Extraction and Analysis of Biomedical Data from Wearables: Towards Monitoring Daily Health of Patients at Home

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Potilaiden vastaanotto ja seuranta käyttää suuren osan aika- ja henkilöstoresursseja seiraanhoidossa, usein rakentaen pullonkaulan potilasvirtaan. Tätä pullonkaulaa voitaisiin laajentaa ulkoistamalla joitakin prosesseja älylaitteiden generoiman dataan perustuvalle automaatiolle. Erityisesti ei kriittisissä potilaissa, esimerkiksi fyysisistä vammoista tai aivohalvauksesta parantuvien potilaiden sekä masennuksesta kärsivien terveyttä ja päivittäisiä aktiviteettejä voitaisiin tarkkailla etänä. Tässä kontekstissa systeemi, joka kykenisi automaattisesti kerätä terveys- ja aktiviteettidataa sekä objektivisesti puettavien laitteiden avulla, että subjektiivisesti kyselyiden avulla on välttämätön. Tämän kandidaattityön tavoite on tarkastella kuluttajatason laitteiden kykyä kerätä psykofysiologista dataa ja lopulta tarkkailla masennuksesta kärsiviä potilaita. Viime kädessä tämä data voi olla hyödyllistä suuremmalle nousevalle tutkimukselle, jossa kerättyjä biometrisiä datapisteitä validoidaan masennuspotilaiden aivoskannauksia vastaan. Perimmäinen tavoite on nähdä, voidaanko opettaa koneoppimismalli auttamaan henkisten tilojen ennustamisessa etätarkkailussa. Toimiakseen esitutkimuksena ennen potilaskokeiluja, tässä kandidaattityössä evaluoidaan erilaisia terveydellisiä parametreja, joita voidaan saada tyypillisistä kaupallisista laitteista, kuten älypuhelimesta tai älykelloista. Näitä parametreja suhteutetaan kirjallisuuteen, arvioidaksemme jos, ja kuinka, ne voisivat liittyä masennukseen. Jälkeenpäin kijoitetaan ohjelmistokehys, automaattisesti kerätäksemme dataa etänä. Kandidaattityössä näytetään, kuinka monia parametreja voidaan tehokkaasti kerätä, mutta datan laatu voi olla riittämätön potilaiden tarkkaa seurantaa varten.

Avainsanat: potilaiden etävalvonta, masennus, datankeruu, kuluttajamarkkinoiden älyseurantalaitteiden käyterttävyys tutkimuksessa

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ABSTRACT OF THE
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Patient monitoring consumes a large number of staff and time resources in medical institutions, often forming a bottleneck in the flow of patients. This bottleneck could be enlarged by outsourcing some of these processes to smart devices, collecting health-related data in an autonomous way. In particular, non vital patients, E.g patients recovering from physical injuries, strokes or suffering from depression could have their health state and daily activities monitored remotely. In this context, a system able to automatically collect health and activity data, both in an objective way through wearables and subjective way through surveys is essential. The objective of this thesis is to evaluate consumer-level tracker devices to collect psycho-physiological data and ultimately monitor patients suffering from depression. Ultimately this data can be valuable for larger emerging study in which collected biometrical datapoints would be validated against the results of brain scans of patients recovering from depression. The underlying objective is to see if a machine learning algorithm could be trained to help predicting mental states through remote monitoring. To serve as a preliminary study before being tested on patients, in this thesis we evaluate the different health-related parameters available for a typical commercial devices such as smartphones or a watch. We then put these parameters in regard to the literature, to evaluate if and how they are related to depression. Subsequently, we create a software framework to automatically collect data from this commercial device remotely. We show several parameters that can be effectively collected but that the quality of the data may not be sufficient for an accurate monitoring of patients.

