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F3

Faculty of Electrical Engineering
Department of Cybernetics

Analysis of Actigraphic and Behavioural Data

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Declaration

I declare that the presented work was developed independently and that I have listed all sources of information used within it in accordance with the methodical instructions for observing the ethical principles in the preparation of university theses.

Prague, January 4, 2022

Prohlašuji, že jsem předloženou práci vypracoval samostatně a že jsem uvedl veškeré použité informační zdroje v souladu s Metodickým pokynem o dodržování etických principů při přípravě vysokoškolských závěrečných prací.

Praha, 4. ledna 2022

Abstract

Sleep belongs among the most critical determinants of a person's health. Consequently, it might prove invaluable to track one's sleeping patterns and establish a healthy sleep routine. In the field of biomedical research, actigraphic data depicting one's activity throughout the day are most commonly employed to determine the sleep duration and quality. However, the means of collecting the data can produce significant blank spots if the user is not conscientious. Furthermore, sleep detection performance based on actigraphic data is limited due to its simplicity. We investigate the usability of behavioural data representing smartphone device usage patterns for sleep detection. We conduct a small-scale research study joined by twenty-one volunteers to produce a reasonably large dataset. Subsequently, we train a random forest classifier on the collected accelerometer data achieving mean accuracy of 89.05% across cross-validation testing sets. We find that gyroscope data cannot be utilised in the same manner due to lower variability and frequent breaks in data collection. Finally, we propose a post-processing extension of a state-of-the-art sleep detection model resulting in a minor improvement in its sleep detection capabilities.

Keywords: actigraphy, behavioural data, digital phenotyping, sleep detection

Supervisor: doc. Ing. Daniel Novák, Ph.D.

Abstrakt

Spánek patří mezi nejdůležitější faktory určující lidské zdraví. Sledování spánkového chování a nastavení zdravých spánkových návyků proto mohou nést nedocenitelný užitek. Aktigrafie líčící lidskou aktivitu v průběhu dne je nejčastěji používanou metodou určování doby a kvality spánku v oblasti biomedicínského výzkumu. Nesvědomitost uživatele však může mít u tohoto způsobu detekce spánku za následek hluchá místa. Jednoduchost aktigrafie navíc limituje možnosti modelů založených čistě na aktigrafických datech. V naší práci zkoumáme využití behaviorálních dat popisujících návyky v užívání chytrého telefonu za účelem detekce spánku. Součástí práce je organizace malé výzkumné studie, jíž se zúčastnilo 21 dobrovolníků, s cílem vytvořit dostačně velký dataset. Následně je na datech získaných z aktigrafického senzoru natrénován náhodný les dosahující ve spánkové detekci přesnosti 89.05% napříč testovacími sety křížové validace. Zjišťujeme, že z důvodů nižší variability a častých výpadků ve sběru dat jsou podobné výsledky nedosažitelné pro data z gyroskopického senzoru. Kromě toho také navrhujeme rozšíření moderního spánkového modelu, jež vede k drobnému zlepšení schopnosti modelu detekovat spánek.

Klíčová slova: aktigrafie, behaviorální data, digitální fenotypizace, spánková detekce

Překlad názvu: Analýza aktigrafických a behaviorálních dat

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Chapter 1

Introduction

Establishing a good sleep routine can greatly benefit any person's health in the long run. Detection and observation of one's sleeping patterns may help in the creation of such routine. The importance of sleep detection is even more pronounced in the field of biomedical science. Specifically, medical professionals use sleep detection models to diagnose psychiatric disorders and subsequently prevent their negative impacts on a patient's life by observing the evolution of their illness. To do so, actigraphy is generally employed as the most reliable alternative that requires little to no direct interaction from patients. By actigraphy, we mean the collection of a person's activity levels in time measured by a wearable motion sensor. Unfortunately, actigraphy is haunted by blind spots caused by removals of the actigraphic device from one's body and limited precision when compared to polysomnography, the gold standard of sleep detection measures, due to its simplicity. In the thesis, we investigate the possibility of improvement of a state-of-the-art sleep detection model based on actigraphy using behavioural data in the form of information on a person's smartphone device usage.

Since there is no dataset combining actigraphic and behavioural data freely available, we conduct a small-scale research study on 21 healthy volunteers lasting for over three months to produce such set of data. Throughout the research study, we collect actigraphic data on study participants using a simple actigraphic wristband and behavioural data by employing a digital phenotyping platform called Beiwe. To assess the quality of our results, we use self-reported sleeps obtained through questionnaires filled in daily by study participants. We find that behavioural can prove useful to enhancement of sleep detection capabilities of a state-of-the-art sleep detection model based on actigraphy. More specifically, we study three types of behavioural data in detail. Firstly, we train a random forest classifier employing accelerometer data depicting movement and vibrations of a smartphone device that achieves mean accuracy of 89.05%, sensitivity of 93.89%, and specificity of 79.41% across testing samples when using k-fold cross-validation with $k = 5$. In consequence, we believe that accelerometer data can be reasonably used to increase the performance of a sleep detection model. Secondly, we try to apply gyroscope data on orientation and angular velocity of a smartphone devices in a similar fashion. However, the final classifier is limited by frequent breaks in data collection of the sensor preventing the use of auto-correlated features and achieves much more sober rates of 73.99%, 86.69%, and 48.45% for accuracy, sensitivity, and specificity, respectively. Finally, we investigate the applicability of power state data on the use of a smartphone device as a post-processing extension of the state-of-the-art model. We achieve a minor increase in performance in terms of accuracy and sensitivity amounting to 0.51% and 1.08%. However, these improvements are made at the cost of 0.68% in terms of specificity. We argue that the loss is caused mainly by evaluation in terms of relatively imprecise self-reported sleeps and a significantly larger improvement could be gained when assessed by a more precise metric.

The remainder of the thesis is organised as follows. In chapter 2, we present a short overview of the literature on topics covered in the thesis. In chapter 3, we summarise the research study conducted as part of the work on this thesis. In chapter 5, we focus on data collected and used in the analysis. In chapter 6, we present results of the analysis. In chapter 7, we discuss the results and their limitations and propose further research directions. In chapter 8, we conclude the work.

Chapter 2

Literature Review

In this chapter, an overview of the literature on topics studied in the thesis is provided. In section 2.1, both traditional and less common tools used for sleep measurement and detection are presented along with examples of studies utilising them. In section 2.2, the recent trend of making use of data on smartphone device usage is detailed.

2.1 Sleep Detection

Nowadays, observing one's sleeping patterns has become relatively easy even without investments in expensive medical equipment. However, the gold standard of sleep measures in the field of medical science remains to be polysomnography (PSG), the simultaneous observation of multiple bodily functions during sleep in a laboratory setting (Van de Water et al., 2011). The method consists of observing one's heart rate, brain activity, muscle motion, eye movement, and other factors allowing a specialist to evaluate sleep objectively and diagnose sleep disorders with a high degree of precision. However, the necessity for examinations to be made in a specially equipped sleeping laboratory and with professional supervision causes PSG to be impractical or even impossible to use in situations where longer-term observations of sleep habits are essential. For this reason, researchers have been developing alternative sleep measures employable in the home environment.

Portable PSG belongs among the first attempts at this challenging task. Portier et al. (2000) shows that the home alternative to traditional PSG provides comparable results for only two-thirds of individuals due to data quality being too dependent on the wearer and their ability to attach all parts of the device to their body correctly. Consequently, researchers began to focus on simpler devices capturing a smaller set of factors that patients could use more efficiently. These measures target either the detection of specific sleep disorders or general sleep–wake cycles. The most prominent one is actigraphy. The measure gathers information about movement subsequently processed to determine activity and sleep cycles. Typical actigraphic devices are a wristband, ankle band, and a set of sensors positioned under bed legs. Many studies, such as those conducted by Cole et al. (1992), Ancoli-Israel et al. (1997), Benson et al. (2004), Choi et al. (2007), and Beecroft et al. (2008), compare these devices to PSG due to their popularity and ease of use with convincing results. We can also note non-contact biomotion sensors recording the movement of an individual's chest and body studied by Fox et al. (2007) and De Chazal et al. (2008). Furthermore, Edinger et al. (2004) and Merilahti et al. (2007) analyse sensors attachable to the eyelids and bed, respectively. Additionally, Hauri (1999) evaluates a sleep switch held between the thumb and the index finger registering the decline in pressure when its user falls asleep.

Recently, hundreds of millions of people began to keep track of their sleep habits due to the emergence of smartphone applications and wearables providing the service while requiring minimal interaction from their users (Chinoy et al., 2021). However, the detection capability varies heavily depending on the technology used. Fino et al. (2020) find that among four generally used smartphone applications, only one based on a smart alarm capability compares at least in part to the portable PSG. According to the authors, the other three applications utilising accelerometer, microphone, and sense do not provide reliable detection of sleep–wake cycles. Bhat et al. (2015) achieve similar results for a smartphone application utilising a smart alarm functionality. On the other hand, most consumer wearables evaluated by Chinoy et al. (2021) were deemed better at detecting sleep than simple actigraphs due to their utilisation of additional factors such as heart rate and motion. Similarly, Roberts et al. (2020) find multi-sensor wearables comparable to actigraphs and support their future use as an alternative to traditional research devices.

2.2 Digital Phenotyping

Behavioural phenotyping, the process of identifying a person's personality traits and behavioural patterns, has been a vital part of biomedical science for decades (Skuse, 2000). Many diagnoses rely upon the practice, especially when it comes to psychiatric disorders. Previously, surveys producing self-reported data served as the primary information source for phenotyping. However, a notable trend referred to as digital phenotyping recently emerged (Torous et al., 2015). The trend employs usage patterns of digital devices for phenotyping purposes. Unsurprisingly, smartphone devices present the main focus of the research string, although other devices such as wearables can also provide valuable data.

We can find the Beiwe platform initially unveiled by Torous et al. (2016) and fully covered by Onnela et al. (2021) among the most prominent representatives of platforms enabling digital phenotyping in practice. Since its original release, many studies have relied upon the data produced by the platform. Staples et al. (2017) show that one can use accelerometer data produced by the Beiwe platform to detect sleep patterns of patients struggling with schizophrenia with a reasonable amount of precision and significantly lowered costs compared to other means of sleep detection. Similarly, Barnett et al. (2018) employ data regarding mobility and social interaction changes to detect relapses prior to their occurrence for schizophrenic patients. Berry et al. (2019) harness speech data to evaluate the disorder progression of amyotrophic lateral sclerosis patients. Furthermore, some projects, including the work of Wang et al. (2021), take advantage of the platform's open-source nature to build upon it and retrieve additional passive data. We apply the Beiwe platform to produce behavioural data throughout our research study.

Chapter 3

Research Study

This chapter presents a research study conducted to obtain data for the empirical part of the thesis. In section 3.1, we explain the decision to organise the research study and its necessity. In section 3.2, we describe the onboarding process of study participants. In section 3.3, we illustrate the day-to-day process of the research study.

3.1 Motivation

The primary goal of this thesis is to test whether it is possible to improve a traditional sleep detection model built using actigraphic data by employing information about the behaviour of the user. Supposing an extension of the model enhances its detection capabilities in a significant manner, practical deployments of the system would allow people to trace their sleep patterns more precisely and benefit from this knowledge in terms of their health. A particularly important practical application can be located in the field of medical science. Specifically, doctors trace sleep patterns of patients suffering from bipolar disorder to establish what phase of the illness a patient is in and how the illness develops in time. However, it is out of the scope of this thesis to conduct a research study on bipolar patients. To do so, a much more strict environment for the study must be created, especially in terms of education of those communicating directly with the patients and in terms of professional and moral supervision over the study. At the same time, it is very important to acknowledge that datasets combining actigraphic and behavioural data are not generally available and a construction of such dataset was necessary to develop the model.

For the aforementioned reasons, we opted to conduct a small research study on a sample of healthy controls participating voluntarily to produce a set of data subsequently used in the empirical part of this thesis. For obvious reasons, the actigraphic and behavioural data are extremely sensitive in nature. Accordingly, we prepared a study protocol ensuring that all data were made anonymous before they were provided to members of the research team for analysis. Specifics of the research study are presented in the following sections of this chapter.

3.2 Onboarding

To participate in the research study, every volunteer had to undergo an onboarding process defined within the protocol of the study. In the beginning of the process, one member of the research team was assigned to a volunteer to become their primary connection point to the study. Subsequently, the volunteer was given two forms. Firstly, they were provided with the *Information About the Study and Informed Consent* form. This document contained all information about the research study that could be relevant to the volunteer. Specifically, the document introduced motivations for the study, rights and obligations of its participants, potential risks, and clarifications about data handling. Secondly, they received the *Consent to the Handling of Personal Information* form. This document provided specifics about all parties involved in the handling of personal data, the nature and means of obtaining the data, and what rights a study participant has with regards to the data. The original versions of the *Information About the Study and Informed Consent* form and the *Consent to the Handling of Personal Information* form written in Czech can be located in Appendix A and Appendix B, respectively. As part of the two forms, the volunteer was asked to sign that they fully understand all information provided to them and agree with the consequences of participating in the study. Unless both of these explicit consents were provided by the volunteer, the onboarding process could not carry on.

