bed being awake but seem to be asleep. Additionally, all residents in LTC follow a "bedtime" policy and PSW know when residents are supposed to go to bed at night and when they need to have breakfast. In this sense, PSW who were responsible for recording could unintentionally report overestimated sleep.

Furthermore, sleep quality reported by PSW might not be accurate because some night shift team members were not available when the interview was conducted. In other words, the reported sleep quality of OAWD from PSW might be overestimated. During data labeling, it was extremely hard to identify when the participant was sleeping or awake from 3-axis accelerometer data (actigraphy), which mostly was because all the OAWD participants experienced much nighttime movement and the level of activity was very similar between day and night (more details are illustrated in Section 5). Additionally, most participants woke up at night and stayed awake multiple times. In this case, extremely accurate data labeling was not possible. Also, labeling daytime naps is difficult. Since a daytime nap can be hard to detect in the data, and no reliable ground truth was obtained to support their identification. Therefore, the daily sleep duration reported above does not include naps. Some short wake-up periods were likely omitted, and the onset/offset might be not accurate for some days. Thus, nighttime sleep duration of OAWD is not as accurate as with healthy older and younger adults and might be shorter or longer than data presented in Table 3.5. The total daily sleep duration might be longer if more detailed daytime naps are included. Although the sleep patterns of OAWD are an approximation, labeled sleep segments are enough to explore and categorize the sleep patterns of OAWD and compare these results to the healthy groups.

There are many differences in high-level sleep patterns among these three groups of

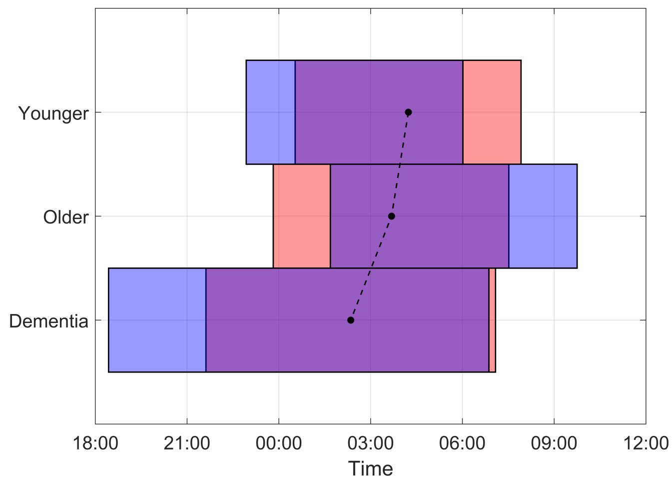


Figure 3.3: Pink bar indicates average sleep onset and offset for each group; blue bar indicates average sleep onset and offset of most pronounced outlier (Younger: Y007, Older: O007, Dementia: O001) in each group. Black dots indicate the average midsleep point for each group.

participants. For the healthy population, younger participants tend to sleep later and wake up later, and older participants tend to sleep earlier and wake up earlier. The midsleep point of the healthy older adults is also about 30 minutes earlier than the younger group. However, each individual has his/her own sleep preference, as well. One younger participant (Y007) exhibited a particularily early sleep schedule, while one older participant (O007) had a quite late sleep pattern (see Figure 3.3). For the general older population, OAWD tended to sleep and wake up even earlier than healthy older participants and their average midsleep point is more than 1 hour earlier. One OAWD (O001) slept as early as 18:26 on average. The findings of sleep patterns and timings are consistent with results from [60], with OAWD having the earliest sleep patterns and the highest daytime sleepiness. It should be noted that the average age of OAWD is eight years older than that of healthy older adults. The early sleep timing and disrupted sleep quality of OAWD might not only be influenced by cognitive function but also partially caused by natural (i.e., not related to dementia) processes related to aging as well.

3.5 Chapter Summary

Three key points can be summarised about sleep patterns of healthy younger, healthy older, and OAWD:

- Sleep timing of the three groups were different. Healthy younger participants had the latest sleep onset and offset, healthy older participants had a slightly earlier onset and offset, and OAWD had the earliest onset and offset.
- More sleep disturbances were observed in the older population. Healthy older adults woke up more during the night than younger adults. OAWD had excessive daytime sleepiness as well as disturbed nighttime sleep.
- It was challenging to get sleep patterns of OAWD. From both self-reported and staff reported sleep patterns, they had the worst sleep quality of the three groups.

Chapter 4

Features of Wrist Temperature Rhythms

A goal of this research was to investigate how wrist temperature rhythms change with aging and dementia. In this chapter, several indices are extracted from wrist temperature to examine whether circadian wrist temperature patterns from different populations differ. Additionally, a visual qualitative analysis of the correlation between wrist temperature and sleep is presented.

4.1 Methods

Before extracting indices, any data point lower than 28 °C (i.e., participants took the wristband off) were removed. Then the remaining temperature data were smoothed by a median filter to reduce noise; a window size of 3 was chosen because a longer window size generalizes temperature rhythm too much.

4.1.1 Feature Extractions

To analyze the circadian wrist temperature patterns of different groups, both parametric analysis methods and non-parametric analysis methods were performed to extract the following indices:

Cosinor Analysis The cosinor analysis assumes that a 24-hour circadian rhythm can be modeled by a single cosine function (see Equation 4.1). This approach is an established way to analyze the circadian rhythm of many biological processes, including the rhythms of heart rate, blood pressure, and body temperatures [61, 62, 63, 14]. Three parameters can be extracted from the wrist temperature data and construct a cosine curve: (1) the **MESOR** (a circadian rhythm-adjusted wrist temperature mean), (2) the **amplitude** (a measure of half wrist temperature change over each 24-hour cycle), (3) the **acrophase** (a measure of when wrist temperature reaches its highest value in a 24-hour cycle). This is calculated using the equation:

$$Y(t) = M + A\cos\left(2\pi t/\tau + \phi\right) + e(t), \tag{4.1}$$

where M represents **MESOR**, A is **amplitude**, ϕ is **acrophase** and e(t) is estimation error. MESOR, amplitude, and acrophase in the above function are calculated by using the least-squares method. For each participant, the cosinor method was run on the averaged wrist temperature rhythm over the experiment period.

Non-parametric Analysis Two metrics called inter-day stability (**IS**) and intra-day variability (**IV**) are proposed by [64, 65] to analyze the regularity and rhythmicity of wrist temperature rhythms. Specifically, IS has been used to measure the stability of rhythms on several consecutive days while IV reflects the fragmentation of the rhythms. IS and IV are calculated using Equations 4.2 and, 4.3 :

$$IS = \frac{N\sum_{N=1}^{p}(\bar{X}_h - \bar{X})^2}{p\sum_{i=1}^{N}(X_i - \bar{X})^2} \tag{4.2}$$

$$IV = \frac{N\sum_{N=2}^{N}(\bar{X}_i - \bar{X_{i-1}})^2}{(N-1)\sum_{i=1}^{N}(\bar{X} - X_i)^2}, \tag{4.3}$$

where N is the total number of data points, p is the number of data points per day (p = 288, as sampling rate is 1 sample per 5 minutes), $\bar{X}$ is the mean of all data, $\bar{X}_h$ is the hourly mean of wrist temperature and X_i is the data point at time i. IS and IV were calculated for each participant over their total experiment period.

Additionally, two non-parametric indices of WT were calculated: (1) the maximum average wrist temperature of 5-hour period from 15:00 to next day's 15:00 (**M5**) and the middle time of the 5-hour period (**TM5**) [66]. Originally, a similar parameter, L5, was calculated on accelerometer data and used to find the least active 5-hour period [67]. As WT is higher during sleep, this study focused on M5 instead of L5.

Other Parameters Descriptive statistics were used to analyze wrist temperature rhythms and sleep patterns. For the wrist temperature rhythm of each day, the **mean**

and **standard deviation** were calculated. Based on the sleep onset and offset from the self-reported and recreated sleep journals, the wrist temperature data were separated into two categories (asleep and awake) and the mean and standard deviation were calculated for both sleeping period and awake periods. In addition, the **median** and **quartile deviation** of wrist temperature during sleep and awake were extracted. Finally, by subtracting the average wake-time temperature from average sleep-time temperature, the average Sleep/wake Temperature Difference (SWTD) was calculated. The index SWTD, similar to the index amplitude from cosinor analysis, is used to measure the extent of temperature change between sleep/wake states in this study.

4.1.2 Statistical Analysis

A t-test was used to compare the circadian rhythm and sleep indices between different groups (young versus old; old versus OAWD), and the Pearson correlation test was used to assess the correlations between different circadian rhythm and sleep indices calculated. $p < 0.05$ was considered to be significant.

4.1.3 Qualitative Analysis of Wrist Temperature and Sleep Quality

Currently, there is no established metric for using wrist temperature to evaluate sleep and quantify sleep quality. Having trouble falling asleep and frequent wake-ups during sleep suggest poor sleep quality and loose coupling of a disturbed circadian rhythm with sleep. Since wrist temperature is very sensitive and responsive to sleep/wake states change, the trend and stability of the temperature rhythm have correlations with sleep latency (i.e., how long it takes for people to fall asleep) as well as night wakening. Therefore, the average wrist temperature is a resultant of sleep patterns for the experiment period and its shape can provide insight into sleep quality. One wrist temperature rhythm was chosen from each group to qualitatively analyze the association between wrist temperature and sleep quality. Y004 was chosen for good sleep quality; O002 was chosen for poor sleep quality among older adults; D009 was chosen for poor and interrupted sleep quality. A descriptive analysis of the morphology of wrist temperature rhythms and their correlation with sleep quality was conducted for three wrist temperature rhythms.

Table 4.1: Averaged descriptive statistics of wrist temperature for three groups in °C. Values are expressed as mean ± SD.

	Healthy Young (n = 10)	Healthy Old (n = 10)	OAWD (n = 8)
Mean			
Sleep	34.98 ± 0.58	34.97 ± 0.32	34.66 ± 0.49
Wake	32.49 ± 0.79	32.94 ± 0.63	33.40 ± 0.97
All day	33.25 ± 0.61	33.63 ± 0.44	33.89 ± 0.80
Standard Deviation			
Sleep	0.92 ± 0.19	0.97 ± 0.22	0.88 ± 0.19
Wake	1.52 ± 0.20	1.32 ± 0.21*	1.10 ± 0.19*
All day	1.85 ± 0.33	1.60 ± 0.29	1.27 ± 0.33*
Median			
Sleep	35.17 ± 0.60	35.18 ± 0.32	34.76 ± 0.47*
Wake	32.52 ± 0.90	32.93 ± 0.70	33.41 ± 1.00
Quartile Deviation			
Sleep	0.61 ± 0.15	0.71 ± 0.19	0.63 ± 0.20
Wake	1.04 ± 0.16	0.91 ± 0.15*	0.80 ± 0.19
Sleep/wake Difference	2.48 ± 0.83	2.04 ± 0.66	1.26 ± 0.76*

$*p < 0.05$ between groups (younger v.s. older, older v.s. OAWD)

4.2 Results

Descriptive statistics of WT are shown in Table 4.1. Averaged wrist temperature patterns for the healthy younger, healthy older, and OAWD participants are presented in Figure 4.1 and their rhythmic characteristics are in Table 4.2. The correlations between different indices can be found in Table 4.3.

4.2.1 Wrist Temperature Comparison between Groups

As seen in Table 4.1, the mean and median wrist temperature during sleep is comparable for the healthy younger group and the healthy older group. While no significant difference was found, healthy older participants tended to have a higher mean and median wrist

Table 4.2: Parameters from cosinor and non-parametric analysis of wrist temperature. Values are expressed as mean ± SD.

	Healthy Younger (n = 10)	Healthy Older (n = 10)	OAWD (n = 8)
Cosinor Analysis			
Mesor	33.34 ± 0.58	33.65 ± 0.44	33.90 ± 0.79
Amplitude	1.72 ± 0.54	1.45 ± 0.48	0.93 ± 0.55*
Acrophase (hh:mm)	04:06 ± 0:56	03:03 ± 1:26 *	0:44 ± 2:15*
Non-parametric Analyses			
IS	0.53 ± 0.10	0.52 ± 0.15	0.32 ± 0.17*
IV	0.40 ± 0.13	0.37 ± 0.13	0.31 ± 0.13*
M5	35.36 ± 0.52	35.43 ± 0.18	35.19 ± 0.43
TM5	3:45 ± 0:50	3:39 ± 1:09	2:28 ± 1:19*

$*p < 0.05$ between groups (younger v.s. older, older v.s. OAWD)

Table 4.3: Correlation matrix of extracted features (IS, IV, amplitude, MESOR, M5 and SWTD).

	IV	Amplitude	MESOR	M5	SWTD
IS	-0.266	0.848 $<1^{-11}$	-0.414 0.0002	0.304	0.757 $< 1^{-9}$
IV		0.368	0.237	-0.196	-0.253 < 0.006
Amplitude			-0.706 $<1^{-4}$	0.161	0.908 $< 1^{-14}$

temperature when they were awake. Younger participants had a higher value in wake-time standard deviation and quartile deviation and significantly more variations of wrist temperature during daytime than older adults.

Between two older groups, OAWD had a lower mean wrist temperature and a significantly lower median wrist temperature at night as well as a significantly higher all-day wrist temperature compared to healthy older adults. With regard to temperature variation, OAWD had significantly lower all-day standard deviation and wake-time standard deviation. For the variation of 24-hour wrist temperature rhythm, OAWD had the least wrist temperature deviation for sleep, awake, and overall all-day temperatures among three populations.

MESOR (a parameter of the cosinor analysis) is the midline of modeled cosine function for 24-hour wrist temperature rhythm. From Table 4.2 it appears that OAWD had the highest MESOR while the healthy younger participants had the lowest MESOR. The definition of MESOR is quite similar to all-day mean temperature; however, no significant difference was found between groups. There was also no significant difference for M5 between groups.

Comparing all three groups, wake-time temperature standard deviation is the only parameter that was significantly different between younger and older adults as well as between older adults and OAWD. While other parameters, such as wake-time mean and median wrist temperature, had no significant differences, a trend can be observed with daytime temperature increasing as people are older and have dementia.

4.2.2 Rhythmicity of Wrist Temperature Rhythm

From Figure 4.1, OAWD have the most flattened averaged wrist temperature rhythm with the lowest night time temperature and the highest daytime temperature. Between 11:00 to 23:00, the average wrist temperature of healthy older adults was higher than that of younger adults but lower than that of OAWD. This temperature difference makes the wrist temperature rhythm curve of older adults slightly flatter than that of younger adults and stronger than that of OAWD.

Two parameters from Table 4.1 and Table 4.2 are used to show the strength of wrist temperature rhythms and day/night temperature contrast: (1) sleep/wake temperature difference (SWTD) and (2) amplitude calculated from cosinor analysis. OAWD had a significantly lower SWTD and amplitude compared to healthy older adults. While there was no significance found, healthy older adults had a lower SWTD and amplitude compared

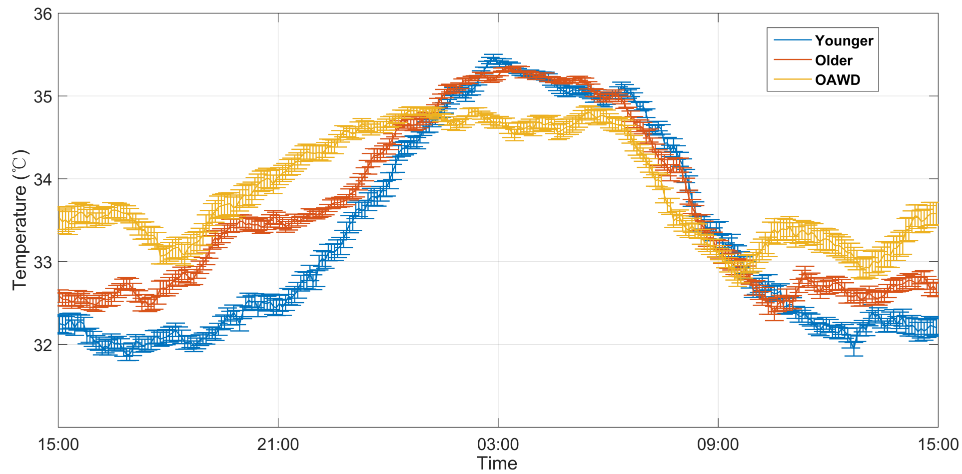


Figure 4.1: Average wrist temperature rhythms for younger (blue line), older participants (orange line), and OAWD (yellow line). Plots are expressed as the mean temperature ± SEM.

to younger adults. Additionally, a decreasing trend of day/night wrist temperature contrast among three groups can be found in Figure 4.2.

With regard to another indicator of rhythmicity of wrist temperature rhythms, *Interdaily Stability (IS)*, healthy younger and older participants showed similar stability while OAWD had a pronounced reduction in this parameter (IS = 0.32). From Table 4.3, IS showed a negative correlation with MESOR and a positive correlation with amplitude and SWTD for all participants.

According to the data presented in Table 4.3, there was no significant correlation found between IS and IV for the whole participant pool. However, within the healthy group (i.e., healthy younger adults and healthy older adults), from Figure 4.3, IS negatively correlates well with IV (excluding one outlier marked in the figure, R = -0.818, $p = 1.91^{-05}$). Within OAWD, IS shows an insignificant negative correlation with IV (R = -0.59, p = 0.12). Similarly, while there is no significant association between IV and amplitude and IV and SWTD for all participants, a significant negative association can be found within the healthy group and within the dementia group (see Figure 4.4). Since amplitude and SWTD both describes the day/night temperature rhythm contrast, only the correlation between IV and SWTD is shown in the figure. The correlation coefficient between IV and SWTD is 0.73 (p = 0.0002) and 0.80 (p = 0.016) for healthy adults and OAWD, respectively. Seen from both Figure 4.3 and 4.4, the correlation disappeared after adding data from OAWD.

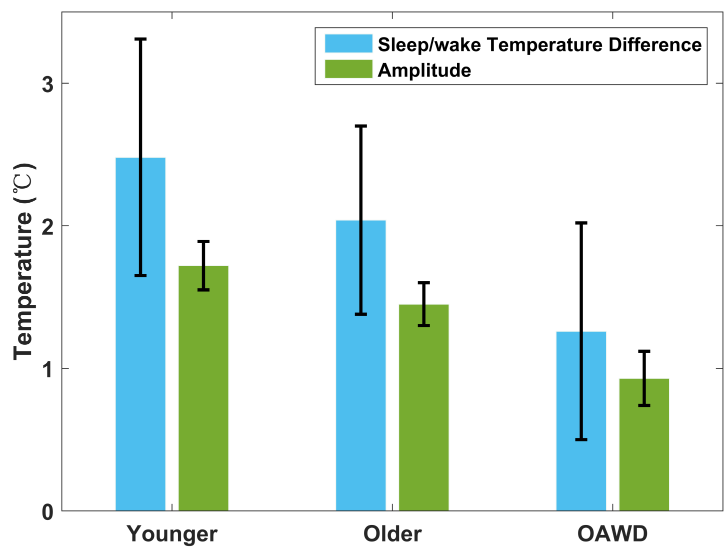


Figure 4.2: SWTD and amplitude (from cosinor) of wrist temperature rhythms compared across three groups.

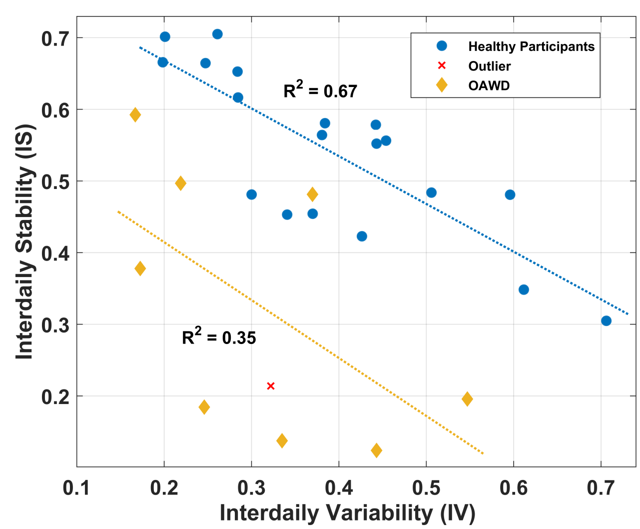


Figure 4.3: Interdaily stability (IS) v.s. interdaily variability (IV) for 28 participants. Blue dots denote healthy participants (n=19) and yellow diamonds denote OAWD (n=8). One outlier (O007) is denoted using a red cross mark and is not included in R^2 calculation.

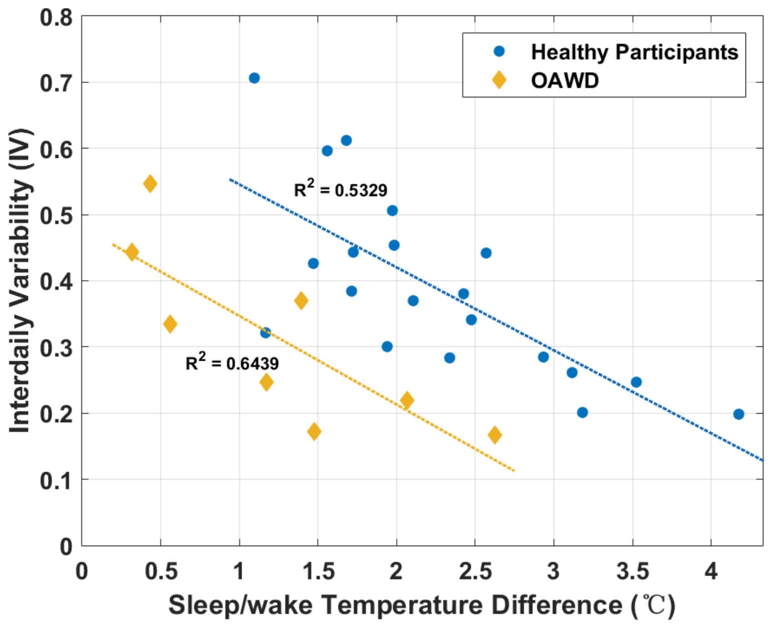


Figure 4.4: SWTD v.s. interdaily variability (IV) for 28 participants. Blue dots denote healthy participants (n=20) and yellow diamonds denote OAWD (n=8).

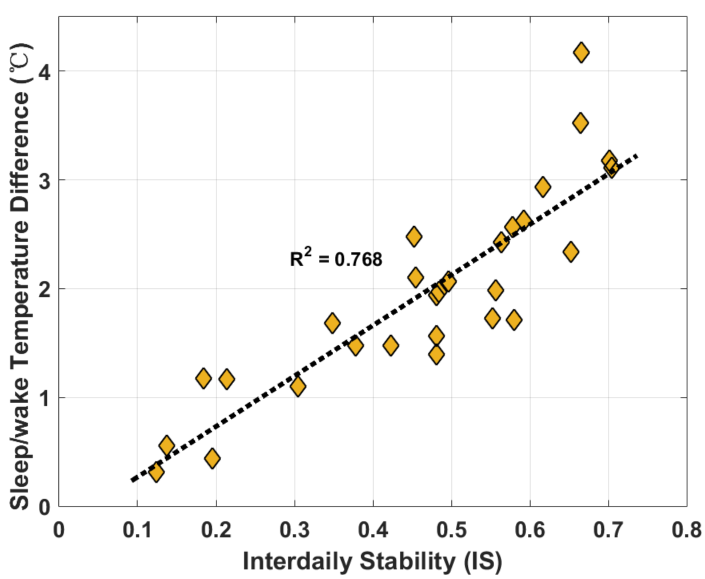


Figure 4.5: Interdaily stability (IS) v.s. SWTD for all 28 participants.

4.2.3 Phase of Wrist Temperature Rhythms

The phase of wrist temperature rhythms or the timing of wrist temperature rhythms were measured by acrophase and TM5, which are shown in Table 4.2. For both parameters, it can be seen that OAWD had the earliest phase, which is consistent with their early sleep timing. Between healthy younger and older participants, while the TM5 for each group was very close, the difference of their acrophases was more than 1 hr. Interestingly, the time difference between TM5 and acrophase was about 30 min for the two healthy groups but was more than 1.5 hr for OAWD. In other words, the phase measurement of wrist temperature rhythms was not very consistent between these two parameters.

4.2.4 Visual Analysis of Wrist Temperature Rhythms

One example from each group was chosen based on the participant's sleep quality to demonstrate how sleep patterns and sleep quality influenced wrist temperature rhythms and are shown in Figure 4.6. The first example, Y004, is a healthy younger adult, who had a very consistent wrist temperature rhythm. The elevated flat temperature period during sleep is distinct, and the temperature increase and decrease at the onset and offset of sleep are very smooth. A square-shaped temperature plot can be observed. Y004's PSQI score indicated no sleep problems, and Y004's self-reported sleep quality was the highest among younger adults.

Compared to Y002, the exemplary temperature rhythms of O002 and D009 had no distinct temperature plateau at night and a noticeable dip at 3 AM could be observed. While they do have a clear temperature decrease in the morning, the temperature increasing periods are not smooth and have many dips in between. The shape of these two temperature rhythms is more triangular-like. O002's PSQI score suggests a high possibility of sleep problems. Additionally, O002 woke up more than two times every night and had the second-worst self-reported sleep quality score among all twenty healthy participants. Concerning the sleep quality of D009, even though the participant was not administered the PSQI, D009 did not sleep very well during the period of the experiment. As can be seen in Table 3.6, D009 took naps in the morning and in the afternoon, which is a sign of excessive daytime sleepiness. Every night, due to Parkinson's Disease, the participant was woken up at 3 AM to take medications. During the last visit with D009, the participant reported only 3 hr of sleep the previous night. In other words, the sleep pattern and sleep quality of D009 are worse than that of O002.

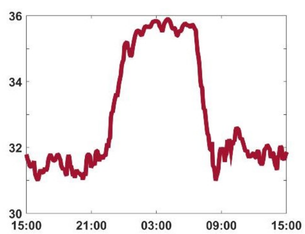
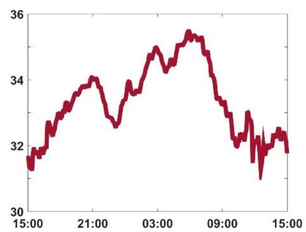
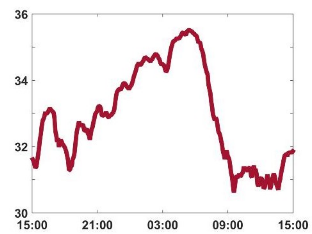
Y004	O002	D009
		
Age: 22 yr PSQI: 5 ESS: 7 Sleep Quality: 21.14 Wake-up Times: 1.36	Age: 66 yr PSQI: 9 ESS: 4 Sleep Quality: 15.25 Wake-up Times: 2.07	Age: 89 yr Sleep: wakes up at 3 AM every night to take medications.
A sharp wrist temperature increase before sleep and a sharp decrease after sleep can be observed. The sleep/wake temperature contrast is very obvious, and the temperature is very stable in the elevated plateau.	A sharp wrist temperature decrease after sleep can be observed. The temperature increasing period is not smooth and one big dip can be observed at approximately 3 AM.	A sharp wrist temperature decrease after sleep can be observed. Three dips occur during wrist temperature increasing period. A great dip occurs at 3 AM. The width of the peak is wider than others.

Figure 4.6: Average 14-day wrist temperature rhythm from healthy younger (Y004), healthy older (O002), and OAWD (D009). Sleep quality score and wake-up times were averaged for 14 days and had no units. $PSQI > 5$ indicates poor sleep quality. $ESS < 10$ indicates normal daytime sleepiness.

4.3 Discussion

From data presented in subsection 4.2.1, 4.2.2 and 4.2.3, there is no significant difference of wrist temperature rhythms between healthy younger adults and healthy older adults despite the wake-time temperature variation and the phase of the rhythm (i.e., when wrist temperature peaks at night). The increased wake-time temperature variance might be partially explained by the experimental time for younger adults. Since they did the experiment during winter and the outdoor temperature was quite cold, the skin temperature may be lower when walking outside. Most healthy older adults them participated in the experiment during the spring, when the outdoor temperature was higher compared to the healthy younger adult group. As such, their daytime wrist temperature might be less affected by the ambient outdoor temperature (i.e., there may be less of a difference between average daytime and nighttime temperature). For OAWD, all of them stayed indoors for most (if not all) of the time so that their daytime/nighttime wrist temperature was less likely to be affected by ambient temperature. While it is true that the environmental temperature varies between the indoors and outdoors, humans are endothermic homeotherms, who tend to dress for the weather so the wrist temperature is usually only be influenced to a small extent and the external influence does not last long.

Another factor could be the average healthier circadian system of healthy younger adults compared to the aged population. When falling asleep and waking up, wrist temperature of younger adults increased and decreased more compared to older adults. Wrist temperature during sleep is comparable between three groups, except a significantly lower median sleep-time temperature for OAWD (as reported in Chapter 3). While OAWD woke up more during the night, short-term wakening was ignored, which could have resulted in a smaller sleep-time median temperature.

Interestingly, disturbed sleep appears to only influence mean sleep-time temperature marginally, and irregular sleep patterns can be better identified by looking at elevated wake-time temperature. Healthy older adults had averagely higher wake-time wrist temperature than younger adults; OAWD had an even higher average temperature. While there is no significant correlation between ESS score and wake-time temperature, the average higher ESS score of the older group can partially be correlated to their higher average wake-time temperature. Although ESS was not administered for OAWD, OAWD were reported to have more naps throughout the day. Therefore, the increased wrist temperature seems to reflect that OAWD have greater daytime sleepiness and more naps during the day. These findings agree with other research that found an older population and a dementia population to have higher mean wrist temperature [65, 53]. Furthermore, SWTD is greatly influenced by wake-time temperature (see Figure 4.7). For example, more daytime

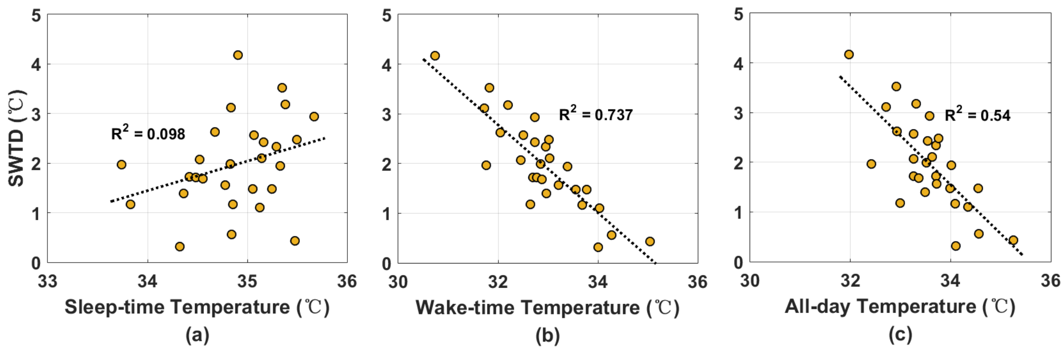


Figure 4.7: Plots of sleep indices. (a) sleep-time temperature vs SWTD, (b) wake-time temperature vs SWTD, and (c) all-day temperature vs SWTD. All 28 participants are included and linear regression was used.

sleepiness and naps lead to a smaller SWTD.