Assuming the volunteer decided to provide the research team with both consents, a meeting was arranged to assess whether the necessary condition of the volunteer being indeed a healthy control is satisfied. To do so, a representative of the research team carried out the *Mini International Neuropsychiatric Interview* (MINI) presented by Lecrubier et al. (1997) and translated to Czech by prof. MUDr. Petr Zvolský, DrSc. with the volunteer. This short structured interview was designed in order to establish a solid tool for detection of severe psychiatric disorders in a much shorter span of time compared to alternatives. Even more importantly, the straightforward nature of the interview allows for it to be conducted by any generally educated individual after only a small amount of training and preparation. Additionally, we extended the interview by a set of eight questions regarding personal characteristics and behaviour to determine the general features of the sample group. By introducing the questions, a possibility of studying particular subsets of the sample group arises. The complete set of questions extending the interview can be found in Table 3.1. The questions were asked in Czech, the table contains their English translation.

Depending on the assessment made based on the interview, the volunteer was either accepted into the study or denied participation. In the case they were accepted into the study, the volunteer was given an actigraphic wristband to wear throughout the research study. Furthermore, a selected member of the research team generated access information to applications used in the study to retrieve data from the actigraphic wristband and to obtain behavioural data from the device used by the volunteer. These tools and platforms used in the

Label	Question
A01	Do you engage in sports? If yes, how many times per week?
A02	Do you smoke?
A03	Do you drink alcohol? If yes, how many times per week?
A04	Do you abuse addictive substances? If yes, in what form and magnitude? How often?
A05	Do you work? If yes, under what contract? What environment do you work in?
A06	Do you study? If yes, in what form? What field of study?
A07	What is your highest level of finished education?
A08	Is there someone from your close family diagnosed with a bipolar disorder, depression, or any other mental disorder? If yes, could you specify?

Table 3.1: Extension of MINI

research study are detailed in chapter 4. The access information was delivered to the volunteer in the form of a secluded document additionally containing short manuals to the applications. Naturally, the volunteer was encouraged to ask questions regarding any information or instructions that they did not fully understand throughout the onboarding process. The member of the research team chosen as their primary connection point to the study was supposed to be always on call to clear any ambiguities.

3.3 Course

At the end of the onboarding phase, there were twenty volunteers accepted into the research study with one additional volunteer joining the study later on during the second half of its course. In accordance with the information given during the onboarding process, the volunteers were asked not to remove the actigraphic wristband provided to them by the research team from their wrist unless absolutely necessary at any time throughout the whole study. Due to concerns about the ability of the wristband to withstand water and also to increase general comfort and hygiene, the volunteers were explicitly supported in removing their wristband when taking a shower, swimming, or engaging in other activities leading to a severe increase in probability of the wristband coming into contact with water. Aside from that, the volunteers were asked to ensure that they start-up the application used for collecting behavioural data from their mobile device each time they restart it. Most importantly, they were also asked to fill in a daily questionnaire detailed in this section.

The research study ran in two terms separated by a break of one week. The length of each term along with the corresponding number of participants can be found in Table 3.2. The originally envisioned length of the study corresponds to the duration of the first term. The second term was conducted

Term	Beginning	End	Days	Participants
1	March 15, 2021	May 9, 2021	56	20
2	May 17, 2021	June 30, 2021	45	17

Table 3.2: Research Study Terms

to extend the dataset. All participants of the first term were approached and asked whether they want to participate in the second term of the study as well. Out of the twenty volunteers joining the first term, four individuals decided not to continue in their participation. On the other hand, one additional volunteer joined the study for the duration of the second term. In the remainder of this thesis, study participants are referred to using labels from BA001 to BA021 assigned at random.

3.3.1 Daily Questionnaire

By far the most important task of every study participant was to fill in a questionnaire appearing daily within a smartphone application called Mindpax.me developed by MINDPAX s.r.o. (2020) used to retrieve data from the actigraphic wristband. The application is described in detail in section 4.2. The questionnaire contained questions regarding each area of interest that members of our research team focus on in their respective theses. Specifically, the areas of interest include sleep, mood, and activity. Due to concerns about ambiguity of some of the questions raised by study participants, some partial adjustments were made after the initiation of the study. Perfect understanding of each question appearing in the daily questionnaire had an utmost importance due to the reliance of data analyses conducted by the research team on these self-reported values. Therefore, every study participant was guided through each of the questions by their connection point to the research study when they filled in the questionnaire for the first time. The final version of the daily questionnaire can be found in Table 3.3. Again, the table contains English translations of questions that were originally asked in Czech.

The first two questions of the daily questionnaire are an irreplaceable source of data for this thesis. The three following questions are aimed primarily at a correlation analysis of mood and behavioural data conducted by two other members of the research team. The last two questions provide a source of information for an analysis conducted by one member of the research team studying the applicability of actigraphic and behavioural data for detection of work days and free days. For many people all around the world, these two day types had become more intertwined than ever before during the course of the study due to the pandemic. In consequence, the formulation of question no. 6 had to capture a broader scope than a simple yes or no question on whether the previous day was a work day. Specifically, the behavioural patterns of a person working from home, working from the office, or enjoying a free day differ significantly.

We gave the study participants an unrestricted time frame of 24 hours to

№	Question	Answer
1	What time did you go to sleep last night?	$\langle$0:00,23:59$\rangle$
2	What time did you wake up this morning?	$\langle$0:00,23:59$\rangle$
3	Mood today:	$\langle$-1,1$\rangle$
4	Inner feeling today:	$\langle$-1,1$\rangle$
5	Energy today:	$\langle$-1,1$\rangle$
6	What kind of day did you have yesterday?	{1,2,3,4}
7	How long did you engage in physical activities yesterday?	$\langle$0:00,23:59$\rangle$

Note: The scale of question no. 3 goes from the worst possible mood (-1) to the best possible mood (1). The scale of question no. 4 goes from the most anxious (-1) to the most relaxed (1). The scale of question no. 5 goes from the least energetic (-1) to the most energetic (1). The set of answers to question no. 6 consists of work from home (1), work from the office (2), combination of both (3), and free day (4) along with corresponding school alternatives to all four answers.

Table 3.3: Daily Questionnaire

fill in the questionnaire for the day. Nonetheless, we suggested that they fill in the questionnaire ideally in the middle of the day. The primary reason was that at that time, they would still quite precisely remember the time frame of their sleep while also being able to confidently specify their mood, inner feeling, and energy level for the day. While this suggestion worked reasonably well in the initial weeks of the research study, it was very easy to divide the study participants into groups based on their responsibility towards the study afterwards. To achieve a solid response rate, one member of the research team had to be selected to check that the daily questionnaire is filled in by all study participants every afternoon and notify those that were yet to fill in their form. Additionally, the course of the study showed later on that the time frame for filling of the questionnaire should have been more restricted. Although we are talking about units of observations, some answers were filled in after midnight. These answers were then tied to the following day. Furthermore, the questionnaire of the following day was considered filled by the system with no possibility of replacement or reassignment of the answers filled in after midnight within the system itself. Manual alternations to these specific days are thus necessary in the data preparation phase of the analysis.

Chapter 4

Technology

This chapter presents tools and platforms used in the research study. In section 4.1, we summarise the means of data collection and their role within the study. In section 4.2, we describe the actigraphic wristband used to collect actigraphic data. In section 4.3, we present the Beiwe platform employed to retrieve behavioural data from smartphones of study participants. In section 4.4, we focus on the LAMP platform prepared as a potential substitute for the Beiwe platform.

4.1 Overview

We used two primary means of data collection throughout the research study. Firstly, we distributed actigraphic wristbands to all study participants with the intention of collecting their actigraphic data. Secondly, we instructed the study participants on installation of a mobile application connected to a platform called Beiwe that allowed us to collect their behavioural data from their mobile devices. Additionally, we prepared a platform called LAMP as a quickly deployable substitute in case the Beiwe platform stopped functioning at some point during the research study. Thankfully, the substitute was ultimately not necessary. Therefore, we avoided having to deal with a distributional shift in observed variables at some point during our study. Furthermore, the switch would result in partially different variables being retrieved from the device before and after its occurrence.

Before the beginning of the study, we acknowledged that all three means of data gathering are at least in part dependent on the dedication, perseverance, and technical skilfulness of the study participants. Therefore, we conducted multiple rounds of testing of the employed platforms in the months preceding the beginning of the research study to avoid as many problems with data collection as possible during the course of the study itself. Furthermore, these testing periods allowed us to carefully evaluate which of the two behavioural data collection platforms was more suited for our needs and more robust to technical difficulties with data collection. As mentioned above, we ultimately chose the Beiwe platform as the superior source of behavioural data. In the remainder of this chapter, all three means of data collection are presented in detail and their primary qualities and disadvantages are noted.

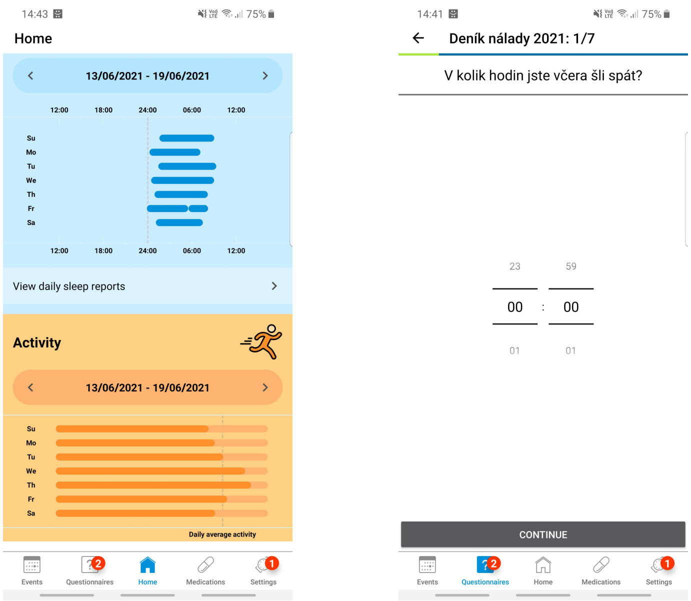
4.2 Actigraphic Wristband

The main technological tool that our research study depended on is the aforementioned actigraphic wristband. Specifically, we are talking about a very simple circular token capable of measuring its own motion. To register movement and its severity, the token contains two plates covered with pressure sensitive stumps positioned against one another. These plates are partially loose and register the touch of opposing stumps and its magnitude during any movement of the token. Specific values are then saved into the memory of the token at predetermined time intervals. To be concrete, the token saves the amount of motion captured once in approximately thirty seconds. This motion registering token is inserted into a wristband made from leather. Ultimately, the device closely resembles watches. It is also equipped with twelve LEDs forming a circle in the front panel of the token. The LEDs are used to display information to the user during the pairing process, to inform them of a low battery level, and to notify them about important errors.

The actigraphic wristbands were provided to our research team by a Czech startup called MINDPAX s.r.o. The company focuses its products and research directly on people suffering from bipolar disorder and schizophrenia. Since the establishment of the company in 2015, it produced two major systems enabling patients to supply their actigraphic data gathered by the wristbands to their doctors along with prior detection of sleep and activity patterns in the data. In turn, doctors can use the received information to determine in what stage of their illness their patients currently are and help them accordingly. Along with the actigraphic wristbands, the company gave us access to its infrastructure. Specifically, we were allowed to utilise its smartphone application called Mindpax.me developed to retrieve data from the wristbands via Bluetooth. Furthermore, we could use the corresponding web application used to access the data stored on a server.

4.2.1 Application Mindpax.me

The smartphone application Mindpax.me developed by MINDPAX s.r.o. (2020) is accessible on both major smartphone operating systems, iOS and Android, through their native application stores. When the application is started for the first time, the user is asked to log in and pair their actigraphic wristband with the application. To do so, one has to carry out a simplistic pairing signal consisting of laying the wristband on a horizontal surface, turning it to an orthogonal angle with the surface, and laying it back down. When performing the pairing signal, the LEDs inform the user about the wristband registering each part of the process. The same signal is subsequently used to force retrieval of data from the wristband during use. Of course, the mobile device the actigraphic wristband is paired with has to be nearby and its Bluetooth must be turned on for the retrieval to be successful. In addition to that, the application tries to retrieve data from the actigraphic wristband without the need for any interaction by the user once a day. During the course of our research study, this functionality worked very well for study participants with Android, however, it rarely collected data without interaction for study participants with iOS. Furthermore, one of the study participants facing pairing difficulties had to undergo the pairing process in its entirety each time they wanted to retrieve data from the wristband. On the other hand, the actigraphic wristband is capable of storing the data for several weeks. Therefore, problems with the iOS version of the application did not obstruct our research study in any important way.