Comparing healthy older adults and OAWD, the all-day temperature for the latter is significantly higher, and OAWD's averaged sleep-time temperature was slightly lower. Since people spend more time awake, the increased all-day temperature for OAWD suggests that the increased daytime temperature counteracted the decreased nighttime temperature. These temperature differences could explain the drastic decrease in OAWD's SWTD and temperature amplitude and also indicate more excessive daytime sleepiness and more time being awake at night for this group. As all OAWD in this study were reported to take naps at least twice a day, it is then worth considering whether it is the naps that caused elevated temperature or the elevated temperature led to excessive sleepiness of OAWD. Regardless of the underlying mechanisms, the wrist temperature rhythm of OAWD appeared to be less regular and less prominent than that of healthy older adults.

There are indeed minor individual differences in baseline wrist temperature (i.e., some individuals tend to have lower/higher body temperature) and some younger participants had worse sleep patterns than some healthy older participants (see Figure 4.8). At a population level, the wrist temperature rhythms of older adults indicate worse sleep than those of the healthy younger population and OAWD were sleeping worse than healthy older adults.

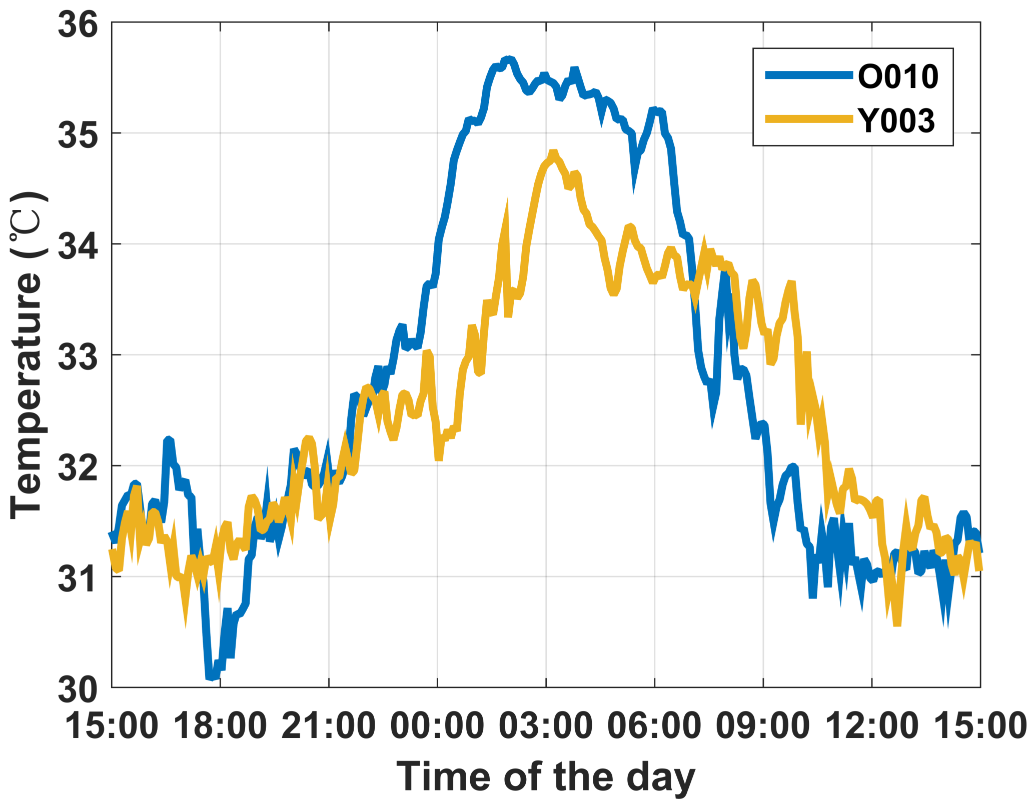


Figure 4.8: Average wrist temperature rhythms from one younger poor sleeper (Y007) and one older good sleeper (O010).

Regarding the analysis of wrist temperature rhythmicity, both IS and IV were originally proposed to measure the strength of rest-activity rhythmicity for aging and Alzheimer's Disease populations [64]. According to [64], a higher IS value suggests a lower day-to-day variation of wrist temperature rhythm and a stronger circadian rhythmicity [68]. Since wrist temperature changes when sleep/wake states change, more variations suggest non-consistent sleep/wake patterns. For those who experience disturbed sleep at night and napping at daytime, the mean nighttime temperature would be lower and mean daytime temperature would be higher, which results in a smaller day/night wrist temperature contrast. This is a key reason for the strong correlation between IS and SWTD (amplitude). A higher IV calculated from accelerometer data indicates daytime napping and/or nighttime arousal. However, the research presented in this thesis found that IV of wrist temperature might not be a useful metric for OAWD. As can be observed in Figure 4.3 and 4.4, data points from the healthy populations are much less scattered than from OAWD. IV correlates nicely with IS for the healthy younger and older populations after excluding one outlier O007. O007 is the oldest participant in the healthy older group, who also experienced poor sleep during the experiment (see subsection 3.3.2). In addition, IV also appears to correlate nicely with SWTD for the healthy population. However, the correlation disappeared after including the data from OAWD. While the values of IV of OAWD do not differ significantly from those of healthy participants, the values of IS and SWTD of OAWD are shown to be different. Comparing the temperature patterns of one healthy younger participant (IV = 0.442) and one OAWD (IV = 0.443) with nearly identical IV scores, it seems that IV cannot convey the fragmentation of wrist temperature variation. From their averaged wrist temperature rhythms, which are shown in Figure 4.9, it is clear that the younger adult has a prominent wrist temperature peak at night, whereas the OAWD's temperature rhythm is hard to differentiate between sleep and awake periods.

From the visual analysis of the wrist temperature rhythms presented in Figure 4.6, three features could be used to evaluate sleep quality in the future. The first is the *smoothness of temperature increasing period*. A rough temperature increasing period suggests day-to-day sleep onset variations and long sleep latency. The second one is the *smoothness of nighttime temperature plateau*. Y004, the best sleeper among the three examples, has the flattest and stablest night time wrist temperature. The temperature plateau indicates Y004's wakening at night to be short, and this participant could get back to sleep very quickly. On the contrary, for people who had poor sleep, such as O002 and D009, the temperature dips reflect that they often wake up at night. Furthermore, their wrist temperature in the second half of the night appeared to be more stable, which suggests a sounder sleep period. The last indicative metric of overall sleep quality could be the *shape of wrist temperature rhythm*. Differences in sleep patterns result in different shapes of averaged wrist tempera-

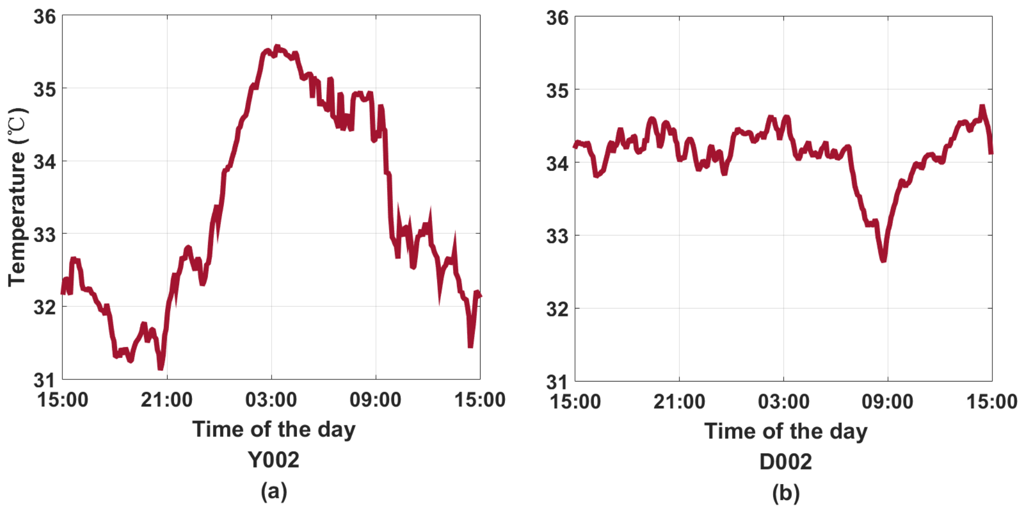


Figure 4.9: Averaged wrist temperature rhythm for (a) younger participant (Y002) and (b) OAWD (D002). Y002's IV is 0.442 and one D002's IV is 0.443.

ture rhythm, such as more square (wrist temperature pattern of Y004) or more triangular (wrist temperature pattern of D009). Six more averaged wrist temperature rhythms from other participants are shown in Figure 4.10 to demonstrate differences between subjects. As seen in the figure, temperature patterns reflecting good sleep (as defined by PSQI score and sleep quality from sleep journal or reported from PSWs) all have square-like shape while the worst patterns are jagged and have more ill-defined, triangular-like shape. In the future, the use and validity of these metrics would have to be examined in more depth using a larger sample size.

The measurement of sleep quality is not straightforward because people's subjective definition of good sleep varies and the most accurate objective sleep quality relies on PSG (as also reported by [69]). Definitive conclusions cannot be made with visual data analysis and with such a small dataset; the effectiveness of the proposed three metrics above needs further validation. What is clear from the visual analysis is that there is a close correlation between wrist temperature and sleep. It can be envisioned how one could use averaged wrist temperature rhythm and measuring wrist temperature provide a promising way to evaluate the overall sleep quality. For example, the morphological analysis of averaged 7-day wrist temperature rhythm can be used to assess the sleep regularity for the past week.

Currently, due to the scope of data analysis, only the self-reported sleep data were used

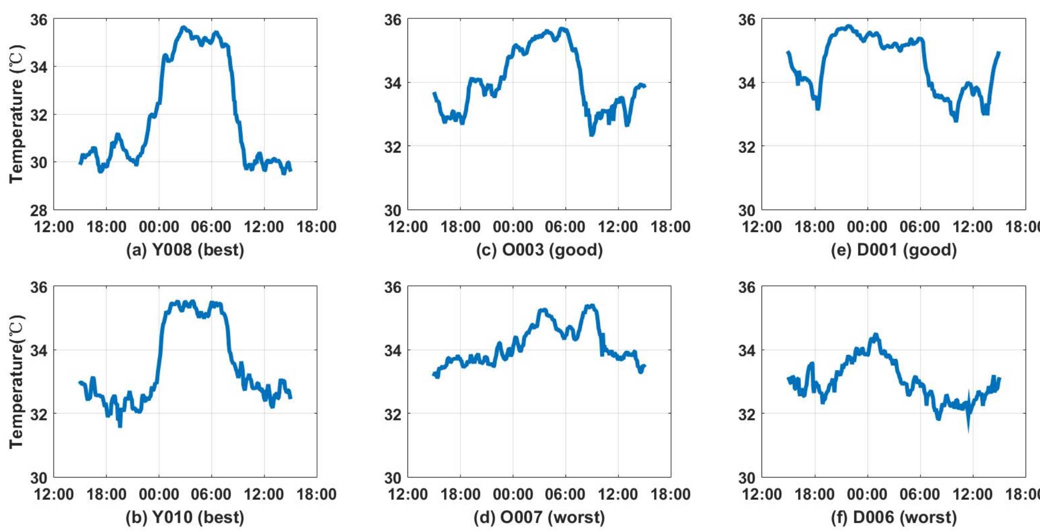


Figure 4.10: Averaged wrist temperature rhythms for two younger participants (Y008, Y010), two healthy older participants (O003, O007), and two OAWD (D001, D006). Y008 and Y010 had the best wrist temperature rhythm patterns with the most prominent temperature peaks, O003 and D001 had good wrist temperature rhythm patterns with less prominent temperature peaks, and O007 and D006 had the worst wrist temperature rhythm patterns with least prominent peaks.

for calculation of parameters related to sleep-time and wake-time, which can be inaccurate due to their subjective nature. A machine learning algorithm based on features from wrist temperature could be built to estimate sleep parameters that could be used to more accurately compute metrics like wake-time temperature and SWTD. Additionally, the shape of wrist temperature rhythm can be an individual biometric feature. One study has already shown that wrist temperature rhythms can be used to predict aging [65]. More features and functions of wrist temperature can be explored with data from a broader population in the future.

In this study, how the wrist temperature is influenced by aging and dementia is investigated with relatively small sample size. Analyzing the wrist temperature rhythms from three groups answers Research Questions 1, 2 and 3: (1) Aging and dementia influence wrist temperature rhythm to be flatter, coupled with an increased daytime wrist temperature and a smaller day/night temperature contrast, but the influences are marginal. (2) Poor sleep quality with multiple night wakings can result in non-stable wrist temperature at night, and irregular sleep patterns can be potentially be observed by the shape of wrist temperature rhythms.

4.4 Chapter Summary

The two key points from the data presented in this chapter are:

- Sleep patterns and sleep quality are reflected in wrist temperature patterns. The sleep timing can influence the phase of wrist temperature rhythm. Sleep quality might influence the shape of wrist temperature rhythm and increased daytime wrist temperature may be a good indicator of daytime sleepiness.

- Age does not appear to impact wrist temperature patterns significantly; instead, it is the quality of sleep the person is getting that impacts wrist temperature patterns. As such, differences in wrist temperature patterns are more likely a cause of other factors, such as morbidity, which are more prevalent in the older adult population. The wrist temperature data from this research supports the premise that dementia is a morbidity that substantially impacts sleep at a circadian rhythm level.

Chapter 5

Sleep Monitoring Using the Mi Band

Mi Band 2 is a smart wristband that monitors sleep based on its built-in three-axis accelerometer sensors and gyroscopes. Research has shown that the sleep monitoring of Mi Band on sleep duration is reliable [70] for the younger population (18 - 27 years old). Also, Mi Band has been reported to have a high level of acceptance for the older population [71]. Therefore, the Mi Band 2 was chosen to monitor the sleep patterns of different populations in this study. In this chapter, the sleep parameters obtained from Mi Band 2 will be compared with the temperature data and sleep journal to explore the effectiveness of this commercial wristband on sleep monitoring for different populations.