(a) : Home screen **(b) :** Questionnaire

Note: The pictures were captured in the Mindpax.me application for Android on Samsung S8+.

Figure 4.1: User Interface of Mindpax.me

While sustaining high levels of simplicity, the application provides some additional tools for its users. Specifically, one can view the detected sleep ranges along with the amount of activity exerted every day compared to their average activity levels over each week. Furthermore, one can use the application as a medication reminder. This is very useful when a patient utilises the application in cooperation with their doctor who is provided with a robust overview of their medication intake. Finally, the application can be used to generate periodically occurring questionnaires to a selected group of users. We used this functionality to gather daily data about sleep, mood, and activity of the study participants as described in section 3.3.

4.3 Beiwe Platform

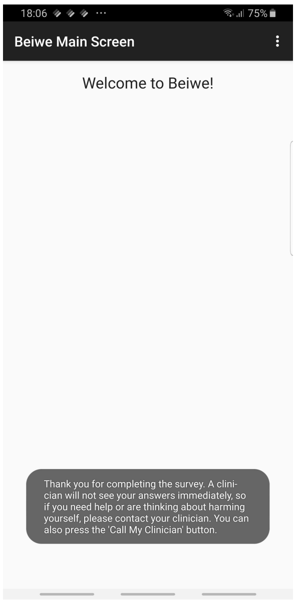
The development of the Beiwe platform began in 2013 by a team overseen by Jukka-Pekka Onnela, an Associate Professor at the Harvard University. Specifically, the project comes under the competence of his Onnela Lab at the Department of Biostatistics at the Harvard T. H. Chan School of Public Health. The initial release of the platform dates back to 2016. The platform aims at providing researchers interested in digital phenotyping with an apt tool encompassing all essential parts of the data gathering process. Specifically, the platform comprises of a web application allowing one to manage ongoing research studies with ease, smartphone applications for iOS and Android retrieving behavioural data from the devices of participants, a database to save all of the captured data, and a data processing pipeline system. The platform is fully open-source and developed under the BSD-3 license. The source codes of its back-end and both smartphone applications are available on GitHub. Onnela et al. (2021) describe the Beiwe platform in full. We cover past studies relying on the platform in section 2.2.

Amazon Web Services (AWS) provide the necessary infrastructure to deploy the Beiwe platform quite easily even without a full prior understanding of the system and its implementation. The use of AWS drives up the overall costs of deployment. However, it also makes the system easily manageable because of the possibility to resolve errors and go through the server's log using a very simple interface. Furthermore, it ensures that scaling of an ongoing research study is just a very small inconvenience rather than a large obstacle requiring infrastructure investments and redeployment of the whole system. The direct monetary costs for running the platform based on our research study joined by twenty volunteers are about \$5 per study participant per month. However, the costs are non-linear and marginally decreasing with an increasing study size. For smaller studies, they can rise up to \$10 per study participant per month.

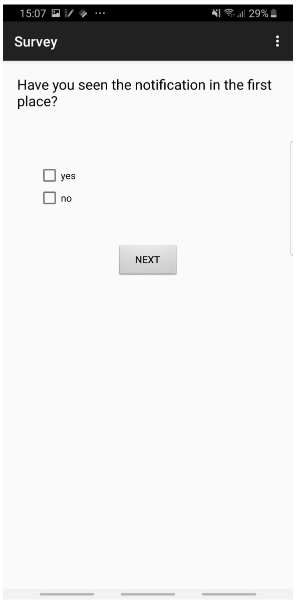
4.3.1 Application Beiwe2

The front-end of the Beiwe platform consists of an application called Beiwe2 that was developed by Harvard University Onnela Lab (2021) for iOS and Android. Even though it is available on both leading operating systems, the diversity of smartphone devices causes the functionality to vary significantly. Our tests show that the application generally tends to perform better on iOS devices. The performance of the Android version relies heavily on the manufacturer of the specific device with full functionality on Samsung devices and severe problems on Xiaomi phones.

Examples of the application's interface on Android is shown in Figure 4.2. Clearly, the authors' primary goal during development was simplicity. The functionality of the application is restricted solely to the possibility of active data gathering through questionnaires that can be set up by organisers of a study. No insight into the retrieved data is provided to the user.



(a) : Home screen



(b) : Questionnaire

Note: The pictures were captured in the Beiwe2 application for Android on Samsung S8+.

Figure 4.2: User Interface of Beiwe2

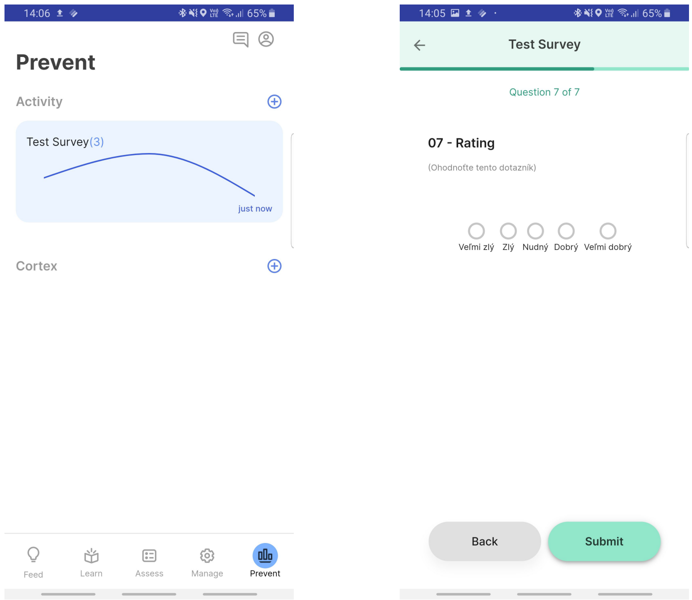
4.4 LAMP Platform

Compared to Beiwe, the LAMP platform is a much younger project initiated by the Division of Digital Psychiatry at the Beth Israel Deaconess Medical Center affiliated with the Harvard Medical School. Similarly to Beiwe, the primary goal of its developers was to create a platform enabling the retrieval of behavioural data used for digital phenotyping. However, while Beiwe focuses primarily on organisation of research studies and minimisation of the amount of interaction with the users, the LAMP platform also offers a stable long-term connection point between medical specialists and their patients with whom it meaningfully engages. Furthermore, LAMP enriches the retrieved information by activity data collected by wearables which are unattainable via the Beiwe platform. There is an ongoing development of the platform with a number of promised features still awaiting their introduction to the code base.

The LAMP platform can be run on one's own server. This drives up the initial investment if one does not have a server at their disposal. On the other hand, the subsequent monthly costs after deployment are significantly lowered when compared to running the platform on AWS. Studies utilising the platform can be managed using a dashboard in the form of a web application. The dashboard provides a large amount of information regarding participants of the study along with figures showing the development of the collected variables in time. When the platform is deployed on one's own server, the possibility of scaling is limited and dependent on additional investments into infrastructure requiring subsequent redeployment. Moreover, the deployment of the platform is more problematic due to differences between servers in terms of architecture and system.

4.4.1 Application MindLAMP 2

Study participants and patients engage with the platform via application called MindLAMP 2 developed by John Torous (2021) for iOS and Android. During our tests, the passive data collection functionality of the application was limited and highly dependent on the device it was installed on.



(a) : Prevent screen **(b) :** Questionnaire

Note: The pictures were captured in the MindLAMP 2 application for Android on Samsung S8+.

Figure 4.3: User Interface of MindLAMP 2

The user interface of the application is visually appealing and offers its users many ways of interaction. The study organiser can set up recurring questionnaires and cognitive games that the user has a timeline of together with visualisations of their answers in time. For personal reasons, users can also keep a journal and prepare to-do lists within the application interface. Additionally, the application enables sharing of news and articles by study organisers with study participants.

Chapter 5
Data and Methods

In this chapter, we investigate the data gathered throughout the research study and specify the means of their utilisation. In section 5.1, we look at the sleep duration data reported daily by study participants. In section 5.2, we shift our focus to the actigraphic data collected via actigraphic wristbands. In section 5.3, we detail the behavioural data obtained using the Beiwe platform. In section 5.4, we describe the sleep detection model and its extension using behavioural data.

5.1 Questionnaire Data

Daily questionnaires as specified in section 3.3 were introduced to study participants within the environment of the Mindpax.me application developed by MINDPAX s.r.o. (2020) to produce self-reported data. The responses were saved in a JSON (JavaScript Object Notation) format and stored in a CSV (Comma-Separated Value) file. Some difficulties were encountered with regards to daily completion of the questionnaire by all study participants, however, it was possible to gather a reasonably large set of answers. The completion rates of all study participants in both research study terms after initial rectifications specified further are shown in Table 5.1.

In Table 3.2, we set out the length of the first term of the study to be 56 days. The maximum amount of observations obtainable is, however, only 32 observations. For this thesis, the first two questions of the questionnaire are utilised. Unfortunately, these two questions were severely altered three weeks after the beginning of the study. In consequence, the prior 24 days of observations are not applicable. Thankfully, all answers gathered in the second term can be used in full.

The self-reporting nature of the data hints at some of its problems. Firstly, the sleep duration is unlikely to correspond to the actual value precisely. Nonetheless, we can consider it a good approximation of the value. Secondly, there are some noticeable outliers in the data. Specifically, the beginning of the sleep is the same as the end of the sleep for some observations. Clearly, this could mean that the person did not go to sleep at all on the given night. However, it could also mean that the person reported the same value to both questions due to inattention. Also, some self-reported sleeps last for eighteen

ID	Term 1		Term 2	
	Obs.	**Completion**	**Obs.**	**Completion**
BA001	32	100%	44	98%
BA002	25	78%	10	22%
BA003	32	100%	43	96%
BA004	28	88%	37	82%
BA005	20	62%	20	44%
BA006	31	97%	44	98%
BA007	29	91%	36	80%
BA008	19	59%	14	31%
BA009	32	100%	43	96%
BA010	31	97%	–	–
BA011	32	100%	44	98%
BA012	30	94%	–	–
BA013	27	84%	–	–
BA014	27	84%	31	69%
BA015	30	94%	38	84%
BA016	29	91%	38	84%
BA017	31	97%	44	98%
BA018	30	94%	–	–
BA019	32	100%	45	100%
BA020	29	91%	41	91%
BA021	–	–	33	73%
Total	576	90%	605	79%

Note: The completion rates are calculated based on the maximum amount of observations obtainable in each term of the research study.

Table 5.1: Daily Questionnaire Completion

hours or more. While these sleeps could be realistic and caused by prior sleep deficits, they mostly originate from a reporting mistake of twelve hours caused by the questionnaire on iOS showing times in the American time format with the person switching up AM and PM. All of these outliers are manually checked against the activity data and those that appear to be misleading are altered or completely removed from the data. Finally, the previously mentioned answers filled in after midnight require manual reassignment to their correct dates. In addition to these difficulties, the iOS version of the application almost always registered duplicate answers that needed to be removed from the dataset. Descriptive statistics of the self-reported sleep duration data are located in Table 5.2.

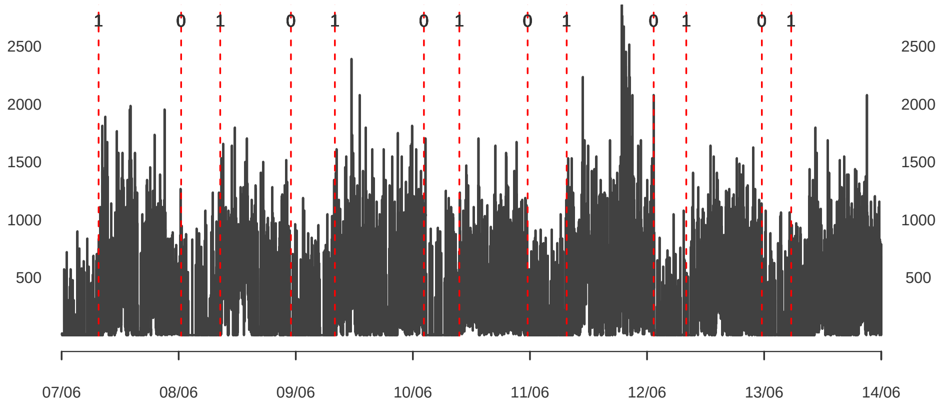
ID	Mean	Median	SD	Min.	Max.
BA001	7:29	7:30	1:09	2:30	9:30
BA002	7:48	8:00	1:33	4:06	10:00
BA003	6:36	6:30	1:37	2:55	11:00
BA004	7:38	7:40	0:50	5:41	11:00
BA005	7:07	7:00	0:47	5:30	9:00
BA006	8:24	8:25	1:03	5:15	11:50
BA007	8:17	8:00	1:32	5:00	14:00
BA008	8:19	9:05	2:30	2:34	11:54
BA009	7:56	8:00	0:47	5:42	9:20
BA010	7:58	8:00	1:54	4:30	13:00
BA011	8:59	9:00	0:53	7:15	11:35
BA012	8:41	8:40	0:31	7:30	9:50
BA013	8:30	8:20	0:47	7:01	10:02
BA014	7:26	7:30	1:21	4:00	11:00
BA015	6:38	7:00	1:45	2:30	11:00
BA016	7:58	8:00	1:40	3:25	12:00
BA017	7:27	7:49	1:34	1:58	11:30
BA018	8:22	8:11	1:27	5:52	11:53
BA019	7:56	7:50	0:38	6:00	9:15
BA020	8:52	8:56	0:56	6:00	11:00
BA021	6:04	6:45	2:59	0:50	11:00

Table 5.2: Self-Reported Sleep Duration

5.2 Actigraphic Data

The data collected with the help of the actigraphic wristband described in section 4.2 were stored in CSV files. There were a total of 5,981,089 data points gathered over the course of the research study. The activity data were saved about once in thirty seconds. Specifically, the predominant number of observations representing 97.17% of the sample lie 27 to 29 seconds apart. A total of 1.67% of observations were taken after a longer span of time between 30 and 35 seconds, while the remaining 1.16% of observations achieve higher frequency of 16 to 26 seconds. An insignificant number of observations corresponds to much larger breaks in data caused by various problems with storing the data, reading the data, and also physical damage to the actigraphic wristbands.

Overall, the actigraphic data are extremely solid in terms of prior processing with little to no need for intervention. Some observations correspond to invalid activity values, however, these observations can be easily cut out of the dataset. The time span between observations is an important determinant for how precise the sleep detection model can ultimately be. An example of a week of activity data observations along with self-reported sleep boundaries is shown in Figure 5.1.



Note: The figure shows an example of actigraphic data observed for one user over the period of seven days. Dashed vertical red lines denoted 0 and 1 correspond to self-reported beginnings and ends of sleep, respectively.

Figure 5.1: Actigraphic Data Example

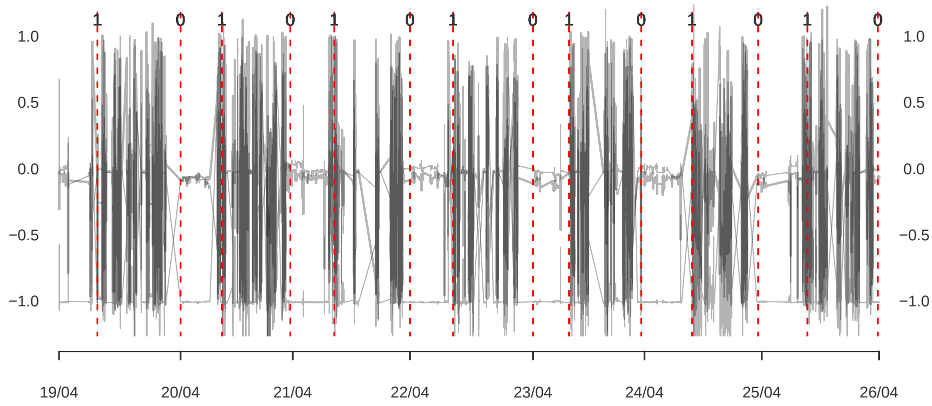
5.3 Behavioural Data

To gather behavioural data, the Beiwe platform detailed in section 4.3 is employed. Unfortunately, as opposed to the actigraphic data collected by a single device and thus sharing the same data generating process across all study participants, the behavioural data are highly varied and dependent on the smartphone that sources the data. Furthermore, the specific information gathered and the overall quality differs for devices with iOS and Android. In consequence, the selection of information used in further analysis is very important.

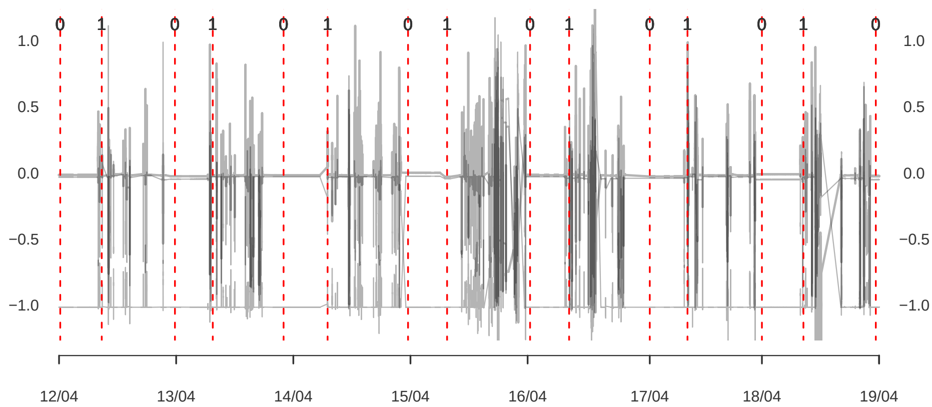
5.3.1 Accelerometer

Accelerometer located in a smartphone device enables identification of its rotation and movement. It captures information about positioning of the device along all three axes. Wearables equipped with an accelerometer can utilise it to determine a specific nature of an activity as shown by Ravi et al. (2005). For our needs, accelerometer data from smartphone devices can be used to differentiate between time sequences when the device is left untouched and when the device is either directly in use or carried somewhere. Consequently, this information can be used to determine time periods when the device's owner is awake and when they are not interacting with the device in any manner. An important assumption that this assessment is based on is that smartphone devices are operated and relocated solely by their owners.

Two examples of accelerometer data captured during the research study can be found in Figure 5.2. However, it is important to note that data of this quality were captured only on iOS devices. For Android devices, most data



(a) : Frequent Usage



(b) : Limited Usage

Note: The figures show examples of accelerometer data observed for two different users over the period of seven days. Dashed vertical red lines denoted 0 and 1 correspond to self-reported beginnings and ends of sleep, respectively. Data for all three axes are plotted on top of each other.

Figure 5.2: Accelerometer Data Example

are missing completely due to problems with implementation of the Beiwe platform on the operating system which we were aware of before the initiation of the research study. In the raw data, there are about ten data points captured every second. In our analysis, these data points are aggregated into periods of one second using arithmetic mean. Otherwise, the size of the data makes it overly difficult to work with due to computational requirements.

The data depicted in Figure 5.2a reflect self-reported sleeps uncommonly well due to the study participant using or at least carrying their smartphone device throughout the whole day. On the other hand, some study participants with data of comparable quality do not show nearly as nice patterns due to their limited smartphone device usage observable in Figure 5.2b. Specifically, some participants tend to look less at their device during the day and do not use it before going to sleep. Furthermore, the observed time period coinciding with the pandemic caused a number of participants beginning to work from home and not carrying their device around nearly as much as they otherwise would. This behaviour diminishes the potential benefits from the use of accelerometer data.

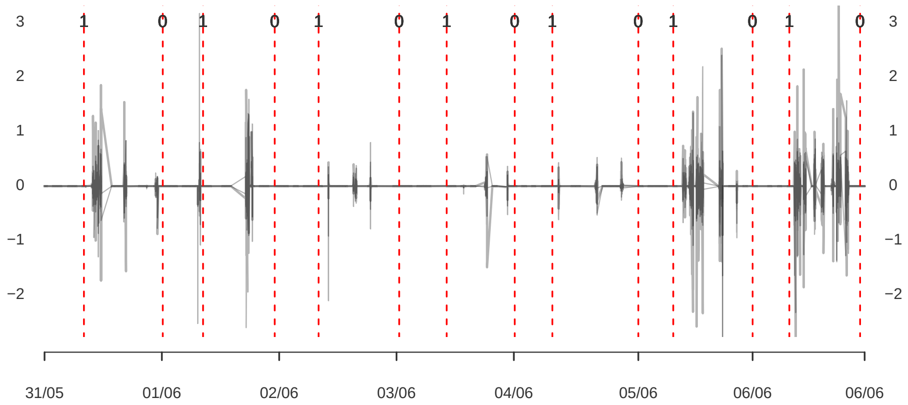
5.3.2 GPS

GPS data are also among the sensors collected by Beiwe. Individual observations contain precise information in terms of longitude, latitude, and altitude, meaning one can pinpoint these observations to specific locations and calculate distances between them. Furthermore, the accuracy of each observation is provided. Approximately 79.44% of observations lie one second apart, 0.81% are seeded within a single second, 14.22% have the frequency from one second to one minute, and the remaining 5.53% of observations lie more than one minute apart. More specifically, the data contain bursts of observations spread around one second apart followed by units to tens of minutes without any observations at all. The bursts occur more often during the day when the device is in use and less often throughout the night.

General movement from one location to another that are at least tens of meters apart can be registered with a large amount of confidence. However, precise movement periods are almost impossible to detect for two reasons. Firstly, the bursts of observations cause any precise identification of beginnings and ends of movement infeasible. Secondly, the GPS locator is generally imprecise and registers shifts in movement even when the phone stays in place. Specifically, the GPS data often indicate significant location shifts, occasionally even of hundreds of meters, even during periods of sleep of a study participant. Consequently, the GPS data are of no help in sleep detection. Furthermore, all true movements of a study participant that would be registered by GPS data would also be registered by accelerometer data. However, Barnett et al. (2018) show that there are other extremely relevant applications of the GPS data.

5.3.3 Gyroscope

Gyroscope is a sensor measuring its orientation and velocity of angular changes in all three axes. Although the sensor functions in a completely different way than an accelerometer and they are used for distinct purposes, the general information that the two sensors provide is the same. Specifically, they provide data on movement. In the dataset obtained as part of the research study, gyroscope data have the same frequency as accelerometer data. Whenever the sensor actively collects the data, approximately 10 observations are made every second on iOS devices. Gyroscope data for Android devices are scarcely available, however, there are usually 5 points of data per second whenever the data are at hand, even though Beiwe is set to gather data on all devices with the same frequency.



Note: The figure shows an example of gyroscope data observed for one user over the period of seven days. Dashed vertical red lines denoted 0 and 1 correspond to self-reported beginnings and ends of sleep, respectively. Data for all three axes are plotted on top of each other.

Figure 5.3: Gyroscope Data Example

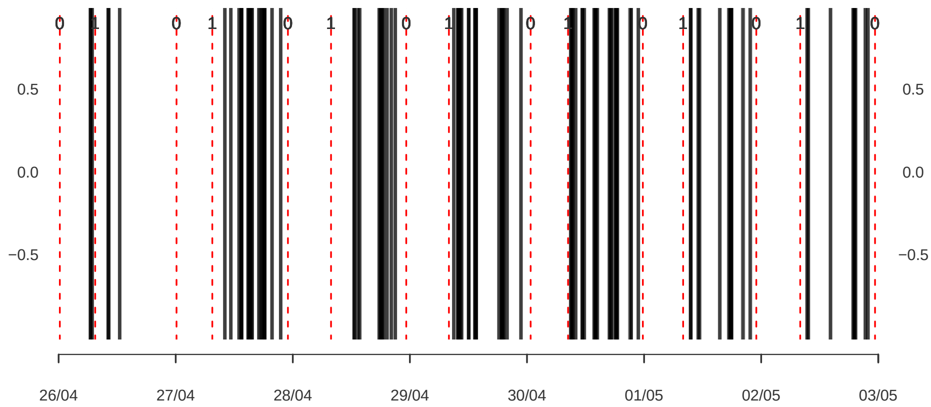
Nevertheless, the informativeness of gyroscope data is slightly lower. Specifically, gyroscope data of equal quality to those gained from accelerometer have much lower variability. This can be noted when comparing an example of gyroscope data shown in Figure 5.3 to examples of accelerometer data shown in Figure 5.2. Both of the figures present data with the same density. Overall, the number of observations collected by gyroscopes is much lower than that of accelerometers. On the other hand, gyroscope data can be partially used to cover time periods where accelerometer data are missing.

5.3.4 Power State

Without any exaggeration, any data on direct usage of one's smartphone device could be considered the most important information of all for many different studies including ours. Thankfully, this information is gathered by Beiwe as well in the form of power state data. Moreover, this stream of data is reliable both on iOS and Android devices as opposed to other data sources.

The data contain information about important events occurring with regards to the smartphone device. A bit unfortunately, the specific information differs for iOS and Android operating systems. For iOS devices, Beiwe captures information on the device being locked, unlocked, plugged into electricity, and unplugged from electricity. Additionally, it captures the current battery status of every event. For Android devices, the platform collects information on the device's screen turning on and off. Furthermore, it captures information on the device shutting down, idleness of the device, and changes in battery saving mode.

In general, the power state data are relatively good. Only a few observations per study participant inform about a change in power state not followed by the appropriate change back. For example, the event of unlocking the device is followed by another unlocking instead of locking. However, these difficulties with the data can be easily resolved while maintaining the quality of the dataset and losing units of observations. We unify the differences across operating systems by describing the event of being turned on when the device is unlocked or its screen is turned on. Similarly, the event of being turned off corresponds to the device being locked or its screen being turned off. None of the other information is retained.