5.1 Methods

A Mi account (i.e., an account for the mobile application Mi Fit, all the data is stored in the Mi account) was set up for each participant specifically for this study. The Mi Band 2 was paired with each participant's experimental Mi account, and the sleep data was transmitted to the account via Bluetooth. The sleep data collected by Mi Band 2 was checked during and after the experiment. As there is no way to export sleep data from Mi account automatically, four parameters were extracted from each participant's account by manually importing data into excel sheet: (1) sleep onset, (2) sleep offset, (3) wake time (waking periods) and (4) sleep score (0-100). The data were compared to the self-reported sleep journal for the healthy younger and healthy older participants. For OAWD, the Mi Band data were compared to the recreated sleep journal mentioned in Section 3.2. As participants were only asked to report the number of times when they awoke during the night, not the exact awake duration, only the number of night time waking periods detected by the Mi Band were used for comparison.

The self-reported sleep journal of the healthy younger and older adults was used as the reference and the time differences of sleep parameters (except sleep quality) from sleep journals and Mi Band 2 were considered errors. The performance of sleep monitoring by the Mi Band 2 was determined by the two ways: (1) detection errors (compared to sleep parameters reported in sleep journal), (2) the number of undetected sleep (Mi Band 2 failed to detect most OAWD's sleep).

Pearson's correlation coefficient was calculated to investigate whether the self-reported sleep quality in sleep journal was correlated to the sleep score given by the Mi Band 2. A t-test was used to check whether the sleep detection error of healthy older groups was significantly higher than that of healthy younger adults.

5.2 Results

5.2.1 Healthy Younger and Healthy Older adults

The errors of estimated sleep parameters from Mi Band 2 for the healthy younger and healthy older participants are summarized in Table 5.1. The average estimation error for the older group appears to be higher than that of the younger group; however, a significance was not detected with a t-test ($p = 0.07$ for onset, $p = 0.06$ for offset). Regarding the estimation of sleep duration, the detection accuracy for the Mi Band 2 for the older group is significantly worse than that for the younger group. No correlation was found between the Mi Band 2 sleep score and the self-reported sleep score, the correlation coefficient for younger participants and older participants is 0.24 and 0.17, respectively. In addition, Mi Band 2 failed to detect most night waking for both groups; on average, it did not identify 0.74 wake-ups for the younger participants and 2.34 wake-ups for the older participants every night.

While there is no significant difference in detecting sleep onset and offset for healthy younger and healthy older adults overall, the detection error of Mi Band 2 was found to be extremely high for two older participants. The average onset detection error for O001 (male, age = 83) was more than two hours (2:17 ± 1:07), while the offset detection for this participant was comparatively more accurate (0:27 ± 1:01). For the other participant O007 (female, age = 88), the participant reported experiencing sleep deprivation due to a car accident happened to her granddaughter during the experiment period. The accident made O007 extremely worried and unable to fall asleep most days. Three nights of o007's sleep were not detected by the Mi Band 2 (these three days of data were not included in detection error calculation). During these three days, the Mi Band did detect daily activity (i.e., step counts) but failed to recognize any sleep. For other days, O007 reported to wake up after midnight and went back to sleep in the early morning again. The Mi Band 2, however, only detected wake-ups between 1 to 4 AM; it estimated 4-hours of sleep for most days and did not capture the second period of sleep in the morning.

Table 5.1: Errors of detected sleep parameters from Mi Band 2 compared to the self-reported sleep journal for healthy younger and healthy older adults. Wake-up times represent the number of wake-up times during the night. Values are expressed as the mean ± SD.

	Sleep Onset Error (hh:mm)	Sleep Offset Error (hh:mm)	Duration Error (hh:mm)	Wake-up Times
Younger	0:39 ± 0:51	0:31 ± 0:52	0:49 ± 0:58	0.74 ± 1.26
Older	0:49 ± 0:58	0:33 ± 0:58	1:04 ± 1:17*	2.34 ± 1.56*

$*p < 0.05$

5.2.2 Older adults living with dementia

The sleep data of OAWD from Mi Band 2 are summarized in Table 5.2. Among the eight OAWD participants, two of them went through 13-day monitoring and six of them went through 14-day monitoring. One participant (D003) did not wear both wrist bands for the last four days so only ten days of valid data were available. Regarding the accuracy of sleep detection for the OAWD group, Mi Band 2 mostly failed in detecting their sleep. For the total 106 days of monitoring, 28 days of data are missing. The average sleep onset for most participants is very late and the detected sleep duration for all participants was extremely short, with the exception of O003. Compared to other participants in OAWD, the Mi Band 2 worked comparatively better in detection sleep for O003.

The comparison of detection error of Mi Band 2 between two older groups does not make sense because Mi Band 2 performed considerably much better for healthy older adults from the presented data in Table 5.1 and Table 5.2. There are two aspects that were considered when analyzing this data. First, the Mi Band did not detect a large portion of the OAWD's sleep on most days. This equated to more than 50% of total sleep data undetected by Mi Band 2, the detection errors of sleep onset and offset could not be accurately calculated. Only days where the Mi Band detected sleep were considered valid data days and included in the analysis (see last column of Table 5.2). Second, as all the OAWD followed a schedule, their bedtime was very close to the same time every night. Assuming they fell asleep shortly after going to bed, this can be used as an approximate sleep onset time, which can be used to examine whether the Mi Band is reporting their sleep time at about the same time every night.

The sleep onset and offset from Mi Band 2 were averaged for valid days of data for the OAWD. The averaged sleep onset/offset/duration from Mi Band 2 was then compared with the averaged data from recreated sleep journal for the OAWD (i.e., the data shown in Table 3.5). The comparison data is shown in Table 5.3. It can be seen that there are large time differences between the averaged sleep onset and duration between the Mi Band and sleep journal; the offset difference is less erratic.

Table 5.2: Mi Band 2 data for sleep onset, offset, duration and valid days of captured data for OAWD. Values are expressed as mean ± SD. Valid days mean the number of days that sleep was detected.

ID	Sleep Onset	Sleep Offset	Duration	Valid days of data /total days wearing the band
D001	2:41 ± 2:13	5:05 ± 1:30	2:06 ± 1:00	14/14
D002	2:59 ± 1:20	4:19 ± 1:07	1:20 ± 0:13	2/13
D003	20:56 ± 1:23	7:29 ± 1:46	10:12 ± 2:31	10/10
D004	2:18 ± 1:23	5:40 ± 0:50	2:54 ± 1:19	7/14
D005	0:33 ± 3:22	5:12 ± 2:15	3:52 ± 1:05	12/14
D006	2:08 ± 0:45	4:11 ± 0:48	1:58 ± 0:46	8/13
D009	2:34 ± 1:57	4:21 ± 1:47	1:34 ± 0:35	11/14
D010	0:40 ± 2:12	5:19 ± 2:28	4:01 ± 1:40	14/14
Mean	1:21 ± 1:52	5:12 ± 0:59	3:29 ± 2:42	-

5.3 Case Studies

To explore why the Mi Band 2 has decreased accuracy in detecting sleep of bad sleepers (i.e., O001, O007, and all OAWD), accemetry data from the three-axis accelerometer sensor from the prototype wristband were studied. Together with wrist temperature rhythms, four different case studies are presented in this section. These case studies illustrate how wrist temperature could compensate for the shortcomings of accelerometer sensors. One case

Table 5.3: Comparison of average sleep parameters from Mi Band 2 and the recreated sleep journal OAWD participants. Values are the absolute difference between averaged sleep onset, offset, and duration from Mi Band 2 and those from the journal.

	Sleep Onset Difference (hh:mm)	Sleep Offset Difference (hh:mm)	Duration Difference (hh:mm)
D001	8:15	1:47	10:19
D002	3:23	2:56	6:18
D003	0:41	0:20	1:22
D004	3:29	1:17	5:05
D005	3:58	2:29	7:11
D006	3:58	1:26	4:58
D009	3:17	4:21	6:29
D010	2:52	1:50	5:19
Mean ± SD	3:44 ± 1:58	1:53 ± 0:50	5:52 ± 2:20

study belongs to a healthy older adult (O001), and the others are from the OAWD group (D001, D002, and D003).

5.3.1 Case study I: O001

One-day exemplary accelerometer data together with wrist temperature data for participant O001 is shown in Figure 5.1. According to Mi Band 2, this participant was detected falling asleep at 2:43 AM on this day. The participant experienced intensive, repetitive wrist movements between around 0 to 3 AM coupled with elevated wrist temperature is shown in Figure 5.1. The magnified excerpt data in the bottom of the figure shows that the intensive movement is quite periodic and the spike occurred at approximately 15 to 30 s intervals. The Mi Band interpreted this periodic movement as the person being awake. A close-up data can be seen in Figure 5.2. In this figure, the signals between two spikes were quite stable and regular respiratory signals (i.e., small repetitive spikes) can be observed as well; this suggests the person was breathing normally. The temperature data in Figure 5.1 is high and stable during the same time period, which suggests the person was asleep. This corroborated by the respiratory data seen in Figure 5.2. The participant did not report a night time waking during this time. Thus, the data suggests that the participant was sleeping during the time when the periodic movement occurred. This trend was seen in the data for O001 for every day of the study. However, due to the periodic movements that occurred in the first half of the night, Mi Band 2 wrongly identified that period to be

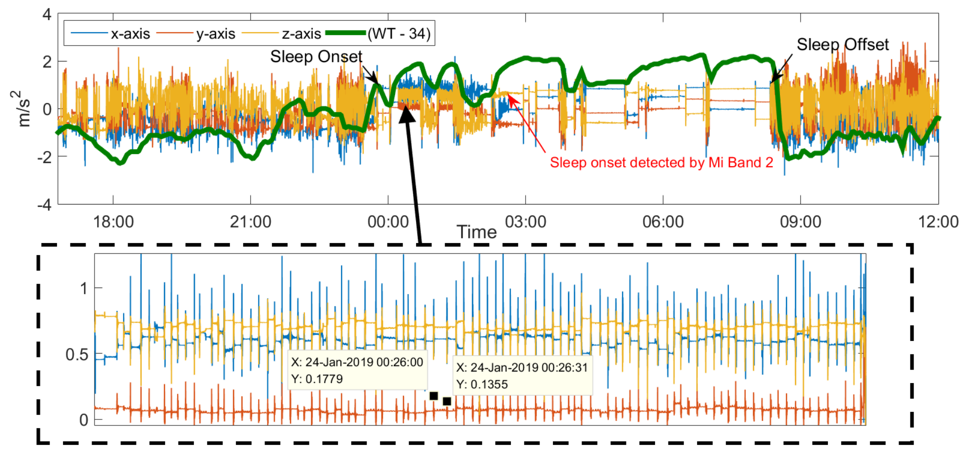


Figure 5.1: Example wrist temperature and accelerometer data for a healthy older adult participant (O001) for (top) a 24-hour period and (bottom) magnified excerpt.

"awake" every night. This was the main cause of the Mi Band 2's high level of error for this participant.

5.3.2 Case study: D001

Most people who are living with dementia also have other co-morbidities [72]. An interesting case study is D001, who is also a stroke survivor. Before starting data collection, it was not known that the participant had a stroke that affected movement of their left hand and arm. According to the protocol, both Mi Band 2 and the customized wristband were put on the left hand for collecting data. During the first visit and check-up, which was after four days of data collection, it was noticed that D001 could only move their right hand, so both bands were moved to the right hand. In the second visit, the wrist temperature patterns on D001's two hands were found to be quite different (as shown in Figure 5.3). Therefore, the customized wristband was put back to the left hand, and the Mi Band remained on the right hand for the last seven days of the experiment. The change of protocol was done to investigate whether there was a temperature pattern difference between two hands and the Mi Band 2 might perform better on the unaffected hand.

From Figure 5.3, it can be seen that the wrist temperature rhythm for the left wrist is more reflective of a "good" sleep pattern (as discussed in Chapter 4); this was true for

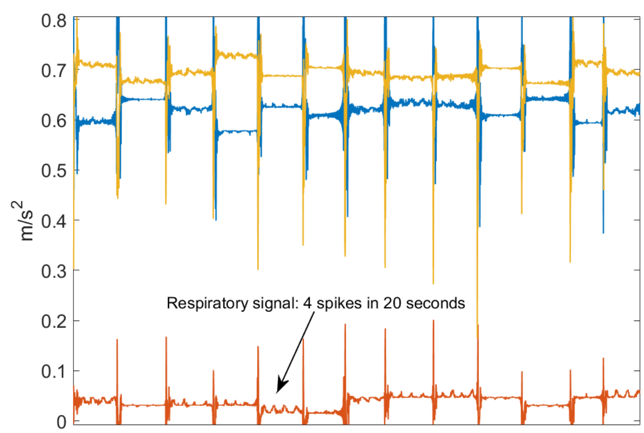


Figure 5.2: A close-up of 5 minutes of periodic movement accelerometer data for O001.

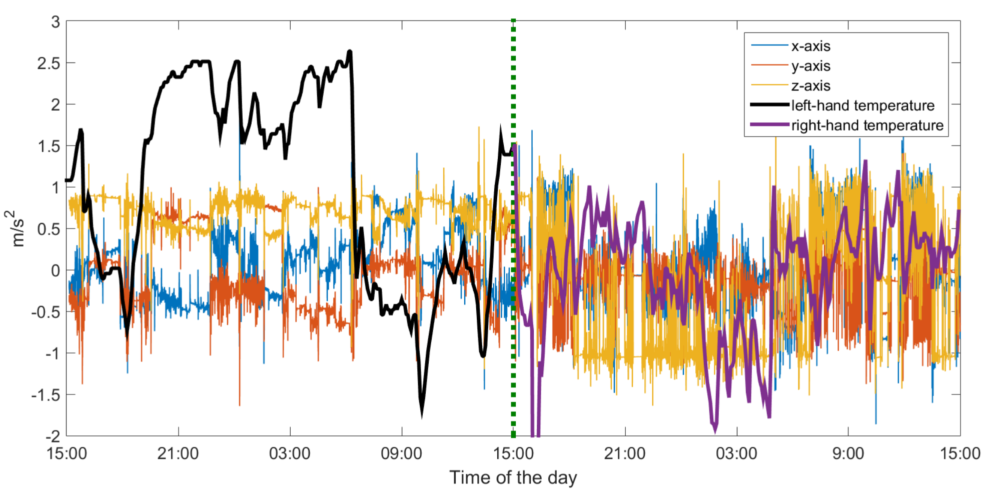


Figure 5.3: Example wrist temperature and accelerometer data of D001 for two consecutive days. The left side of the figure shows the data collected on his left hand (immobile because of a stroke) and the right figure shows the data collected on his right hand (unaffected by stroke). Wrist temperature was moved to the same scale-level of accelerometer data for visual presentation.

all data collected on his left wrist. On the other hand, wrist temperature measured from the right wrist had no distinct day/night temperature contrast and had more variability, which made it impossible to identify the increased temperature period. As D001 cannot move his left hand, there were very few variations in accelerometer data compared to his right hand, which he used for most tasks. However, both of D001's hands had intense movement at night, and the right hand experienced more severe movement than the other hand. From Figure 5.3, it is very hard to discern when D001 was awake or sleeping from inspecting the accelerometer data alone.

5.3.3 Case study: D002

Participant D002 is a 68-year-old female who has diagnosed sleep apnea and insomnia. From time-to-time, D002 reported not sleeping the whole night to PSW. For the entire experiment, D002 was reported to wake up multiple times during sleep.

Among the eight OAWD participants, D002 had the worst Mi Band 2 detection rate (see Table 5.2). As such, only two days of sleep data were detected. Wrist temperature and accelerometer data from her for two days are shown in Figure 5.4. On the first day, it can be observed from the accelerometer that she did not sleep so well (i.e., lots of more significant movements) and her sleep was not detected by Mi Band 2 at all. The temperature data were also highly variable with no detectable smooth periods. The next day, while D002's sleep was still much worse than other people's, the Mi Band 2 detected one short sleep episode between 1:39 to 3:12 AM; it did not catch other sleep episodes that occurred before 1 AM and after 5 AM, which were reported by the LTC staff (identified by arrow in Figure 5.4). These sleep periods can also be seen by higher, less variable temperature data during correlating periods.

From Figure 5.4, there are no clear temperature plateaus for the first day and no distinguishable long, static accelerometer data period. Figure 5.5 shows a zoomed-in section of nighttime data from the first day, which shows are multiple short static periods that suggest she might be asleep. From the sleep journal recorded by the LTC staff, D002 transited between sleep and wake states often on this day (see Table 5.4). Comparing data from Table 5.4 and Figure 5.5, it can be seen that most short sleep periods are consistent with reports from PSW. However, some sleep periods were overly reported, while some short sleep periods were not captured by PSW. On the next day, D002 seemed to sleep better. Two temperature peaks together with two relatively static accelerometer data periods can be identified.

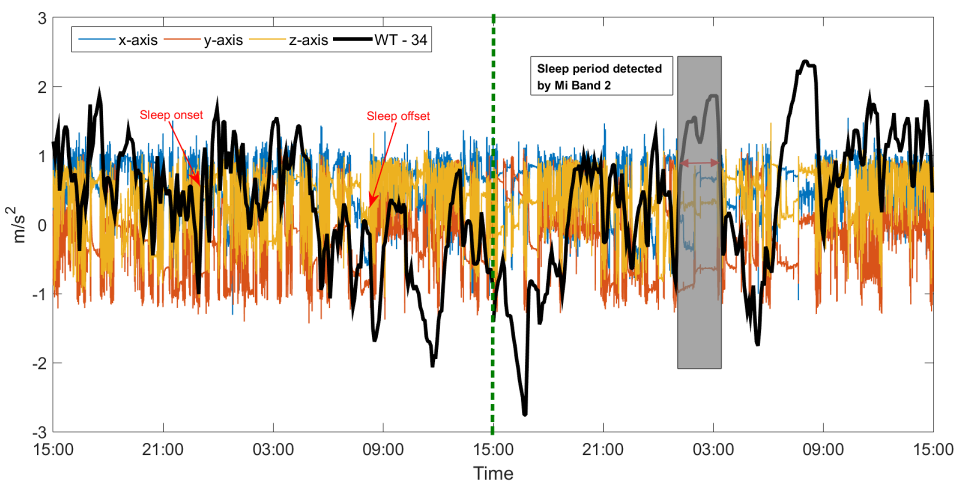


Figure 5.4: Example of 48 hours of wrist temperature and accelerometer data for D002. Shaded box on the second day highlights where Mi Band 2 recognized sleep.

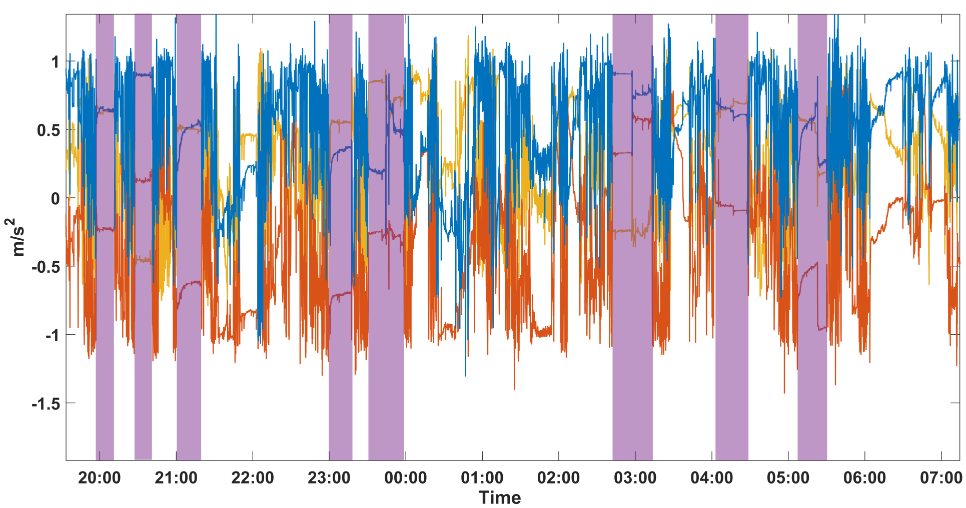


Figure 5.5: A close-up of 11-hour (between 20:00 and 7:00) of accelerometer data for D002. Eight short sleep periods that were identified by visual analysis manually are highlighted by shaded boxes.

Table 5.4: Recordings of 14-hour sleep/wake from DOS sheet for D002.

1 = awake, 2 = sleeping			
1900	1	1930	**2**
2000	**2**	2030	**2**
2100	**2**	2130	**2**
2200	1	2230	1
2300	1	2330	1
2400	1	0030	1
0100	**2**	0130	**2**
0200	**2**	0230	**2**
0300	1	0330	1
0400	**2**	0430	**2**
0500	**2**	0530	**2**
0600	1	0630	1
0700	1	0730	**2**
0800	**2**	0830	**2**

5.3.4 Case study: D010

Participant D010 is a 68-year-old male who has diagnosed sleep apnea and Parkinson's Disease. Due to Parkinson's Disease, D010 needs to be awakened at 3 AM every night to take medications. According to the MMSE score (score = 21), D010 has only mild cognitive impairment. An example of the participant's wrist temperature and accelerometer data for two consecutive days is shown in Figure 5.6. For each day, the sleep period detected by Mi Band 2 is indicated by the shaded box. As can be seen, the wrist temperature rhythm has a prominent peak. At around 3 AM, the wrist temperature experienced a dip on both days, which coincided with D010's dosing time. While the level of movement is less severe than that of D001 and D002, Mi Band 2 only detected a small portion of sleep for D010 as well.

5.4 Discussion

There are two reasons that the exact detection accuracy of Mi Band 2 for the dementia group can not be easily computed as well as why only the averaged sleep parameters from Mi Band 2 and the recreated journal are compared. First, as mentioned in Section 3, it

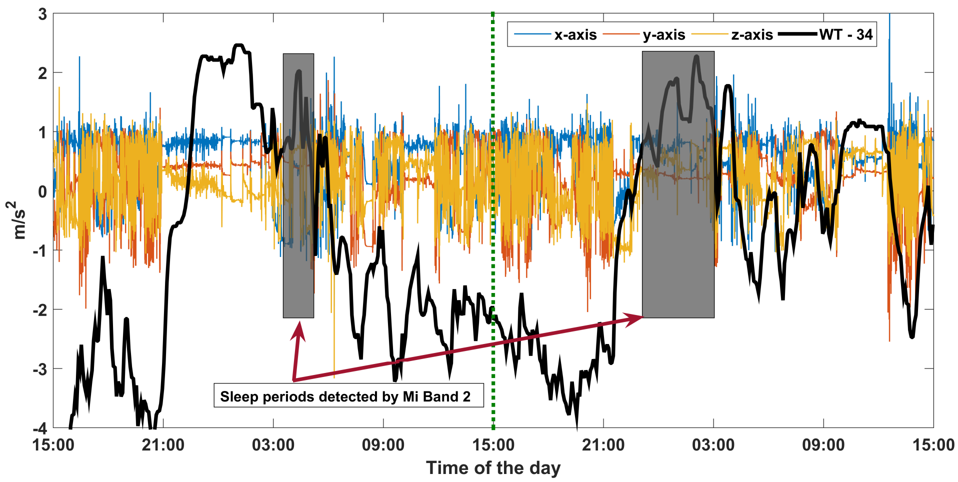


Figure 5.6: Example of 48 hours of wrist temperature and accelerometer data for D010. Shaded boxes represent where Mi Band 2 recognized sleep.

was challenging to get an accurate sleep journal for this group. The other reason is that the Mi Band 2 did not capture sleep data for every participant (except D003) every day in this group. According to Table 5.2, only sleep of two nights was captured for D002, the sleep of seven nights were captured for D004 and sleep of nights were captured for D004. Incomplete sleep data capture also occurred to other two participants (D005 and D009).

Despite the missing sleep data, the detected sleep onset, offset, and duration from Mi Band did not match the sleep data presented in Table 3.5 either. From Table 5.3, Mi Band 2 tended to underestimate most people's sleep while only one participant's sleep was more accurately captured. According to data from Mi Band 2, most participants started sleeping pretty late and had only around 1 to 4 hours of sleep per night. Except D003, all the rest participants woke up much earlier than reported. Furthermore, the standard deviation of each sleep parameters is quite high for everyone. For example, the SD of D005's sleep onset is more than 3 hours, and the SD of his sleep offset is higher than 2 hours.

Therefore, the performance of Mi Band 2 was not consistent among the three groups. It works reasonably well for the healthy younger adults and most of the healthy older adults, but it did not detect most sleep of OAWD. In LTC, it is possible that the participants did not wear the Mi Band 2 on some days. However, for most days where sleep was not detected by the Mi Band, the band still captured their daily steps, which supports that they did wear the Mi Band 2 at night and that it was working correctly. Therefore, missed sleep classifications are a result of an inaccurate sleep detection algorithm for this population.

While the algorithm behind Mi Band 2 or many other commercial wristbands is not known, their sleep detection algorithms are mostly built based on the level of motion (other sensors like PPG might also be used); if the movement level exceeds a certain threshold, the user is identified to be awake. Also, it is probable that the Mi Band 2 sleep detection algorithm is built and trained based on a healthier population (i,e., healthy younger, and middle-aged adults). When the Mi Band 2 is used by a frail and low-mobility population, such as the OAWD in this study, the data do not align with the training data, resulting in misclassification. It is likely that the Mi Band failed to detect most dementia participants' sleep because of increased periodic movement and frequent wake-ups at night, as shown in the case studies.

From the case studies presented above, Mi Band 2 did not perform well for all the participants mentioned. As there is substantial limb movement shown in Figure 5.1, 5.3, 5.4 and 5.6, it is not surprising that Mi Band 2 failed to detect their sleep correctly. The limb movement presented for O001 was more periodic and it "tricked" the Mi Band 2 into thinking the user was still awake. Similarly, the limb movements of D001, D002, and D003 resulted in the inability to detect sleep of Mi Band 2. It is interesting to note that both of D001's wrists had many movements at night, even though his left (stroke-affected) arm was relatively stationary during the daytime.

The periodic movement detected is of interest as it appears to be related to aging and is present in all OAWD participants' data. Post-OAWD data collection, the researcher wore the same wristbands a day after data collection from an OAWD participant to rule out that the periodic movement was an artifact of a dysfunctional device. There were no similar movements in this test data. Therefore, the hand motion was indeed caused by the participants' involuntary movement. All OAWD participants had a much higher level of limb movement at night than healthy participants, which is an unexpected finding of this research. As mentioned before, the only exception is D003. An example of 48-hour of wrist temperature and accelerometer data for her is shown in Figure 5.7. Compared to the accelerometer data for D001, D002, and D010, the nighttime hand movement for D003 was significantly reduced. The sleep detection of Mi Band 2 for her is the most accurate in OAWD group. Visually analyzing these OAWD's data, it can be concluded that Mi Band 2 can lose the ability to detect sleep when the user is experiencing severe limb movement.

Wrist temperature appears to be more robust in responding sleep/wake states change compared to the accelerometer sensor. As the case studies illustrate, when people are sleeping, wrist temperature increases. There appears to be periodic limb movement for many older adults, with an increased prevalence for OAWD (all of the eight participants exhibited this). While this study was not able to identify what is the cause of this periodic limb movement, it seems to occur when people are sleeping. It also appears that this is

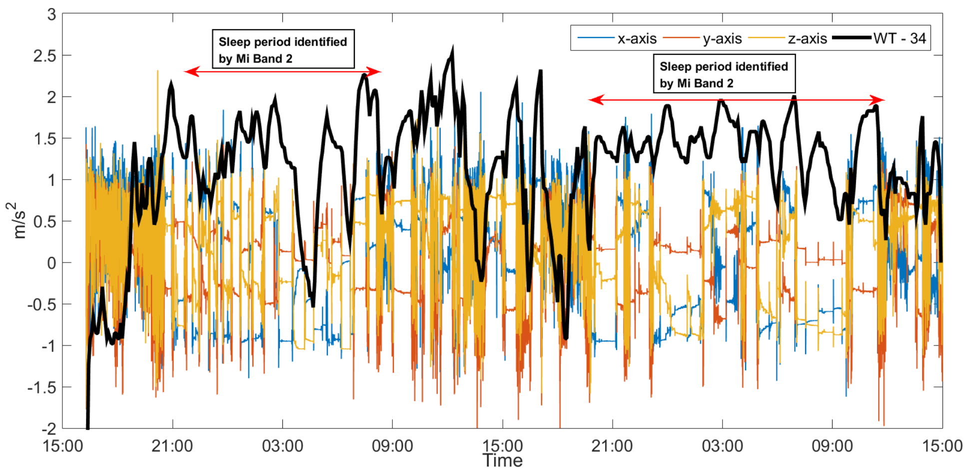


Figure 5.7: Example wrist temperature and accelerometer data of D003 for 48 hour period.

not considered by the Mi Band 2 sleep detection algorithm, causing a misclassification for people who exhibit this movement. For all the participants in this research, D002 had the worst sleep as well as the most irregular wrist temperature patterns. It can be observed that D002's temperature rhythm had no obvious high wrist temperature plateau and no long static accelerometer period on the first day. While it is unknown why sleep of D002 was this bad, frequent wake-ups during the night may have been caused by sleep apnea, as D002 did not wear any nasal mask for sleep apnea. Regardless, for each short sleep episode, it appears the wrist temperature did not have enough time to rise to its highest value to reach a stable plateau before she woke up again. This high level of sleep disruption caused both accelerometer and wrist temperature sensor data not to perform well. For people as such, commercial sleep monitoring wearables trained on normal sleep data may not be useful at all.

This research supports the correlation between wrist temperature and sleep, and with more data, it is plausible that a more advanced algorithm can be built for people like D002. Additionally, as wrist temperature is coordinated by internal circadian system, integrating a temperature sensor into a wearable wristband could help monitor the health of the circadian system.

Compared to accelerometer data, the wrist temperature pattern appears to be more robust and has a higher correlation to sleep for the aging and dementia population. Among the 28 participants in this study, only two participants had less prominent wrist temperature patterns: D002 and D003. As depicted in Case Study 1 and Figure 5.7, both participants had irregular sleep, as shown by wrist temperature rhythms with no distinct plateaus at night. For D002, both activity pattern and wrist temperature patterns were not distinctive between day and night, therefore made it very hard to determine her sleep patterns even by manually inspecting her data. For D003, while her wrist temperature pattern was not as good as others', the accelerometer data had much fewer movements than other people during sleep. Also, it was noticed that D003 sometimes wore the wristband quite loosely (i.e., the temperature sensor was not touching the skin well), which might cause temperature reading to be less reliable than other people.