Note: The figure shows an example of power state data observed for one user over the period of seven days. Dashed vertical red lines denoted 0 and 1 correspond to self-reported beginnings and ends of sleep, respectively. Vertical black lines represent time periods spent using the smartphone device.

Figure 5.4: Power State Data Example

In Figure 5.4, we show an example of processed data on the use of a device compared to self-reported sleep. Clearly, the data correspond very well, although some overlaps can be noticed for all study participants. Surprisingly, these overlaps are both frequent and extreme for particular study participants. A thorough look into the data shows that these study participants tend to fall asleep while using their device, possibly while watching some entertainment media. The device is then turned off deep into the night or early in the morning, sometimes solely due to the battery depleting. Furthermore, the information provided for Android devices is problematic due to the screen turning on and off because of incoming notification while the user is asleep. Unfortunately, tests show that duration of the screen being turned on due to an incoming notification is not constant, especially when the device uses facial recognition for unlocking. These problems with the data are resolved within the analysis.

5.3.5 Other Behavioural Data

The data presented thus far are available on both iOS and Android devices, albeit their quality differs significantly across devices as discussed above. They present a reasonable core of behavioural data that can be collected on any device. However, some other behavioural data with very limited applicability to the tasks set out as part of this thesis were collected during the research study as well. For example, Beiwe collected data on Bluetooth and WiFi connections available to the smartphone device at any time. This data could be used to differentiate between locations that a person spends time at and also time periods spent at crowded places such as public transport and shopping centres. However, they are of no use for sleep detection purposes. Secondly, operating system logs are collected. Nonetheless, these logs only inform on various sensors being registered for other data collection processes. Additionally, iOS devices provide information about the reachability status of the device. Specifically, they informs on whether they are connected to WiFi, cellular, or fully disconnected from all networks at different points in time. Unfortunately, the data are not continuous and lack usability for our purposes.

5.4 Sleep Detection Model

The primary goal of this thesis is to investigate the possibility of behavioural data employment for improvement of detection capabilities of a state-of-the-art sleep detection model. We use a model developed by MINDPAX s.r.o., the company that provided us with actigraphic wristbands used to collect actigraphic data from participants of the research study. The company uses the model to detect sleep patterns of patients suffering from bipolar disorder or schizophrenia. The model is based on a trained logistic regression model combined with algorithmic processing and detection in certain parts of the data. It detects three different states. Apart from differentiating between sleep and wakefulness of a person, the model also detects so called layoff periods representing sequences of time when the actigraphic wristband was removed from one's wrist.

To study possible enhancements in sleep detection capabilities of the model, we focus on three types of behavioural data. Specifically, we investigate the applicability of accelerometer, gyroscope, and power state data. We argue that these data types enable us to pinpoint periods of time a person was surely awake since they were manipulating with their smartphone device. For example, a person may operate their smartphone device with their dominant hand while laying in bed. Since the dominant hand is traditionally not used to wear wristbands and watches, data obtained using an actigraphic wristband could paint an improper picture about the sleep behaviour of such person. Furthermore, we might detect activity beyond any reasonable doubt during layoff periods and consequentially make the detection more robust to the user removing their wristband. Ultimately, the analysis focuses on potential restrictions of detected sleep and layoff periods since very little can be said about whether a person is sleeping or not when they are not using their smartphone.

Chapter 6

Results

This chapter presents results of data analysis. In section 6.1, we investigate the performance of the state-of-the-art model in terms of conformity with self-reported sleeps. In section 6.2, we investigate correlations for accelerometer data and train two sleep detection models to evaluate the employability of the data in practice. In section 6.3, we do the same for gyroscope data. In section 6.4, we focus on power state data and their potential utilisation in sleep detection improvement.

6.1 Model Performance

Before we investigate possible applications of behavioural data to improve sleep detection capabilities of the state-of-the-art model, it is necessary to propose some measure of success. An obvious candidate is some measure of conformity between detected and self-reported sleep-wake cycles. The sleep detection model establishes three states - sleep, wakefulness, and layoff. Whenever data are provided by the actigraphic wristband, one of these three states is assigned to every period of 30 seconds. Time periods without any activity data caused by errors in collection or retrieval of data from the wristband are not assigned a label. The best way to asses the power of the model in terms of agreement with self-reported sleep data is by looking at the confusion matrix. To produce it, layoff state periods must be removed from the dataset in order to have the same labels for both detected sleep-wake cycles and reported sleep-wake cycles available.

		Self-Reported	
		Wake	Sleep
Detected	Wake	1,901,019	114,898
	Sleep	101,688	860,212

Note: The total number of observations used to compose the confusion matrix is 2,977,817. All 24-hour periods from noon to noon for which study participants reported sleep are included in the dataset. Two study participant are removed due to actigraphic wristband difficulties.

Table 6.1: Confusion Matrix: Original Model

In Table 6.1, the confusion matrix of self-reported sleep-wake cycles and those detected by the state-of-the-art model are shown as a cumulative measure over all study participants with two exception who faced difficulties with their actigraphic wristbands. The sleep detection model achieves a very high accuracy of 92.73%, sensitivity of 94.92%, and specificity of 88.22%. The no information rate (NIR) enabling the assessment of whether the achieved accuracy is not caused by imbalances in classes is 67.25%. The null hypothesis that the model is insignificant tested by checking that accuracy is significantly larger than NIR is rejected at any commonly used level of significance. Clearly, the model performs well in terms of agreement between detection and self-reported duration of sleep.

ID	Obs.	Layoff	Acc.	Sens.	Spec.	NIR
BA001	217,322	194	96.51%	96.97%	95.51%	68.96%
BA002	96,221	4,614	89.65%	90.16%	88.58%	67.90%
BA003	209,660	653	92.15%	96.80%	80.18%	72.01%
BA004	145,029	40,796	90.37%	95.53%	77.13%	71.94%
BA005	93,763	21,477	81.34%	94.25%	50.34%	70.61%
BA006	195,142	19,493	94.48%	96.82%	90.61%	62.24%
BA007	182,177	2,207	94.32%	97.64%	88.04%	65.44%
BA008	88,416	6,657	83.22%	95.01%	61.58%	64.75%
BA009	210,850	3,785	95.23%	98.34%	88.84%	67.24%
BA010	77,882	11,429	90.39%	88.42%	95.49%	72.09%
BA011	211,384	4,691	88.24%	84.63%	94.28%	62.57%
BA012	84,128	2,302	95.92%	97.10%	93.83%	63.97%
BA013	75,397	2,390	86.39%	97.07%	67.82%	63.47%
BA015	192,655	372	94.53%	96.22%	90.08%	72.43%
BA016	189,421	725	91.22%	90.92%	91.83%	66.83%
BA017	207,749	5,445	96.10%	95.52%	97.42%	69.49%
BA018	85,999	431	87.12%	93.24%	75.77%	64.96%
BA019	219,707	690	97.59%	97.41%	97.96%	66.96%
BA020	194,915	3,874	96.19%	96.00%	96.51%	62.96%
Total	2,977,817	132,225	92.73%	94.92%	88.22%	67.25%

Note: The table contains individual results of sleep detection using the state-of-the-art sleep detection model when compared to self-reported data.

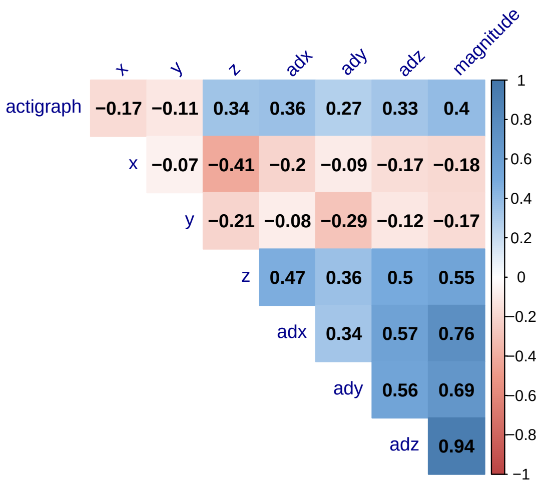
Table 6.2: Individual Model Performance: Original Model

In Table 6.2, we present the sleep detection performance of the state-of-the-art sleep detection model for 19 individuals for which valid data are available. The data show that around 4.25% of the total number of observations are detected as layoff periods. The distribution of layoffs across study participants is extremely uneven. The layoff proportion of data ranges from 21.95% and 18.64% in the worst cases to 0.19% and 0.09% in the best cases. Similarly, although the model is significant at any commonly used level of significance for all 19 individuals, the accuracy ranges from 81.34% up to 97.59%.

6.2 Accelerometer

When preparing the accelerometer data for subsequent use, it is necessary to recognise that we are working with time series data. Sleep detection models always involve some information about activity levels in periods both before and after the period that is being labelled. However, there is a lot of missing information in our datasets. Therefore, it is vital to prepare auto-correlated features before removing any observations with missing data. Otherwise, non-sensible features depending on completely unrelated periods of time would be computed. As far as the data go, the only accelerometer data of reasonable quality were all collected on iOS devices. In consequence, we are left with data on 10 study participants for the investigation of the use of accelerometer data.

6.2.1 Correlation Analysis



Note: The figure shows correlations of actigraphic data and accelerometer data aggregated over hourly periods for participant *BA019*. The accelerometer data include raw data, their first differences in absolute value, and a cumulative measure of all three axes in first differences. The total number of observations is 1,861.

Figure 6.1: Correlation Plot: Actigraphic and Accelerometer Data

In Figure 6.1, we present an example correlation plot between actigraphic data and accelerometer data aggregated over hourly periods for one study participant. Four features are extracted from the data, namely absolute values of first differences of raw data in all three axes and a cumulative measure calculated as

$$m_t = \sqrt{(x_t - x_{t-1})^2 + (y_t - y_{t-1})^2 + (z_t - z_{t-1})^2}, \tag{6.1}$$

where m_t denotes magnitude at time t and x_t, y_t, and z_t correspond to raw data in the x-axis, y-axis, and z-axis, respectively. All of the calculated correlation coefficients are statistically different from zero at 99% level of significance. The results show that there is a statistically significant positive correlation between actigraphic data and the features extracted from the accelerometer data. In other words, the magnitude of activity measured by an actigraphic wristband corresponds to the activity measured in terms of smartphone device movement. However, the correlations are rather mediocre and differ significantly across individuals. The differences in correlations across study participants indicate that while the accelerometer data may be very well used for sleep detection in a similar manner to actigraphic data, it is vital to use a model allowing the introduction of individual effects to it.

6.2.2 Sleep Detection Models

We use two standard approaches to classification. First, we train a simple classification tree. Second, we use a random forest classifier enhancing the capabilities of a simple tree by providing randomised subsets of features among many classification trees subsequently used for majority voting to determine the final class of a classified observation. We use data aggregated over periods of one minute. Apart from the features presented in the correlation analysis, we also introduce five lags and five leads of magnitude m_t along with their aggregation as two mean values, one lagging and one leading the classified observation. After the removal of observations with missing values, we are left with 294,229 observations. We apply the k-fold cross-validation technique with $k = 5$ to the set of data.

Classification Tree

		Self-Reported	
		Wake	Sleep
Detected	Wake	3,559.6 (33.3)	859 (15.4)
	Sleep	534.4 (9.1)	1,202.8 (23.4)

Note: We use k-fold cross-validation with $k = 5$ using a full set of 294,229 observations. The values reported represent mean prediction results on testing sets across the five rounds of cross-validation. Standard deviations are reported in parentheses. All 24-hour periods from noon to noon for which study participants reported sleep are included in the dataset.

Table 6.3: Confusion Matrix: Accelerometer Classification Tree

The confusion matrix comparing classification performance of the classification tree on the cross-validation testing sets with self-reported sleep values are presented in Table 6.3. The corresponding values for accuracy, sensitivity, and specificity are 77.36% (0.40%), 86.95% (0.29%), and 58.34% (0.67%), respectively, with standard deviations reported in parentheses. We reject the null hypothesis that the accuracy rate is insignificant at any commonly used confidence level for all testing sets.

Random Forest

		Self-Reported Wake	Self-Reported Sleep
Detected	Wake	36,772.8 (51.3)	4,051.8 (66.8)
	Sleep	2,391.6 (76.0)	15,629.6 (24.4)

Note: We use k-fold cross-validation with $k = 5$ using a full set of 294,229 observations. The values reported represent mean prediction results on testing sets across the five rounds of cross-validation. Standard deviations are reported in parentheses. All 24-hour periods from noon to noon for which study participants reported sleep are included in the dataset.