It is interesting to notice that the failure of Mi Band 2 indicated more than poor sleep quality of some participants. Especially, if significant differences between wrist temperature rhythm and activity rhythm are observed, it is quite possible that these people have sleep disorders (e.g., restless leg syndrome). Detecting sleep accurately of older adults and OAWD can be more meaningful than for the younger population, as they are more likely to have sleep disorders [73]. As discussed above, wrist temperature and accelerometer data can compensate each other in sleep monitoring. In Chapter 6, two algorithms are proposed to detect sleep. One algorithm is purely based on the wrist temperatures while the other utilizes features from wrist temperature and accelerometer data. The preliminary results show that by combining two types of data, the sleep can be more accurately detected even for data presented in case studies (O001 and D010). For an impaired sleep population like OAWD, a new system with wrist temperature monitoring might infer more information on sleep other than onset and offset, such as helping the diagnosis of Circadian Rhythm Sleep-Wake Disorders [74].

The performance difference of different population makes the usefulness of commercial wristband (or at least wristbands detect sleep based on accemetry sensors) questionable as it is more important for the sleep-compromised population to accurately monitor sleep than for a healthy population. Capturing all the sleep episodes for the frail geriatric population like OAWD is essential as it could help physicians and caregivers to develop strategies for best-supporting sleep, which may help to mitigate symptoms such as memory difficulties and irritability. While the validity of other wearable devices remains unknown for the older adult and dementia populations, the positive potential of including wrist temperature into a sleep monitoring system has been shown by the data presented in this study. Analyzing the sleep data collected by the Mi Band 2 answers Research Questions 4 and 5: Aging and dementia negatively impacts the accuracy of the commercially available Mi Band 2 smart wristband.

5.5 Chapter Summary

There are three key points to related to the work presented in this chapter:

- The Mi Band 2 generally performs well for the healthy group (except O001 and O007) and performs poorly for the OAWD group.
- A significant cause of poor performance of the Mi Band 2 is associated with the more erratic sleep patterns of participants.
- Compared to the accelerometer data, wrist temperature is more robustly correlated to sleep. This feature of wrist temperature could be used in sleep detection.

Chapter 6

Algorithm Development and Testing

As can be seen in Figure 1.1 and from presented case studies in Section 5.3, wrist temperature will increase during sleep regardless of body movements. The value of wrist temperature can therefore be used as a core feature in building a sleep/wake detection algorithm for people with any sleep disorders (e.g., restless leg syndrome). In this chapter, two algorithms will be introduced. The first algorithm is solely based on the value of wrist temperature while the second makes classifications based on both wrist temperature and accelerometer data. Preliminary evaluations are provided and compared with sleep journal and data from Mi Band 2. Preliminary results have shown promising potential of wrist temperature and pave the way for a more scalable and accurate sleep detection algorithm.

6.1 Wrist Temperature-based Algorithm

6.1.1 Algorithm Development

According to [14], when wrist temperature reached over 34.8 °C, 90% of their tested participants were asleep. Therefore, a rule-based sleep detection algorithm based on the value of wrist temperature was proposed in [16] on wrist temperature rhythms. As wrist temperature during sleep is higher than daytime temperature, this algorithm first extracts a series of time when the temperature is higher than the daily mean temperature. Then, the longest time-consecutive period in the extracted series is identified as the sleep period. The sleep onset and offset are then estimated as the onset and offset of the identified sleep period. The pseudo-code of this algorithm is shown in **Algorithm 1**. In [16], the algorithm was tested on the wrist temperature from 14 healthy younger adults, and the average detection errors for the onset and offset were both below 30 minutes. The same algorithm was used to estimate sleep of data collected in this study.

Algorithm 1: Temperature-based Estimation Algorithm

```
dTemperature: Orderd 288 × 1 wrist temperature samples of 24 hours
Outputs     : Estimated sleep onset and offset
/* Discarding wrist temperatures which are lower than 30℃          */
θ ⟵ Mean(dTemperature)
for i ⟵ 0 to 288 do
    if dTemperature_i > 0 then
        overThre_i ⟵ 1;
    else
        overThre_i ⟵ 0;
    end
end
overperiod ⟵ FindConsecutive1Periods(overthre);
sleepDuration ⟵ argmax(overperiod);
sleepOnset ⟵ onset(sleepDuration);
sleepOffset ⟵ offset(sleepDuration);
```

Table 6.1: Difference between reported sleep onset and offset from the WT-based algorithm and sleep journal. The sleep journal was self-reported for healthy younger and older adults; it was recreated for OAWD. Values are expressed as the mean ± SD.

	Sleep Onset Error (hh:mm)	Sleep Offset Error (hh:mm)
Younger	1:21 ± 1:18	1:05 ± 1:01
Older	1:32 ± 1:40	1:24 ± 1:52
OAWD	2:38 ± 3:07	2:59 ± 3:10

6.1.2 Algorithm Evaluation

The estimated sleep onset and offset time differences for three groups from the WT-based algorithm are presented in Table 6.1. It can be seen that the differences of onset and offset of younger participants are the smallest while those of OAWD is the largest. It is also

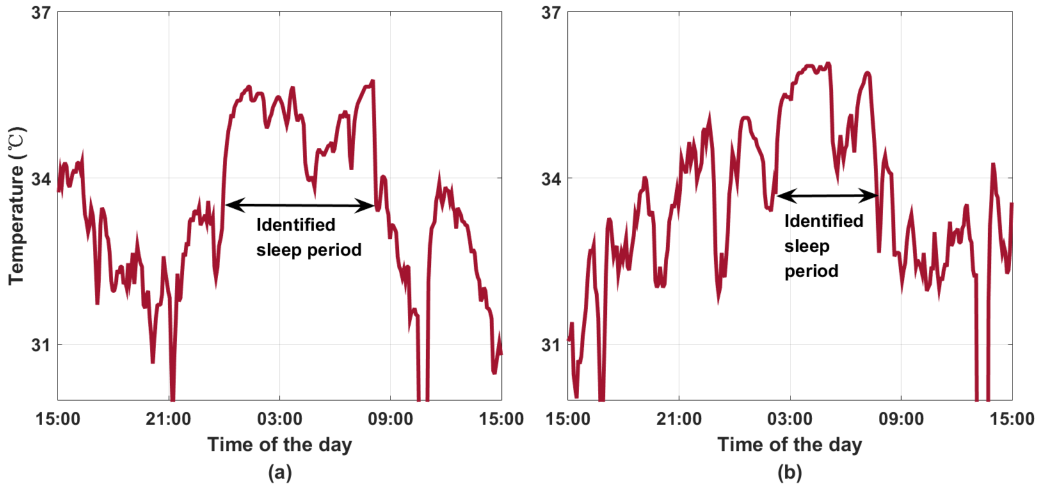


Figure 6.1: An example of wrist temperature-based sleep detection algorithm error. Only the a second part of sleep was detected.

noteworthy that the standard deviation of errors is very prominent; the detection time differences of participants in this study are more significant than the errors in [16].

6.1.3 Discussion

The large standard deviation of detection errors suggests that sometimes the algorithm works very well, but it is not robust at other times. However, despite the significant detection errors, the wrist temperature based sleep detection algorithm can perform better than Mi Band 2 for OAWD for some cases (e.g., it is easy to detect sleep from wrist temperature for D001). While Mi Band 2 can only detect three-hour sleep on some days, as long as the wristband is not taken off, this algorithm can identify any long periods that have higher wrist temperatures.

Since the algorithm tries to estimate sleep period by identifying the longest time-consecutive high-temperature period, it can fail when the user wakes up in the middle of the night. An example from participant (O004) is shown in Figure 6.1. In the left figure (a), the detection errors of onset and offset are both 8 min. In the right figure (b), the detection errors of onset and offset are 2 hr 16 min, respectively. In a case like (b), the algorithm can only identify a part of sleep (i.e., from 2:03 to 7:38).

The reason that the performance of this algorithm for participants in this study is worse than results reported in [16] could be the difference in sleep patterns. Even both studies recruited healthy younger adults, the participants in [16] were undergraduate students while the participants of this study are mostly graduate students, their sleep might therefore be more disturbed than undergraduate students. Also, the sampling rate and resolution of temperature sensor in the two studies are different. In the former study, the sampling rate (1 sample per 10 min) is lower, and resolution (0.5 °C) was higher compared to this study, which had 1 sample per 5 min as sampling rate and 0.0625 °C as resolution. This could have inadvertently added a 'filter' that smoothed temperature changes at night, causing the nighttime temperature has fewer variations and therefore a much better algorithm performance.

While this preliminary evaluation indicates that sleep detection based solely on wrist temperature can be accomplished to some extent, it will likely still not perform well even if this algorithm is further optimized (i.e., improve the algorithm to identify more than one sleep episode). Furthermore, the wrist temperature sometimes can be influenced by ambient temperature. Therefore, an algorithm that uses features from accelerometer data and wrist temperature together is introduced in the following section.

6.2 Wrist temperature + accelerometry-based Algorithm

6.2.1 Algorithm Design

To overcome the shortcoming of using solely wrist temperature, an unsupervised machine learning algorithm based on the combination of wrist temperature and accelerometer data for sleep detection was proposed in my publication [75]. Data labeling can be time-consuming; the unsupervised learning method was therefore considered first. Also, unsupervised sleep detection using k-means has been shown to be comparable to supervised sleep detection algorithm[76]. Therefore, the simplest unsupervised learning method k-means algorithm was used in this study to test the validity of building an algorithm that uses both wrist temperature and accelerometry. Five commonly used features ([42, 43, 77]) from 3-axis accelerometer data were extracted for every 30-s epoch of data: (1) root mean squares (RMS) of three axes combined ($\sqrt{x^2 + y^2 + z^2}$), (2) standard deviation of RMS, (3-5) standard deviation of angles extracted along each axis (e.g. standard deviation of $\tan^{-1} \frac{x}{\sqrt{y^2+z^2}}$). The feature matrix was then applied with a k-means algorithm to cluster

Algorithm 2: Wrist temperature + accelerometry-based Algorithm

```
Input accelerometer: accelerometer data for 24-hour
Input temperature  : wrist temperature data for 24-hour
Outputs            : Estimated sleep onset and offset
/* Discarding wrist temperatures which are lower than 28℃                */
θ ⟵ Mean(wrist temperature)
featureMatrix ⟵ extractFeatures(accelerometer data)
binarySeries ⟵ kMeans(featureMatrix)
/* Compare the RMS of two clusters to determine which cluster
   represents sleep and which cluster represents awake.                   */
if RMS(Cluster-1) > RMS(Cluster-0) then
 |  Cluster_1 ⟷ WakeCluster, Cluster_0 ⟺ SleepCluster
else
 |  Cluster_0 ⟷ WakeCluster, Cluster_1 ⟺ SleepCluster
end
binarySeries ⟵ AssignOneToSleepCluster(SleepCluster);
/* Find any consecutive 1 periods longer than 3 minutes.                  */
consecutive1Periods ⟵ FindConsecutive1Periods(binarySeries);
/* Determine if each consecutive period has a higher wrist temperature
   */
if Mean(consecutive1Periods) > θ then
 |  consecutive1Periods ⟷ SleepPeriod
else
 |  consecutive1Periods ⟷ WakePeriod
end
sleepOnset ⟵ onset(sleepPeriod);
sleepOffset ⟵ offset(sleepPeriod);
```

the data into two categories (i.e., sleep and awake). Since cluster representations, "sleep" and "awake", are unknown, the label for "sleep" and "awake" is determined by calculating the average RMS for each cluster. The cluster with an average smaller RMS represents sleep and with an average larger RMS represents awake. Once the labels for "sleep" and "awake" was known, the consecutive series with label "sleep" longer than 3 min (more than six 1 s in a row) among the binary label series was identified. As some data can be wrongly identified as asleep (e.g., people lie in bed and have fewer motions), the wrist temperature was then used for further classification; for each identified "sleep" series, the corresponding average wrist temperature is calculated. The daily average wrist temperature (i.e., temperature over the past 24 hour period) was used as the threshold. The only series with an average temperature higher than the threshold remained and classified as a sleep period. The sleep onset was then determined by the onset and offset of the identified sleep period. The pseudo-code of this algorithm is shown in **Algorithm 2**.

6.2.2 Algorithm Evaluation

Pre-processing of data can be time-consuming (i.e., prepare raw accelerometer data for classification). As data collection with OAWD went late into the study because of ethics and access delays and because the labeling of OAWD's sleep data took longer than expected (explained in Chapter 3.1), only results from four younger adults, one healthy older adult, and one OAWD were assessed. These are presented in Table 6.2.

Table 6.2: Errors of detected sleep parameters from the WT+accelerometry algorithm and the self-reported sleep journal for four healthy younger adults (Y001, Y002, Y003 and Y004), one healthy older adult (O001) and one OAWD (D010). Errors are defined as time difference in sleep parameters between algorithm estimations and sleep journal data. Values are expressed as the mean ± SD.

	Sleep onset (hh:mm)		Sleep offset (hh:mm)	
	WT + ACC	Mi	WT + ACC	Mi
Younger	0:28 ± 0:23	0:22 ± 0:23	0:18 ± 0:43	0:19 ± 0:37
O001	0:36 ± 0:32	2:17 ± 1:10	0:09 ± 0:09	1:04 ± 1:02
D010	0:19 ± 0:06	2:51 ± 2:16	0:55 ± 0:39	2:42 ± 1:27

From Table 6.2, the average detection error of onset for the four younger adults was comparable to the results of Mi Band 2 (onset: 0:28 ¿ 0:22, offset: 0:18 ¡ 0:19). Older adult

O001's data is presented as a case study in Section 5.3.1. For O001, the average sleep onset detection error of Mi Band 2 was more than two hours, and the average offset error was more than 60 minutes (the error for one day was more than four hours). Applying the WT+accelerometry based algorithm appeared to reduce the detection error for him to less than 40 minutes for sleep onset and less than 10 min for sleep offset. As for the OAWD D001, compared to the average detection errors of Mi Band 2, the detection errors were also significantly reduced by including wrist temperature into classification.

6.2.3 Discussion

These preliminary results have shown that the proposed algorithm had similar or slightly better performance for younger adults compared to Mi Band 2. Furthermore, the results of O001 and D010 suggested that this algorithm can work more robustly than the Mi Band 2 for people who might have sleep disorders.

Among these six participants, the offset detection error for D010 was most substantial, and a high standard deviation suggested that the algorithm did not work so well for some days. As mentioned before, the sleep data for OAWD often quite fractured; they woke up multiple times, and their accelerometer data was not as stable as healthy people during sleep. Even by manually identifying their sleep from accelerometer data, the recreated sleep journal might not be accurate (e.g., exemplary data of D010 are shown in Section 5.3). Therefore, the errors can be caused by "inaccurate ground truth". Moreover, PSW reported that some OAWD could play with the wristband and OAWD can be less careful when washing hands (hand-washing can influence wrist temperature), both of which can result in inaccurate temperature reading. In this case, the algorithm can make a wrong classification about sleep and awake.