Table 6.4: Confusion Matrix: Accelerometer Random Forest

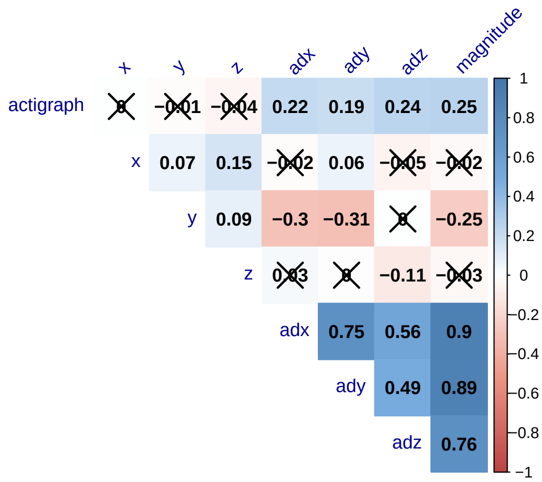
The classification results of the random forest classifier on the testing set are presented in Table 6.4. The corresponding values for accuracy, sensitivity, and specificity are 89.05% (0.12%), 93.89% (0.19%), and 79.41% (0.28%), respectively. The null hypothesis that the quality of the model is caused by an imbalance of classes is rejected at any commonly used level of significance for all five testing sets.

6.3 Gyroscope

During the initial exploration of the data in section 5.3, we note that gyroscope data generally provide information comparable to accelerometer data. However, we state that the knowledge retrievable from gyroscope data is inferior to that gained from accelerometer data for the dataset collected during the research study due to less variability being present in gyroscope data. Moreover, accelerometer provides long and continuous blocks of data easily spanning whole hours. In contrast, gyroscope data rarely do and mostly present observations across a few minutes followed by a complete absence of information for another few minutes. In consequence, we believe that by repeating the exercises previously done for accelerometer data, we obtain results that point in the same direction but are overall worse.

6.3.1 Correlation Analysis

In Figure 6.2, we show correlation coefficients between actigraphic data and features extracted from gyroscope data aggregated into hourly periods in an example focusing on *BA019*. When aggregating the data over the periods of one minute, gyroscope provides data that are about one fifth of the size of accelerometer data. For hourly data, the final size is comparable for the two sensors. As predicted, the correlation coefficients are much smaller than the ones obtained for accelerometer data. Again, all of the features extracted from raw data are positively correlated with actigraphic data at 99% confidence level. Although the data are still likely to be usable for modelling, the limited



Note: The figure shows correlations of actigraphic data and gyroscope data aggregated over hourly periods for participant *BA019*. The gyroscope data include raw data, their first differences in absolute value, and a cumulative measure of all three axes in first differences. Crossed values indicate that the correlation is not significantly different from zero at 99% level of confidence. The total number of observations is 1,842.

Figure 6.2: Correlation Plot: Actigraphic and Gyroscope Data

magnitudes of correlation coefficients indicate that much more sober results should be expected.

6.3.2 Sleep Detection Models

We approach the gyroscope data similarly to the accelerometer data. Again, we train a classification tree and follow by training of a random forest classifier. We remove periods of 24 hours from noon to noon from the dataset for days on which study participants did not fill in the daily questionnaire. We use data aggregated over periods of one minute. However, the gyroscope data contain very frequent collection outages. Because of that, even if only a single lag and lead of the magnitude feature is used, the final size of the dataset diminishes to hundreds of observations. Therefore, auto-correlated features are not extracted to preserve a dataset of a reasonable size of 30,779 observations. Again, the k-fold cross-validation technique with $k = 5$ is used.

Classification Tree

The results of classification on cross-validation testing sets using a classification tree trained on gyroscope data can be found in Table 6.5. The corresponding values for accuracy, sensitivity, and specificity are 68.84% (0.69%), 91.67% (1.10%), and 22.94% (3.13%), respectively with values in parentheses representing standard deviation across testing sets. The null hypothesis that the performance of the classifier is given by the imbalance in classes is rejected at any commonly used level of confidence for all testing sets.

		Self-Reported Wake	Self-Reported Sleep
Detected	Wake	3,769.2 (31.5)	1,575.8 (86.5)
	Sleep	342.6 (47.1)	468.2 (58.1)

Note: We use k-fold cross-validation with $k = 5$ using a full set of 30,779 observations. The values reported represent mean prediction results on testing sets across the five rounds of cross-validation. Standard deviations are reported in parentheses. All 24-hour periods from noon to noon for which study participants reported sleep are included in the dataset.

Table 6.5: Confusion Matrix: Gyroscope Classification Tree

Random Forest

		Self-Reported Wake	Self-Reported Sleep
Detected	Wake	3,564.6 (50.1)	1,053.8 (23.7)
	Sleep	547.2 (21.8)	990.2 (14.5)

Note: We use k-fold cross-validation with $k = 5$ using a full set of 30,779 observations. The values reported represent mean prediction results on testing sets across the five rounds of cross-validation. Standard deviations are reported in parentheses. All 24-hour periods from noon to noon for which study participants reported sleep are included in the dataset.

Table 6.6: Confusion Matrix: Gyroscope Random Forest

The classification results of the random forest classifier on the cross-validation testing sets are presented in Table 6.6. The corresponding values for accuracy, sensitivity, and specificity are 73.99% (0.60%), 86.69% (0.60%), and 48.45% (0.44%), respectively. We reject the null hypothesis that the quality of the model is determined by the imbalance of classes at any commonly used significance level for all testing sets.

6.4 Power State Extension

It is quite reasonable to assume that when a study participant is directly engaging with their smartphone device, they are surely not asleep. We base our application of power state data on this notion. Power state data allow us to specify points in time when a device is unlocked for iOS devices and when a screen of a device is turned on for Android devices. Unfortunately, the data show that certain study participants tend to fall asleep from time to time while watching something on their smartphone devices. To give an example, the data contain observations indicating that a device of a person was unlocked from eleven o'clock in the evening until six o'clock in the morning even though the person reported that they slept from midnight until eight o'clock in the morning. Moreover, data from Android devices frequently report on the screen being turned on and off all through the night, always for a similar period of time from ten to fifteen seconds. This indicates that incoming notifications are registered and need to be removed to correctly assess times at which the person truly interacted with their device. More specifically, we decided to remove observations shorter than twenty seconds from the datasets of users with an Android device. Also, we shortened observations lasting for more than two hours to the initial five minutes of the window. It is quite safe to assume that a person would not have fallen asleep in these initial few minutes of consuming content on their smartphone device.

		Self-Reported	
		Wake	Sleep
Detected	Wake	1,938,036	121,549
	Sleep	80,789	853,879

Note: The total number of observations used to compose the confusion matrix is 2,994,253. All 24-hour periods from noon to noon for which study participants reported sleep are included in the dataset. Two study participant are removed due to actigraphic wristband difficulties.

Table 6.7: Confusion Matrix: Extended Model

After processing the power state data, we use them to correct labels assigned to observations by the state-of-the-art sleep detection model based on actigraphic data. This post-processing extension of the model results in a very slight increase in accuracy of sleep detection. The confusion matrix over all 19 study participants included can be found in Table 6.7. The corresponding values for accuracy, sensitivity, and specificity are 93.24%, 96.00%, and 87.54%, respectively. The NIR remains to be significantly lower than accuracy at any commonly used level of statistical significance. The overall number of observations increased since the use of power state data allowed for detection of some layoff periods as active instead.

In Table 6.8, we report on the performance of the model extended by power state data for each individual. The differences between results for the original model and for the extended model vary significantly across study participants.

ID	Obs.	Layoff	Acc.	Sens.	Spec.	NIR
BA001	217,422	94	96.86%	97.97%	94.39%	68.98%
BA002	96,221	4,614	89.99%	90.69%	88.50%	67.90%
BA003	209,888	425	92.64%	97.84%	79.27%	72.04%
BA004	152,338	33,487	91.84%	97.60%	76.12%	73.17%
BA005	95,395	19,845	81.75%	94.51%	50.32%	71.11%
BA006	198,149	16,486	94.88%	97.51%	90.43%	62.82%
BA007	182,880	1,504	94.55%	99.25%	85.58%	65.57%
BA008	88,416	6,657	83.77%	96.02%	61.27%	64.75%
BA009	210,924	3,711	95.32%	98.61%	88.58%	67.25%
BA010	79,275	10,036	92.54%	91.99%	93.98%	72.46%
BA011	212,007	4,068	89.67%	87.99%	92.49%	62.68%
BA012	84,387	2,043	95.94%	97.38%	93.37%	64.08%
BA013	75,664	2,123	86.46%	97.16%	67.78%	63.60%
BA015	192,807	220	95.21%	97.68%	88.73%	72.45%
BA016	189,665	481	92.43%	92.85%	91.57%	66.87%
BA017	207,749	5,445	96.10%	95.52%	97.42%	69.49%
BA018	86,045	385	87.17%	93.32%	75.77%	64.97%
BA019	219,866	531	97.63%	97.48%	97.94%	66.98%
BA020	195,155	3,634	96.51%	96.61%	96.34%	62.99%
Total	2,994,253	115,789	93.24%	96.00%	87.54%	67.42%

Note: The table contains individual results of sleep detection using the state-of-the-art sleep detection model extended by power state data when compared to self-reported data.

Table 6.8: Individual Model Performance: Extended Model

Chapter 7
Discussion

This chapter presents a discussion of topics covered in the thesis. In section 7.1, we note on important considerations when applying behavioural data to sleep detection in the proposed manner. In section 7.2, we discuss the metric used for evaluation of sleep detection and propose better alternatives. In section 7.3, we weigh up the advantages and disadvantages of actigraphic and smartwatch devices when utilised for medical purposes. In section 7.4, we ponder over the current state of digital phenotyping platforms.

7.1 Digital Phenotyping and Sleep Detection

We propose some ways that behavioural data can be used to improve a state-of-the-art sleep detection model based on actigraphy. More specifically, we argue that accelerometer, gyroscope, and power state data obtained using one's smartphone device can benefit accuracy of sleep detection when used for post-processing of sleep detection results. From our experience, behavioural data collection is always at least partially inconsistent. For example, data can be missing because of the smartphone device shutting down or being restarted without subsequent start of the digital phenotyping smartphone application. Therefore, we believe that behavioural data should not be included in the sleep detection model directly. Direct inclusion would mean that the model would not be usable for detection whenever a single piece of behavioural data was missing.

Rather, another sleep detection model should be built using the behavioural data. Subsequently, the behavioural data model can be used to resolve layoff periods detected by the actigraphic data model. Moreover, the confidence in assessment of individual periods by each model could be calculated and the final labelling could be based on the model with more confidence in each period. However, the combination of the models is outside of the scope of this thesis and requires further research. Unlike accelerometer and gyroscope data, power state data cannot be used to train a sleep detection model. Nonetheless, they allow one to specify time periods of wakefulness with a very high amount of precision since a person must be awake to interact with their smartphone device. Therefore, power state data can be used in post-processing for amending of incorrectly labelled observations.

7.1.1 Assumption of Sole Ownership

An extremely important consideration that should be remembered is that the smartphone device collecting behavioural data should be manipulated with exclusively by the person whose sleep patterns are studied. For example, we put a lot of confidence into power state data and the notion that if the smartphone device is unlocked, the study participant must be awake at the time, unless the phone is unlocked for too long of a period implicating the possibility that the study participant fell asleep while using the device. However, this is a relatively strong assumption since it is not unlikely that someone else, more specifically a partner of the studied person, might occasionally engage with the device in order to check the time, look something up when their own smartphone device is out of reach, or simple move the device from one place to another. Thankfully, such situations should be relatively rare and the overall implications of the data should remain the same.

7.1.2 Individual Specific Usage Patterns

It as also necessary to recognise that smartphone device usage patterns are very individualistic, which must be considered when modelling with the help of behavioural data. Specifically, it is unlikely that a model trained on the data of one person could be confidently applied to the data of another person since a significant distribution shift occurs. From the technical standpoint, the smartphone devices sourcing the data might differ in their data collection processes and sensors. From the behavioural standpoint, one person might use their device solely in short spikes, one might engage in running with their phone in hand, and another might leave it on a table for most of the day and not even pick it up from the table when manipulating with it. All of these patterns generate very different sets of data. While the final detection model should utilise the same set of extracted features across all individuals, weights assigned to these features during training will differ across individuals.

7.1.3 Time Specific Usage Patterns

Individualistic behaviour is one thing that must be recognised when modelling with behavioural data. However, changes in smartphone usage patterns might occur also in time. Under normal circumstances, people tend to change their behaviour in time especially when they are younger and have less strict routines. For example, the smartphone device usage patterns of a student will be extremely different during semesters, exam periods, and holidays. However, the pandemic has shown that unprecedented structural breaks resulting in large behavioural changes in time across whole populations might take place as well. In consequence, it might prove valuable to detect such distributional shifts and retrain the models employing behavioural data when necessary.

7.2 Sleep Detection Evaluation

To evaluate the results of our work, we compute the accuracy of the sleep detection model results in comparison to self-reported data on sleep obtained via questionnaires provided to study participants on daily basis. However, it is very important to acknowledge deficiencies of our approach that we did not foresee. Specifically, we allowed study participants to fill in the questionnaire at any time during the day following the sleep that questions in the questionnaire referred to. However, most study participants filled in the questionnaire late in the evening. It is likely that after the passing of ten hours and more, they had a very limited recollection of precise times when they went to sleep and when they woke up. One study participant, for example, rounded their reported times to whole hours.