6.3 General Discussion Regarding Sleep Detection Algorithm Development and Evaluation

Both algorithms are not fully optimized. However, from the two algorithms and preliminary results presented above, it can be seen that wrist temperature can add value in a sleep detection algorithm; using only wrist temperature is not as robust. However, even if there is much movement that occurs during sleep, the wrist temperature still has a certian pattern and remains high when the person is sleeping. The wrist temperature can also be extremely useful when people are lying in bed with minimal movement but having trouble

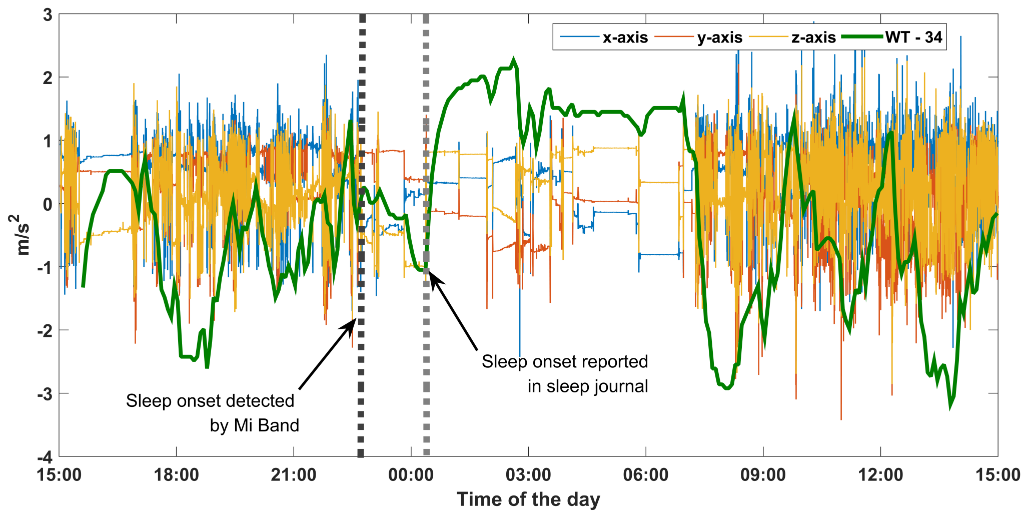


Figure 6.2: Wrist temperature and accelerometer data of participant O003 on an example day. Two sleep onsets from sleep journal and Mi Band 2 are identified. She reported that she spent around two hours to fall asleep, yet Mi Band 2 detected her sleep two hours earlier.

falling asleep. An example from O003 is shown in Figure 6.2). O003 reported falling asleep at around 0:45, and it can be seen that wrist temperature increased after 0:00. The accelerometer-based algorithm from Mi Band 2 was able to tell whether the participant was asleep or not, but the value of wrist temperature might. When combining features from temperature and accelerometer data, the sleep detection algorithm appears to work much better than Mi Band 2 for cases such as O001 and D010.

The second algorithm needs to be tested for all participants and needs further optimization. In future work, more features could be extracted and tested for effectiveness in clustering the accelerometer data. Additionally, people who are sleep disturbed may not be able to sleep soundly for the whole night. For example, older adults and OAWD tend to wake up multiple times during the night. Therefore the algorithm will be trained to identify wakening and more sleep episodes (i.e., night waking and naps at daytime). In such a cases, not only detecting sleep onset and offset is important, but identifying night wakings can be important as well. Future development of the WT+accelerometry approach is promising as a more sophisticated, accurate algorithm that could better meet the needs of sleep monitoring for everyone, including frail older adults.

6.4 Chapter Summary

Two key points from the research presented in this chapter are:

- The potential of unsupervised sleep detection algorithm based on features from combined wrist temperature and accelerometry has demonstrated better performance than accelerometry or wrist temperature alone.
- The WT+accelerometry algorithm can be further tested and optimized so that the sleep patterns of people with sleep impairments can be better monitored.

Chapter 7

General Discussion

Sleep patterns and sleep quality are influenced by aging and dementia. Chapter 3 showed that high-level sleep quality varies among the three groups of participants. Generally, younger participants had better sleep quality than healthy older participants. But some younger adults reported worse subjective sleep quality than good sleepers in the healthy older group. This finding suggests that sleep quality is more dependent on the specific individual and his/her lifestyle than on age.

Younger participants tended to sleep later and had a shorter sleep duration than older participants. Compared to younger adults who need to study and work, all older adults in this study were retired and lived a more flexible schedule; they were likely better able to choose their sleep timing and had more opportunity to make up sleep deprivation during the day. With regards to OAWD, their sleep timing is comparatively quite early and their temperature suggests they all had excessive daytime sleepiness. It is very challenging to measure their sleep patterns and even to define their sleep onset and offset, as they might take naps after dinner or breakfast. Living in a LTC, participants from OAWD can more readily sleep when they want. However, due to the nature of LTC environments, the residents will never sleep in an entirely dark environment (their doors need to be open during the night and there are routine checks). Many OAWD either need to take medications that can influence their sleep, or they need to be woken up at 3 AM to take drugs. Living a less restricted lifestyle can help people follow their internal circadian clock to sleep and to wake up. But as aging and dementia progress, the circadian system gradually becomes less regular and stable; environmental changes, such as LTC living, may not support better sleep habits. Also, co-morbidities could increase poor sleep patterns and sleep quality. Therefore, it is essential to measure both circadian rhythms and sleep patterns of people to understand the real reason behind poor sleep quality.

In this thesis research, wrist temperature was chosen for its correlations with both circadian rhythm and sleep. The findings of wrist temperature in Chapter 4 are consistent with sleep patterns of the three groups. Except for the phase and slightly higher wake-time temperature, there is a minor difference in wrist temperature rhythm between younger participants and healthy older participants.As mentioned above, the circadian system can be more stable if living in a "more free", supportive environment. In fact, choosing to participate in this sleep study suggests a good health status for all non-OAWD participants. It is a different case for OAWD. With the sleep timing to be the earliest, most OAWD also had a very early phase of wrist temperature rhythm. Furthermore, the circadian rhythmicity of OAWD is found to be weaker compared to healthy younger and older participants. In addition to IS, OAWD had the least prominent SWTD, meaning that their wrist temperatures do not contrast between day and night. It is interesting to find that the wake-time wrist temperature is mostly influenced by sleep patterns, which is consistent with one other study [53]. As the contact between the temperature sensor and wrist skin was the poorest for OAWD, this may have impacted accuracy and might have lowered the measured temperature. However, the value of SWTD is significantly determined by the high wake-time temperature instead of sleep-time temperature, which suggests that the lower SWTD of OAWD was not caused by poor contact of the sensor. This finding suggests that the sleep-time wrist temperature does not vary among three groups and for people who experience sleep disturbances, their daytime sleepiness will primarily increase. Increased daytime sleepiness can then cause the wake-time wrist temperature to rise. Considering that both older groups had a higher wake-time wrist temperature, this change might be caused by natural aging and dementia can further increase wrist temperature.

For comparison and supplementing to self-reported sleep journal, the commercial wristband Mi Band 2 was used to measure sleep patterns of participants. The data is presented in Chapter 5. The experiments were first done for healthy younger adults and older adults, and Mi Band 2 worked well except for two participants. For OAWD, Mi Band 2 failed to identify their sleep. Four inspected case studies illustrate that the actigraphy-based sleep monitor cannot correctly identify the sleep of OAWD. This is mainly attributed to the fact that all the OAWD exhibited body movements during sleep; the cause for this movement during sleep is unknown.

While higher-end commercial wristbands like Fitbit were not tested for these participants, these results question the validity of commercial wristbands for monitoring sleep. This is particularly true for OAWD since the accelerometry-based sleep detection is used in most commercial systems; this reseach shows that accelerometry data alone is not a good measure of sleep for OAWD. Despite the inaccuracy of the Mi Band 2 when detecting sleep for OAWD, the apparent cause sheds lights on another piece of knowledge; namely, if the commercial wristband has highly inaccurate sleep detection, the user might have a movement disorder during sleep (i.e., body movements during sleep causes misidentification of the person being awake when they are not). This "diagnosis" function of actigraphy-based sleep monitoring can be further strengthened by integrating a temperature sensor to the system, as the wrist temperature's association with sleep is regardless of the occurrence of body movement. This type of data might then be used to support better sleep diagnosis, management, and monitoring, including by caregivers and physicians to support better sleep in OAWD.

To further explore the usefulness of wrist temperature in sleep monitoring, two algorithms for sleep detection were presented in Chapter 6. When solely using wrist temperature as an indicator of sleep or wake, the first algorithm is not robust for people who had irregular and fragmented sleep. When combining wrist temperature and accelerometer data together, the validity of an unsupervised sleep detection algorithm (Algorithm 6.2) has been demonstrated by preliminary results. The unsupervised algorithm using clustering is more suitable for sleep-impaired population, as it is not trained solely on healthy sleepers' data. With further algorithm development and improvement, a wearable sleep monitoring system with accelerometer sensor and temperature sensor could not only detect sleep for people with sleep disorders but might help discover irregular body movements.

Finally, wrist temperature has been shown to be an important element that should be considered in future sleep monitoring systems. This research has pointed out three potential roles of wrist temperature: (1) measuring the circadian system, (2) help to detect sleep of irregular sleepers, and (3) help in the identification of movement-related sleep disorders. With these roles, new sleep monitoring wearable systems with a temperature sensor can benefit a broader population, especially frail populations such as OAWD.

Chapter 8

Conclusions and Future Work

To conclude, the thesis answered the six Research Questions outlined in Chapter 3 as follows :

- Answer to **Research Question 1.1**: At a group level, aging does influence the circadian wrist temperature curve of healthy older adults to be flatter coupled with marginally increased daytime wrist temperature. On average, the peak of wrist temperature rhythm of older adults occurs earlier.

- Answer to **Research Question 1.2**: At a group level, dementia influences the circadian wrist temperature curve and causes it to be even flatter than healthy older adults. OAWD's fragmented sleep (i.e., more night waking and daytime naps) results in sleep-time wrist temperature to be lower, wake-time temperature to be higher, and the amplitude of their temperature rhythm is significantly smaller.

- Answer to **Research Question 2**: The shape of wrist temperature rhythm is largely influenced by sleep patterns and the stability of nighttime temperature is mostly influenced by the amount of wakening. The shape and variability of wrist temperature can potentially be used to evaluate sleep quality.

- Answer to **Research Question 3.1 and 3.2**: Aging and dementia negatively impact the usefulness of Mi Band 2 on sleep monitoring. The poor performance of Mi Band 2 (and likely any smart wristband that uses only accelerometry data) is mostly caused by increased body movement of users.

- Answer to **Research Question 4**: Wrist temperature can be used to detect sleep. When combined with accelerometer data, the sleep detection algorithm works much better for people with movement-related sleep disorders compared to the Mi Band.

In addition to exploring the research questions above, this thesis research has made the following noteworthy contributions to the field of sleep monitoring:

- Comparison of wrist temperature rhythms of three different populations (healthy younger adults, healthy older adults, and OAWD) is concurrently investigated for the first time. The findings in wrist temperature rhythms further support that the association between increased daytime wrist temperature and increased daytime sleepiness in the older adult and dementia populations.

- The usefulness of commercial actigraphy-based wristband is proven to be questionable for the older adult and dementia populations; the addition of wrist temperature adds an element of understanding regarding sleep patterns.

- A promising new sleep detection algorithm with wrist temperature and accelerometer is proposed, and the preliminary results show the algorithm performs well for users with excessive body movement during the night (i.e., O001 and D010). By integrating wrist temperature, a further optimized algorithm could benefit to a broader population than the current commercial wearable devices.

8.1 Future Work

In this research, the potentially significant role of wrist temperature in sleep monitoring is highlighted. However, more work remains to be done to better understand wrist temperature and to build a more robust sleep monitoring system. Firstly, wrist temperature rhythms of people from other populations (e.g., middle-aged population and children) should be investigated to get a more comprehensive understanding as well as to explore how temperature might change because of health conditions, such as obesity and cancer. The sample size in this exploratory work is small; larger data sets would be needed to achieve more conclusive evaluations. With the collection of more data, the association between wrist temperature and sleep could be better understood. Secondly, more reliable measurements of sleep like PSG need to be used and more reliable methods for capturing ground truth should be used in future studies. By doing so, the accuracy and validity of the sleep detection algorithm can be improved and validated with solid ground truth.

Lastly, more sensors (e.g., gyroscopes) could be used together with a temperature sensor to build a new sleep monitoring system for the aging and dementia population.

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APPENDICES

Appendix A

Questionnaires

- **Demographic Form**
- **Morningness-eveningness Questionnaire (MEQ)**
- **Pittsburgh Sleep Quality Index (PSQI)**
- **Epworth Sleepiness Scale (ESS)**
- **Sleep Journal**
- **Mini-Mental State Examination (MMSE)**

Demographic Information Form

Instructions: Please provide a response for each of the following questions:

1. **What is your age?** __________

2. **What is you sex?**

   Female O Male O

3. **What is your height and weight?**

   __________ __________
   Height Weight

4. **Do you have any sleep-related disorder?**

   Yes O No O

If "yes", what type(s) of disorder do you have?

- Trouble Falling Asleep Yes O No O
- Insomnia Yes O No O
- Circadian Rhythms Disorder Yes O No O
- Excessive Daytime Sleepiness Yes O No O
- Sleep Apnea Yes O No O
- Sleepwalking Yes O No O
- Other (please specify):

5. **Do you take any medications that might influence your sleep?**

   Yes O No O

If "yes", what medication(s) do you take? __________ __________ __________

MORNINGNESS-EVENINGNESS QUESTIONNAIRE (MEQ)

Instructions:
- Please read each question very carefully before answering.
- Please answer each question as honestly as possible.
- Answer ALL questions.
- Each question should be answered independently of others. Do NOT go back and check your answers.

1. What time would you get up if you were entirely free to plan your day?

5:00 – 6:30 AM	5
6:30 – 7:45 AM	4
7:45 – 9:45 AM	3
9:45 – 11:00 AM	2
11:00 AM – 12 NOON	1
12 NOON – 5:00 AM	0

2. What time would you go to bed if you were entirely free to plan your evening?

8:00 – 9:00 PM	5
9:00 – 10:15 PM	4
10:15 PM – 12:30 AM	3
12:30 – 1:45 AM	2
1:45 – 3:00 AM	1
3:00 AM – 8:00 PM	0

3. If there is a specific time at which you have to get up in the morning, to what extent do you depend on being woken up by an alarm clock?

Not at all dependent	4
Slightly dependent	3
Fairly dependent	2
Very dependent	1

4. How easy do you find it to get up in the morning (when you are not woken up unexpectedly)?

Not at all easy	1
Not very easy	2
Fairly easy	3
Very easy	4

5. **How alert do you feel during the first half hour after you wake up in the morning?**

Not at all alert	1
Slightly alert	2
Fairly alert	3
Very alert	4

6. **How hungry do you feel during the first half-hour after you wake up in the morning?**

Not at all hungry	1
Slightly hungry	2
Fairly hungry	3
Very hungry	4

7. **During the first half-hour after you wake up in the morning, how tired do you feel?**

Very tired	1
Fairly tired	2
Fairly refreshed	3
Very refreshed	4

8. **If you have no commitments the next day, what time would you go to bed compared to your usual bedtime?**

Seldom or never later	4
Less than one hour later	3
1-2 hours later	2
More than two hours later	1

9. **You have decided to engage in some physical exercise. A friend suggests that you do this for one hour twice a week and the best time for him is between 7:00 – 8:00 am. Bearing in mind nothing but your own internal "clock", how do you think you would perform?**

Would be in good form	4
Would be in reasonable form	3
Would find it difficult	2
Would find it very difficult	1

10. **At what time of day do you feel you become tired as a result of need for sleep?**

8:00 – 9:00 PM	5
9:00 – 10:15 PM	4
10:15 PM – 12:45 AM	3
12:45 – 2:00 AM	2
2:00 – 3:00 AM	1

11. You want to be at your peak performance for a test that you know is going to be mentally exhausting and will last for two hours. You are entirely free to plan your day. Considering only your own internal "clock", which ONE of the four testing times would you choose?

8:00 AM – 10:00 AM	4
11:00 AM – 1:00 PM	3
3:00 PM – 5:00 PM	2
7:00 PM – 9:00 PM	1

12. If you got into bed at 11:00 PM, how tired would you be?

Not at all tired	1
A little tired	2
Fairly tired	3
Very tired	4

13. For some reason you have gone to bed several hours later than usual, but there is no need to get up at any particular time the next morning. Which ONE of the following are you most likely to do?

Will wake up at usual time, but will NOT fall back asleep	4
Will wake up at usual time and will doze thereafter	3
Will wake up at usual time but will fall asleep again	2
Will NOT wake up until later than usual	1

14. One night you have to remain awake between 4:00 – 6:00 AM in order to carry out a night watch. You have no commitments the next day. Which ONE of the alternatives will suite you best?

Would NOT go to bed until watch was over	1
Would take a nap before and sleep after	2
Would take a good sleep before and nap after	3
Would sleep only before watch	4

15. You have to do two hours of hard physical work. You are entirely free to plan your day and considering only your own internal "clock" which ONE of the following time would you choose?

8:00 AM – 10:00 AM	4
11:00 AM – 1:00 PM	3
3:00 PM – 5:00 PM	2
7:00 PM – 9:00 PM	1

16. You have decided to engage in hard physical exercise. A friend suggests that you do this for one hour twice a week and the best time for him is between 10:00 – 11:00 PM. Bearing in mind nothing else but your own internal "clock" how well do you think you would perform?

Would be in good form	1
Would be in reasonable form	2
Would find it difficult	3
Would find it very difficult	4

17. Suppose that you can choose your own work hours. Assume that you worked a FIVE hour day (including breaks) and that your job was interesting and paid by results). Which FIVE CONSECUTIVE HOURS would you select?

5 hours starting between 4:00 AM and 8:00 AM	5
5 hours starting between 8:00 AM and 9:00 AM	4
5 hours starting between 9:00 AM and 2:00 PM	3
5 hours starting between 2:00 PM and 5:00 PM	2
5 hours starting between 5:00 PM and 4:00 AM	1

18. At what time of the day do you think that you reach your "feeling best" peak?

5:00 – 8:00 AM	5
8:00 – 10:00 AM	4
10:00 AM – 5:00 PM	3
5:00 – 10:00 PM	2
10:00 PM – 5:00 AM	1

19. One hears about "morning" and "evening" types of people. Which ONE of these types do you consider yourself to be?

Definitely a "morning" type	6
Rather more a "morning" than an "evening" type	4
Rather more an "evening" than a "morning" type	2
Definitely an "evening" type	0

Name:____ Date: _________________

Pittsburgh Sleep Quality Index (PSQI)

Instructions: The following questions relate to your usual sleep habits during the past month only. Your answers should indicate the most accurate reply for the majority of days and nights in the past month. **Please answer all questions.**

1. During the past month, what time have you usually gone to bed at night? ___________________
2. During the past month, how long (in minutes) has it usually taken you to fall asleep each night? __________
3. During the past month, what time have you usually gotten up in the morning? ___________________
4. During the past month, how many hours of actual sleep did you get at night? (This may be different than the number of hours you spent in bed.) ___________________

5. During the past month, how often have you had trouble sleeping because you…	Not during the past month	Less than once a week	Once or twice a week	Three or more times a week
a. Cannot get to sleep within 30 minutes				
b. Wake up in the middle of the night or early morning				
c. Have to get up to use the bathroom				
d. Cannot breathe comfortably				
e. Cough or snore loudly				
f. Feel too cold				
g. Feel too hot				
h. Have bad dreams				
i. Have pain				
j. Other reason(s), please describe:				
6. During the past month, how often have you taken medicine to help you sleep (prescribed or "over the counter")?				
7. During the past month, how often have you had trouble staying awake while driving, eating meals, or engaging in social activity?				
	No problem at all	Only a very slight problem	Somewhat of a problem	A very big problem
8. During the past month, how much of a problem has it been for you to keep up enough enthusiasm to get things done?				
	Very good	Fairly good	Fairly bad	Very bad
9. During the past month, how would you rate your sleep quality overall?				

	No bed partner or room mate	Partner/room mate in other room	Partner in same room but not same bed	Partner in same bed
10. Do you have a bed partner or room mate?				
	Not during the past month	Less than once a week	Once or twice a week	Three or more times a week
If you have a room mate or bed partner, ask him/her how often in the past month you have had:				
a. Loud snoring				
b. Long pauses between breaths while asleep				
c. Legs twitching or jerking while you sleep				
d. Episodes of disorientation or confusion during sleep				
e. Other restlessness while you sleep, please describe:				

Epworth Sleepiness Scale

Name: ____ Today's date: _________________

Your age (Yrs): _______________ Your sex (Male = M, Female = F): ________

How likely are you to doze off or fall asleep in the following situations, in contrast to feeling just tired?

This refers to your usual way of life in recent times.

Even if you haven't done some of these things recently try to work out how they would have affected you.

Use the following scale to choose the **most appropriate number** for each situation:

0 = would **never** doze
1 = **slight chance** of dozing
2 = **moderate chance** of dozing
3 = **high chance** of dozing

It is important that you answer each question as best you can.

Situation	**Chance of Dozing (0-3)**
Sitting and reading ____	___
Watching TV ____	___
Sitting, inactive in a public place (e.g. a theatre or a meeting) _________	___
As a passenger in a car for an hour without a break _________________	___
Lying down to rest in the afternoon when circumstances permit ________	___
Sitting and talking to someone __________________________________	___
Sitting quietly after a lunch without alcohol ________________________	___
In a car, while stopped for a few minutes in the traffic ________________	

THANK YOU FOR YOUR COOPERATION

Date ____________________

Went to bed last night at ____________________

Attempted to fall asleep at ____________________

Minutes until fell asleep ____________________

Finally woke at ____________________

- Please estimate the time, your answer do not need to be very accurate

Awakened by ____ in the morning:

- ❒ Alarm clock
- ❒ Someone whom I asked to wake me
- ❒ Noises
- ❒ Just woke up naturally

After falling asleep, woke up how many times during the night?

0 1 2 3 4 5 or more

Total times of wakeups at night ____________________

- Woke to use bathroom
- Awakened by noises/child/bedpartner
- Awakened due to discomfort or physical complaint/pain
- Just woke

Ratings:

Sleep quality (1-8, very bad to very good):

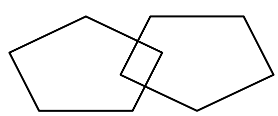
Mood on Final Wakening (1-8, very tense to very calm):

Alertness on Final Wakening (1-8, very sleepy to very alert):

Mini-Mental State Examination (MMSE)

Patient's Name: ________________________________ Date: ____________

Instructions: ***Ask the questions in the order listed. Score one point for each correct response within each question or activity.***

Maximum Score	Patient's Score	Questions
5		"What is the year? Season? Date? Day of the week? Month?"
5		"Where are we now: State? County? Town/city? Hospital? Floor?"
3		The examiner names three unrelated objects clearly and slowly, then asks the patient to name all three of them. The patient's response is used for scoring. The examiner repeats them until patient learns all of them, if possible. Number of trials: ___________
5		"I would like you to count backward from 100 by sevens." (93, 86, 79, 72, 65, …) Stop after five answers. Alternative: "Spell WORLD backwards." (D-L-R-O-W)
3		"Earlier I told you the names of three things. Can you tell me what those were?"
2		Show the patient two simple objects, such as a wristwatch and a pencil, and ask the patient to name them.
1		"Repeat the phrase: 'No ifs, ands, or buts.'"
3		"Take the paper in your right hand, fold it in half, and put it on the floor." (The examiner gives the patient a piece of blank paper.)
1		"Please read this and do what it says." (Written instruction is "Close your eyes.")
1		"Make up and write a sentence about anything." (This sentence must contain a noun and a verb.)
1		"Please copy this picture." (The examiner gives the patient a blank piece of paper and asks him/her to draw the symbol below. All 10 angles must be present and two must intersect.) 
30		TOTAL

(Adapted from Rovner & Folstein, 1987)

Source: www.medicine.uiowa.edu/igec/tools/cognitive/MMSE.pdf Provided by NHCQF, 0106-410

Appendix B

Questions for Personal Support Workers

1. Do you think [participants name] has trouble falling asleep?
2. Do you think [participants name] has trouble to wake up in the morning?
3. Normally, when [participants name] goes to bed *at night*, wakes up *in the morning*?
4. Will [participants name] sleep after having breakfast/lunch?
5. From your observation, do you think [participants name] tosses and turns/wake up multiple times at night?
6. In the daytime, do you observe [participants name] has multiple naps/has excessive daytime sleepiness? If he/she does, when does [he or she] usually take naps? Morning or evening?
7. Do you think [participants name] sleep is overall good or bad? (Scale: 1 to 8)
8. From your observation, do you think [participants name] is a morning person or evening person?
9. Is [participants name] more active in the morning or in the afternoon?

Appendix C

Comprehensive Demographics

Table C.1: Comprehensive demographic data for healthy younger and older adults.

ID	Age	Sex	BMI	MEQ	PSQI	ESS
Y001	23	M	18.98	55	4	4
Y002	25	M	25.41	51	5	3
Y003	23	F	22.56	45	7	6
Y004	22	F	21.57	57	5	7
Y005	22	M	31.89	52	4	11
Y006	26	F	18.48	49	4	9
Y007	25	F	36.95	56	11	8
Y008	26	M	23.92	51	6	7
Y009	28	F	17.19	51	3	7
Y010	21	F	19.92	44	3	6
O001	83	M	21.60	54	6	7
O002	66	F	31.01	62	9	4
O003	73	F	25.83	51	10	12
O004	71	M	29.52	55	3	7
O005	76	M	22.93	46	7	9
O006	83	F	27.42	68	7	7
O007	88	F	27.95	59	15	3
O008	67	F	23.48	68	9	2
O009	72	F	26.56	62	8	6
O010	71	M	23.10	65	4	6

Table C.2: Comprehensive demographic data for OAWD.

ID	Age	Sex	BMI	MMSE	PD	Sleep Apnea	Insomnia	Take Medications
D001	85	M	29.45	19				✓
D002	68	F	44.53	24		✓	✓	
D003	85	F	34.67	16				✓
D004	97	M	22.62	19				
D005	91	M	24.95	22				
D006	83	F	39.64	19				
D009	89	F	19.35	20	✓			✓
D010	68	M	23.96	21	✓	✓		✓

Appendix D

Sleep Patterns

Table D.1: Sleep onset, offset, midsleep, duration, wake-up times and sleep quality score of healthy participants. Onset, offset, midsleep, duration are expressed in hh:mm, wake-up times and sleep quality score have no units. Values are presented as mean ± SD.

ID	Onset	Offset	Duration	Midsleep	Wake-up Times	Sleep Quality Score
Y001	0:09 ± 0:52	8:18 ± 1:24	8:08 ± 1:12	4:13 ± 1:00	0.86 ± 0.91	18.36 ± 1.59
Y002	1:36 ± 0:42	8:54 ± 1:14	7:17 ± 0:56	4:47 ± 1:15	1.79 ± 1.08	19.29 ± 2.71
Y003	1:17 ± 0:57	9:12 ± 1:12	7:55 ± 1:10	5:15 ± 0:55	0.29 ± 0.45	17.64 ± 1.59
Y004	23:29 ± 0:44	7:07 ± 0:36	7:37 ± 0:47	3:18 ± 0:32	1.36 ± 2.29	21.14 ± 1.96
Y005	1:24 ± 0:52	8:19 ± 0:51	6:54 ± 0:37	4:51 ± 0:48	0.13 ± 0.34	19.33 ± 1.35
Y006	1:13 ± 1:11	7:57 ± 0:32	6:44 ± 1:09	4:35 ± 0:43	1.79 ± 1.32	17.79 ± 2.24
Y007	22:56 ± 0:53	6:01 ± 1:19	7:05 ± 1:01	2:29 ± 1:00	0.71 ± 0.59	17.57 ± 2.80
Y008	0:48 ± 1:02	7:52 ± 0:52	7:04 ± 1:30	4:20 ± 0:36	0.53 ± 0.81	18 ± 2.48
Y009	0:32 ± 1:45	7:58 ± 1:17	7:26 ± 1:54	4:15 ± 1:12	1.57 ± 2.16	17.21 ± 3.72
Y010	0:02 ± 0:29	7:36 ± 0:27	7:34 ± 0:33	3:49 ± 0:23	0.13 ± 0.34	17.57 ± 3.31
O001	0:35 ± 1:05	8:07 ± 0:10	7:32 ± 1:10	4:23 ± 0:31	4.46 ± 1.00	17.5 ± 1.99
O002	23:28 ± 0:54	7:19 ± 0:46	7:50 ± 1:05	3:24 ± 0:38	2.07 ± 1.59	15.25 ± 3.53
O003	23:24 ± 0:51	7:27 ± 0:38	8:03 ± 1:09	3:26 ± 0:29	3 ± 1.56	17.64 ± 3.35
O004	0:11 ± 0:25	8:03 ± 0:43	7:51 ± 0:46	4:07 ± 0:27	2 ± 1.11	19.46 ± 2.57
O005	1:18 ± 0:38	9:24 ± 0:32	8:06 ± 0:31	5:21 ± 0:31	4.77 ± 0.80	17.62 ± 2.56
O006	23:01 ± 0:29	5:56 ± 0:42	6:55 ± 0:57	2:28 ± 0:22	2.36 ± 0.72	21.71 ± 0.96
O007	1:41 ± 1:29	9:45 ± 1:32	8:03 ± 1:48	5:43 ± 1:13	3.95 ± 1.62	14.55 ± 2.18

O008	22:42 ± 0:23	7:01 ± 0:28	8:19 ± 0:40	2:51 ± 0:16	3.56 ± 0.98	16.36 ± 2.38
O009	22:35 ± 1:17	5:24 ± 0:46	6:48 ± 1:16	1:59 ± 0:51	1.86 ± 1.12	16.14 ± 2.07
O010	23:19 ± 0:18	6:47 ± 1:03	7:28 ± 0:57	3:03 ± 0:36	0.43 ± 0.49	20.5 ± 1.5