To better evaluate the performance of the models, we should have put more emphasis on information on sleep gained from the questionnaire. Firstly, we should have required that the questionnaire on sleep is filled in shortly after study participants wake up, for example by inducing an upper limit on the time that study participants were provided to fill in the questionnaire. Secondly, we should have introduced two additional questions. We required information on times when the person went to sleep and woke up. It would be much more informative to require information on times when the person fell asleep and left their bed as well. Still, these two changes would have still been only the third best option.

The second best option would have been to require study participant to keep a sleep diary. More specifically, we would ask the four questions mentioned in the previous paragraph, however, we would ask study participants to fill in these four questions on every single sleep. While the data might remain unchanged for many users, some users would be allowed to report information on their naps and uncommon sleeping patterns. To give an example, one study participant sometimes used to sleep for four hours in late afternoon, then woke up and functioned normally, and went to sleep again in the morning for another four hours during the research study. This information can be hardly registered by the questions presented in the questionnaire. Of course, the best option would have been to evaluate the sleep detection model in comparison to PSG data, however, the study requirements would be incomparable and potentially even impossible when the length of our research study and the number of study participants are considered.

In conclusion, there are certain problems with the way we measure the quality of our work. However, no better option is available after the conclusion of the research study. Therefore, we should consider this more of a lesson for the future. Furthermore, the purpose of our research study was to investigate the general use of digital phenotyping rather than focus on its applicability for sleep detection. Specifically, the self-reported data used by other members of the research team would be worsened by the requirement to fill in the questionnaire early in the morning since, for instance, one might not have enough information to evaluate their mood for the day. At the same time, introducing multiple daily questionnaires is generally unwise. An overwhelming amount of different reporting requirements could easily drive the study participants away before any reasonable data are collected. Overall, the results are satisfactory even without a more precise evaluation measure.

7.3 Technology and Medical Research

Even though the PSG remains to be the gold standard of sleep detection measures, it is burdened with operational difficulties when applied in home environment and heavy costs when used in a laboratory setting. Furthermore, it is impractical for longer-term observations of sleep patterns. In consequence, the main stream of research turned to actigraphy as the next best option. Recently, actigraphy has been challenged by newly developed alternatives usable under comparable circumstances, more specifically by smartphone applications utilising smartphone device sensors and by smartwatch devices gathering additional relevant information such as heart rate and body heat. Fino et al. (2020) show that smartphone applications tend to perform worse than a simple actigraphic device, meaning their practical use for medical purposes is insignificant. On the other hand, Roberts et al. (2020) and Chinoy et al. (2021) find evidence of smartwatch devices unambiguously outperforming simple actigraphs in terms of accuracy of sleep-wake cycle detection when compared to remote PSG.

In light of these facts that we mention earlier on in the thesis, one might question the relevance of our attempt to investigate possible enhancement of a sleep detection model based on actigraphic data using behavioural data. Specifically, one might ask whether the biomedical field is not bound to gravitate towards the use of smartwatch devices in place of simple actigraphs due to their improved sleep detection accuracy. We argue that unless unforeseen advancements in technology follow, actigraphy will prevail as the leading tool for longer-term sleep studies and medical diagnoses for three primary reasons.

Battery

Firstly, actigraphic devices require very little energy for their operation. Specifically, the actigraphic wristband used in our research study is powered by a button cell allowing the device to function without the need for battery replacement for up to a year. When the time comes, the button cell can be replaced in a matter of seconds. On the other hand, smartwatch devices require charging. Batteries of specific devices may last for up to two weeks, however, most devices necessitate a much more frequent charging, sometimes even on a daily basis. Furthermore, the total battery capacity of a smartwatch device depletes over time. Whenever the device is being charged and it is not placed on one's hand, important data are lost. Moreover, people tend to forget about the device and leave it connected to a charger for much longer periods than necessary. In consequence, very large blocks of missing data are produced and cannot be recovered.

Monetary Costs

Secondly, the data generated by smartwatch devices vary significantly across manufacturers and models. Moreover, many of these devices provide solely fully process data in the form of activity statistics with no possibility of raw data retrieval. Consequentially, smartwatch devices already owned by study participants or diagnosed patients cannot be used to obtain data in a reasonable manner and all must be provided with a single carefully selected smartwatch device. However, the costs of smartwatch devices are in the multiples of the costs of simple actigraphic devices. Because of that, researchers and medical facilities with limited financial resources are unlikely to choose smartwatch devices over actigraphy.

Behavioural Effects

Thirdly, smartwatch devices are likely to induce unwanted behavioural effects leading to further missing data. Proportions and weight of smartwatch devices frequently prevent one from wearing them during their sleep with the necessary amount of comfort. When compared to smartwatch devices, actigraphic devices are much less intrusive primarily because of their simplicity. Similarly, people might opt to remove smartwatches from their wrist more often throughout the day due to concerns about their durability and potential costs of having to replace them. Generally, this does not hold for actigraphic devices which are then capable of collecting a much more complete set of data in the long run.

7.4 Digital Phenotyping Platforms

One of the largest drawbacks of our research is the amount of behavioural data that could have been collected but were not because of technological difficulties with the platform used for data collection. Unfortunately, this was the result even though a significant amount of time was put into the selection of a digital phenotyping platform to use for the research study. Specifically, we researched a wider range of platforms. Based on the results of studies they were utilised in, costs, deployment ease, and general responses, we selected two platforms to test before the beginning of the study.

Beiwe Platform

The Beiwe platform was selected as a relatively old but stable choice that was used many times before. However, the platform has not been updated in any significant way for the past two years. It is likely that changes in protocols resulted in the unsatisfactory performance of the platform on Android devices with only the power state and GPS data collected in a manner comparable to the data from iOS devices. Nonetheless, some data such as anonymous communication logs which were supposed to be collected by the platform were not gathered even on iOS devices.

LAMP Platform

The LAMP platform was picked as the most prominent successor of Beiwe. However, the platform is still in active development. Many of extremely important features such as data caching and data collection frequency settings are yet to be introduced to the system. During our tests, we found that the platform can provide better data for Android devices compared to the Beiwe platform. However, the general quality of the data collected by the LAMP platform is much lower and the collection process results in much larger blocks of missing data on iOS devices because of the platform's inability to cache data when they cannot be uploaded to the server. In other words, the platform requires constant internet collection and even then provides data of dubious quality. However, the platform also offers multiple additional data types including anonymous call records, distance travelled, steps made, and data collected from smartwatch devices. If the necessary functionalities are introduced, it is likely that LAMP will become the mainstream digital phenotyping platform of future research.

Future Research

Digital phenotyping has already become an extremely important string of research. It is unfortunate that a more robust digital phenotyping platform is not currently available. However, our results shows that the Beiwe platform remains to be a viable choice in certain situations. When all devices used in a research study run on the iOS operating system, the platform can be used with no difficulties. Similarly, when the focus is laid upon specific behavioural data types such as GPS and power state, the platform works reasonably well even on many Android devices, although not all. In the future, a more rigorous investigation of various brands of smartphone devices and their performance in terms of data collection when using the Beiwe platform could be carried out. In turn, this would provide medical researchers interested in digital phenotyping with some confidence that their work will not amount to nothing when applying digital phenotyping if they ensure that the observed individuals possess a device for which the platform works well. Furthermore, a research providing an extensive comparison of all currently available digital phenotyping platforms and their functioning on various brands of smartphone devices would be of great importance to the field.

Chapter 8

Conclusion

In the thesis, we investigate the employability of data on smartphone device usage patterns for sleep detection purposes. More specifically, we focus on the applicability of the data for improvement of a state-of-the-art sleep detection model based on actigraphic data. Since no dataset combining actigraphic and behavioural data is publicly available, we carried out a small scale research study on 21 healthy controls lasting for over three months. We used simple actigraphic wristbands to collect actigraphic data and a digital phenotyping platform called Beiwe frequently found in the literature to gather behavioural data. For the duration of the study, we required volunteers to fill in daily questionnaires to collect self-reported data on sleep that are subsequently used to train our models and to evaluate the quality of results.

We establish three behavioural data types as having a large potential of applicability for sleep detection purposes. Firstly, accelerometer data describing movement and vibrations of a smartphone device are used to create a sleep detection model. Using a k-fold cross-validation technique with $k = 5$, the random forest classifier achieves a mean accuracy of 89.05%, sensitivity of 93.89%, and specificity of 79.41%. The results are impressively good since only a limited amount of information on daily activities of a person can be gained from their smartphone usage patterns. Secondly, we try the same approach with gyroscope data on orientation and angular velocity of a smartphone device. However, collection process of gyroscope data is defined by frequent breaks in data gathering. In consequence, auto-correlated features cannot be used since their use severely limits the size of the dataset. Therefore, the random forest classifier achieves much more mediocre results with mean accuracy, sensitivity, and specificity at 73.99%, 86.69%, and 48.45%. Finally, we use power state data on a smartphone device having its screen powered on for Android devices and being unlocked for iOS devices. The data require heavy processing due to study participants falling asleep while watching their device and incoming notification being registered for Android devices as well. However, we base a post-processing extension of data labelled by the state-of-the-art model on the power state data. We are able to slightly increase the overall accuracy and relabel 12.43% of invalid data as active due to confirmed activity at the time. However, we do so at the cost of a modest decrease in specificity.

The research study was conducted by a team of four members, each focusing in their respective thesis on a different application of digital phenotyping. The author of this thesis was primarily responsible for organisation of the study. More specifically, the author created the study protocol, prepared consent forms and questionnaires, distributed actigraphic devices, and subsequently ensured that the research study was proceeding as planned. The other three members of the research team were mainly responsible for deployment of both Beiwe and LAMP platforms, their selection, comparison, testing, and maintenance throughout the course of the research study. All of the work presented in the thesis is solely the author's work.

We believe that there are two primary directions that further research pursuits could follow up on the work presented in this thesis. Firstly, a research on a direct interconnection of the accelerometer model presented in this thesis and the state-of-the-art actigraphic model could be carried out. We show that the accelerometer model might prove useful in situations where actigraphic data are unavailable. Moreover, the accelerometer model might assess certain situations with more precision than the actigraphic model. Thus, weights could be created based on confidence of the two models in their classification of concrete observations. Secondly, a more exhaustive analysis of digital phenotyping platforms should be conducted. More specifically, the deployment and testing of other digital phenotyping platforms than just the ones discussed as part of this thesis could enable easier pursuit of assessment based on digital phenotyping by medical specialists in the future. As part of this analysis, specific smartphone devices interacting well with specific platforms could be identified for future reference.

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BACHELOR‘S THESIS ASSIGNMENT

I. Personal and study details

Student's name: **Žíla Eric** Personal ID number: **483633**

Faculty / Institute: **Faculty of Electrical Engineering**

Department / Institute: **Department of Cybernetics**

Study program: **Open Informatics**

Specialisation: **Artificial Intelligence and Computer Science**

II. Bachelor’s thesis details

Bachelor’s thesis title in English:

Analysis of Actigraphic and Behavioural Data

Bachelor’s thesis title in Czech:

Analýza aktigrafických a behaviorálních dat

Guidelines:

In the field of mental health, actigraphic data collected using medical devices have been recently used to estimate the mental state of a patient and react accordingly. The goal of this thesis is to examine the usefulness of behavioural data, which can be collected both passively during the use of various electronic devices and actively through direct interaction, for the same purpose.

1) Research types of behavioural data and their collection procedures.
2) Analyse collected data and discuss their possible use.
3) Perform a correlation analysis of behavioural and actigraphic data.
4) Summarise results and contemplate on possible obstacles in the use of behavioural data.

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Name and workplace of bachelor’s thesis supervisor:

doc. Ing. Daniel Novák, Ph.D., Analysis and Interpretation of Biomedical Data, FEE

Name and workplace of second bachelor’s thesis supervisor or consultant:

Date of bachelor’s thesis assignment: **18.01.2021** Deadline for bachelor thesis submission: **04.01.2022**

Assignment valid until: **30.09.2022**

doc. Ing. Daniel Novák, Ph.D. Supervisor’s signature	prof. Ing. Tomáš Svoboda, Ph.D. Head of department’s signature	prof. Mgr. Petr Páta, Ph.D. Dean’s signature

III. Assignment receipt

The student acknowledges that the bachelor’s thesis is an individual work. The student must produce his thesis without the assistance of others, with the exception of provided consultations. Within the bachelor’s thesis, the author must state the names of consultants and include a list of references.

.

Date of assignment receipt Student’s signature

CVUT-CZ-ZBP-2015.1

Appendix A

Information About the Study and Informed Consent

In accordance with information provided in section 3.2, all volunteers wishing to participate in the research study were required to sign the *Information About the Study and Informed Consent* form. Its original version in Czech can be found below.

Informace o studii a informovaný souhlas
Analýza aktigrafických a behaviorálních dat

Zodpovědná osoba: doc. Ing. Daniel Novák, Ph.D.

Úvod

Dovolujeme si Vás pozvat k dobrovolné účasti ve výzkumné studii, která si klade za cíl prozkoumat využití aktigrafických a behaviorálních dat k detekci a predikci nálad a spánkových vzorců.

Projekt bude vyžadovat nošení malého náramkového senzoru pohybové aktivity a užívání aplikace sbírající behaviorální data ze senzorů mobilního zařízení. Předtím, než vyjádříte svůj souhlas s Vaší účastí v této výzkumné studii, je důležité, abyste si přečetl/a tyto informace a porozuměl/a jim. Informace popisují účel studie, postupy použité ve studii, rizika a přínos Vaší účasti ve studii. Pokud vyjádříte souhlas s účastí, obdržíte kopii této informace pro svou vlastní potřebu.

Proč studii provádíme

Studii provádíme za účelem zkoumání využití aktigrafických dat sbíraných s pomocí náramkového senzoru pohybové aktivity a behaviorálních dat získávaných prostřednictvím aplikace na mobilním zařízení sbírající data z jeho senzorů k detekci a predikci nálad a spánkových vzorců.

Jedním z primárních výzkumných cílů je rozlišení pracovních a odpočinkových dnů na základě behaviorálních dat a jeho srovnání s modely sestrojenými s využitím aktigrafických dat. Na základě těchto dat také hodláme detekovat a predikovat nálady se zaměřením na senzory GPS a zapnutí obrazovky mobilního zařízení při současném využití dalších senzorů ke zlepšení výsledků. Podobně budeme přistupovat také k detekci spánkové aktivity na základě behaviorálních dat a případné zlepšení kvality detekce s pomocí aktigrafických dat.

Jak bude studie vypadat

Studie bude zahrnovat zhruba dvacet dobrovolníků, jež budou po dobu dvou měsíců užívat malý náramkový senzor pohybové aktivity a s ním spojenou aplikaci Mindpax.me, jejímž prostřednictvím budou ve formě dotazníků na denní a týdenní bázi sdíleny informace o subjektivní náladě. Kromě toho budou pasivně využívat aplikaci Beiwe2, s jejíž pomocí budou sbírány data o mobilním zařízení a jeho užívání. Alternativou k této aplikaci v případě nefunkčnosti je aplikace mindLAMP 2 fungující na podobném principu. Následně proběhne analytické zpracování dat se zaměřením na výzkumné otázky popsané v předchozím bodu tohoto dokumentu.

Konkrétní senzory mobilního zařízení, které budou aplikací Beiwe2 (případně mindLAMP 2) využívány k získávání behaviorálních dat, se liší dle operačního systému mobilního zařízení a aplikace samotné. Nezávisle na užívaném mobilním zařízení budou sbírána data z akcelerometru, GPS, gyroskopu, magnetometru, rotaci, pohybu, gravitaci, wi-fi a bluetooth připojení, stavu nabití a stavu obrazovky mobilního zařízení. Aplikace Beiwe2 sbírá nad rámec společných dat také informace o síťové dostupnosti zařízení na iOS. Aplikace mindLAMP 2 potom nad rámec společných dat sbírá na zařízeních s operačním systémem iOS sbírá také data o volání (výhradně začátek, délka a typ volání bez jakékoliv bližší informace), počtu kroků a ušlé vzdálenosti.

SHRNUTÍ: Co Vás čeká v případě souhlasu s účastí ve studii

Nejprve Vás požádáme o podstoupení vstupního vyšetření pomocí dotazníku M.I.N.I. (Mini mezinárodní neuropsychiatrické interview). V případě, že splníte vstupní kritéria, budete zařazeni do studie. Na zápěstí potom budete nosit malý a nenápadný senzor v podobě náramku, který bude snímat kontinuálně Vaši pohybovou aktivitu. Senzor bude data předávat do centrální databáze, kterou provozuje MINDPAX s.r.o. a Mindpax GmbH, pomocí mobilní aplikace Mindpax.me. V aplikaci Mindpax.me budete také na denní a týdenní bázi vyplňovat jednoduchý dotazník, který mapuje charakter vaší nálady. Informace o Vašem mobilním zařízení sbírané senzory v něm budou pasivně získávány a sdíleny s výzkumným týmem pomocí mobilní aplikace Beiwe2 či mindLAMP 2.

Přirozeně, Vaše účast ve studii je dobrovolná a kdykoliv během studie z ní můžete vystoupit.

Rizika

Diskomfort ve studii může být vnímán při nepřetržitém nošení senzoru snímajícího pohybovou aktivitu či pravidelném vyplňování požadovaných dotazníků.

Neexistují žádná známá rizika spojená se studijními procedurami.

Důvěrnost informací

Vaše záznamy budou uchovávány výzkumným týmem jako důvěrné a nebudou sdíleny s žádnou třetí stranou.

Výsledky, které nebudou obsahovat údaje umožňující odhalení Vaší totožnosti, mohou být zveřejněny v rámci výsledků výzkumu nebo sdíleny s jinými osobami v rámci vědeckých diskusí.

Vaše studijní údaje budou uloženy a zpracovány na počítači, údaje však budou plně zabezpečeny a chráněny před přístupem nepovolaných osob.

Máte právo nahlédnout, případně i získat kopii svých záznamů shromážděných pro účely studie v době, kdy jsou uchovávány. Avšak z důvodů zajištění vědecké ucelenosti studie nebudete mít k některým studijním informacím přístup dříve, než bude studie dokončena.

Svůj souhlas s použitím a zpracováním údajů o Vašem zdravotním stavu získaných v rámci studie máte právo kdykoli odvolat zasláním oznámení kontaktní osobě. Pokud svůj souhlas odvoláte, nebudete se moci nadále účastnit studie.

Abyste se mohl/a studie zúčastnit, musíte potvrdit svůj souhlas se zařazením do studie připojením svého podpisu a data na stránku s podpisy.

Informace o studii a formulář pro informovaný souhlas. Strana s podpisy

Abyste se mohl/a účastnit této studie a poskytl/a souhlas k použití a zpřístupnění údajů o Vašem zdravotním stavu, je zapotřebí, abyste se podepsal/a a vlastnoručně uvedl/a datum podpisu na této stránce. Připojením svého podpisu na tuto stránku potvrzujete, že:

· Jste si přečetl/a a porozuměl/a všem informacím uvedeným v těchto “Informacích o studii a informovaném souhlasu” a měl/a jste dostatek času na rozmyšlenou.

· Byl/a jste podrobně a v dostatečné míře informován/a o tomto výzkumu a všechny Vaše otázky byly zodpovězeny k Vaší spokojenosti.

· Obdržel/a jste a ponechal/a jste si kopii této Informace pro zdravého dobrovolníka a formuláře pro informovaný souhlas.

· Souhlasíte s procedurami, které jsou spojeny s touto studií.

· Byl/a jste informován/a o tom, že Vaše účast ve studii je dobrovolná a kdykoli během studie z ní můžete vystoupit.

· Byl/a jste informován/a o tom, že Vaše osobní údaje a získané výsledky vyšetření nebudou zveřejňovány a jsou důvěrné, přístup k nim mají pouze výzkumníci.

· Prohlašujete, že jste způsobilý/á k právním úkonům v rozsahu nezbytném pro právoplatný podpis tohoto protokolu a že jste obsah a význam protokolu pochopil/a.

______________________________ ______________________________

Podpis dobrovolníka **Datum (den, měsíc, rok)**

____

Jméno dobrovolníka

____

Jméno osoby, která s dobrovolníkem vedla diskusi o informovaném souhlasu

______________________________ ______________________________

Podpis osoby, která s dobrovolníkem vedla diskusi o informovaném souhlasu **Datum (den, měsíc, rok)**

Appendix B

Consent to the Handling of Personal Information

In accordance with information provided in section 3.2, all volunteers wishing to participate in the research study were required to sign the *Consent to the Handling of Personal Information* form. Its original version in Czech can be found below.

Souhlas se zpracováním osobních údajů
Analýza aktigrafických a behaviorálních dat

Zodpovědná osoba: doc. Ing. Daniel Novák, Ph.D.

Úvod

Žádáme Vás o udělení souhlasu se zpracováním osobních údajů pro účely výzkumné studie “Analýza aktigrafických a behaviorálních dat”.

Poskytnutí souhlasu je dobrovolné, bez jeho udělení Vás však nebudeme moci zařadit do výzkumné studie.

Kdo bude s údaji disponovat

Studii provádí výzkumný tým z FEL ČVUT pod vedením doc. Ing. Daniela Nováka, Ph.D. ve spolupráci se společnostmi MINDPAX s.r.o. a Mindpax GmbH, jež se starají o technické zpracování dat z náramkových senzorů.

Za analytické zpracování dat zodpovídají:

- doc. Ing. Daniel Novák, Ph.D.
- Michal Kubina
- Lukáš Sláma
- Ondrej Sakači
- Eric Žíla

Jaké osobní údaje budeme zpracovávat

Budeme zpracovávat:

- Vaše identifikační a kontaktní údaje
- informace o Vašem zdravotním stavu a subjektivní náladě
- informace o Vašich pohybových aktivitách sbírané senzorem v náramku
- informace o Vašem mobilním zařízení a jeho užívání sbírané senzory v něm

Rozsah je blíže popsán v informovaném souhlasu, který Vám zároveň předkládáme.

K Vašim identifikačním údajům bude mít výhradní přístup výzkumný tým z FEL ČVUT. MINDPAX s.r.o. a Mindpax GmbH bližší údaje o Vaší totožnosti nebude mít k dispozici.

Pro jaké účely budeme osobní údaje používat

Osobní údaje budou použity pro účely zkoumání využití aktigrafických a behaviorálních dat k detekci a predikci nálad a spánkových vzorců. MINDPAX s.r.o. a Mindpax GmbH bude údaje používat k vývoji a testování technologií predikce vývoje zdravotního stavu. Vaše osobní údaje budou uchovávány pro účely zde uvedené po dobu 6 měsíců ode dne ukončení sběru dat do studie, ledaže právní předpisy vyžadují delší dobu uchování.

Jak budeme osobní údaje získávat

Na zápěstí budete nosit malý a nenápadný senzor v podobě náramku, který bude snímat kontinuálně Vaši pohybovou aktivitu. Senzor bude data předávat do centrální databáze, kterou provozuje MINDPAX s.r.o. a Mindpax GmbH, pomocí mobilní aplikace Mindpax.me. V aplikaci Mindpax.me budete také na denní a týdenní bázi vyplňovat jednoduchý dotazník, který mapuje charakter vaší nálady. Informace o Vašem mobilním zařízení sbírané senzory v něm budou pasivně získávány a sdíleny s výzkumným týmem pomocí mobilní aplikace Beiwe2 či mindLAMP 2.

Před začátkem studie proběhne vyšetření pomocí dotazníku M.I.N.I. (Mini mezinárodní neuropsychiatrické interview).

Kdo další může mít k údajům přístup

Vaše záznamy budou uchovávány výzkumným týmem jako důvěrné a nebudou sdíleny s žádnou třetí stranou.

Výsledky, které nebudou obsahovat údaje umožňující odhalení Vaší totožnosti, mohou být zveřejněny v rámci výsledků výzkumu nebo sdíleny s jinými osobami v rámci vědeckých diskusí.

Vaše práva

Máte právo požadovat, abychom Vám poskytli informace o zpracování Vašich osobních údajů.

Pokud se domníváte, že jsou Vaše osobní údaje zpracovávány v rozporu s ochranou Vašeho soukromého a osobního života nebo v rozporu s právními předpisy, můžete požádat o vysvětlení nebo nápravu situace (např. blokování, provedení opravy, doplnění nebo likvidaci osobních údajů). Máte práva požadovat opravu nepřesných osobních údajů.

Svůj souhlas s použitím a zpracováním údajů o Vašem zdravotním stavu získaných v rámci studie máte právo kdykoli odvolat zasláním oznámení kontaktní osobě. Pokud svůj souhlas odvoláte, nebudete se moci nadále účastnit studie.

Souhlasím se zpracováním osobních údajů:

- **výše uvedenými osobami, tj. ze strany výzkumného týmu z FEL ČVUT, MINDPAX s.r.o. a Mindpax GmbH,**
- **v rozsahu identifikačních a kontaktních údajů, informacích o zdravotním stavu, subjektivní náladě, pohybové aktivitě, mobilním zařízení a jeho užívání,**
- **pro účely provádění výzkumné studie zde popsané a vývoj a testování technologií pro predikci vývoje zdravotního stavu,**
- **po dobu 6 měsíců ode dne ukončení sběru dat do studie, ledaže právní předpisy vyžadují delší dobu uchování.**

Podpis dobrovolníka

Datum (den, měsíc, rok)

Jméno dobrovolníka