Keywords: remote patient monitoring, major depressive disorder, data collection, usability of consumer-market wearables and smart trackers in research

Contents

Abbreviations

API	Application programming interface
BMR	Basal metabolic rate
COVID-19	Coronvirus disease 2019
EEG	Electroencephalogra
EMA	Ecological momentary assessment
GPS	Global positioning system
HTTP	Hypertext transfer protocol
IoT	Internet of things
MDD	Major depressive disorder
ML	Machine learning
PAL	Physical activity level
PANAS	Positive and negative affect schedule
REE	Resting energy expenditure
REM	Rapid eye movement
TEE	Total energy expenditure

1 Introduction

1.1 Background

The development of smartphones and wearable sensors such as smartwatches embedded with bio-metric and physiologic sensors together generate a vast amount of health and activity related data for the general consumer market. This data utilized by machine learning (ML) algorithms can successfully describe e.g. the user's activities, health condition, stress, mood, and many more bits of information that can be taken into advantage of to improve health and quality of life. With these new tools continuous data collection has been made possible for remote patient monitoring systems, allowing wider and easier healthcare patient recruitment and monitoring, and reducing the bottleneck in the flow of patients. The importance and huge value of these technological achievements become even more obvious during the COVID-19 pandemic.

1.2 Motivation

Major Depressive Disorder (MDD), commonly known as depression, is one of the most prevalent mental health disorders in our modern society, only rivaling anxiety disorder [1]. Treating MDD requires constant medical monitoring and treatment with medicine or other therapeutical interventions. Unfortunately, mental health issues have raised with the recent COVID-19 pandemic. Social restrictions and lockdowns, school and business closures, loss of livelihood, decreases in economic activity, etc. have affected the mental health of the population. Globally an increase of 28% has been observed in MDD cases on contrary to pre-pandemic estimations. Meeting the added demand for mental health services, physical distancing requirements and travel restrictions that make medication acquirement, attending treatment facilities and receiving in-person care, redirection of resources to other healthcare fields all contribute to the acutity of situation. MDD patients have also become less likely to seek for care in lockdown settings [2].

Recovery from MDD is typically a slow process and it may not be beneficial for patients to stay at the hospital for extended periods of time. A proposed idea to have more success treating MDD patients is giving the clinicians (psychiatrists, psychologists, neuroscientists, etc.) the possibility to monitor daily activities remotely through wearable devices. This may result in facilitated and personalized recovery by quantifying responsiveness to the treatment and modifying the treatment according to recorded parameters. Yet, a daily monitoring of patients suffering from pathologies such as anxiety or depression is not straightforward for the clinicians.

The initial motivation for this work is that presently a very large variety of smartphones, wearables and applications are available for everyone to monitor health-related parameters, including wristbands, smartwatches, and sleep monitoring rings. Those elements are pretty much "transparent" for the end user, i.e. one would wear a smartwatch as a regular watch, keep smartphone in daily activities, data would be recorded and synchronized via Bluetooth/apps without efforts. Due to this increased ergonomy this trend ithis trend can be followed by the clinicians and directly collect patient's data through these applications in order to have a better and even real-time view on the patient's daily activities that can be directly or indirectly connected to their responsiveness to treatment.

1.3 Objectives

The main objective of this work is twofold: 1.) to identify the physiological or psychological biometrical parameters required to accurately evaluate patient's mood, stress levels and mental health state and how this is connected to the responding to the given depression treatment; 2.) to define a way to reliably collect the data from different remote monitoring devices, i.e. a smartwatch and a smartphone. A set of parameters must be determined that could be useful to monitor patients, and ideally quantify their mental health condition, so clinicians adjust the treatment on time when this is urgently needed.

For this, we need to create an easy way to extract data from a commercial widely used smartwatch so the researchers pinpoint the optimal strategy for collecting smartwatch data in the background, unobtrusively. In parallel, we will create digital questionnaire and a pipeline to retrieve patients' subjective assessment reports using a smartphone or a watch.

1.4 Organization of the thesis

This thesis work is organized as follows. In section 2, we provide a general theoretical background of this study and analyze previous work in the area. In section 3 we detail the possible psycho-physiological features from everyday-generated data of smart devices are gathered from numerous studies. We also propose a way of enumerating and categorising these features as well as the data gathering devices. In section 4 we detail experimental results using a commercial wearable and a custom-design software to gather the everyday life data. The objective is to highlight potential advantages and limitations regarding the use of commercial wearables. In section 5, we summarize our findings and draw conclusions.

2 Previous Studies and Theoretical Background

2.1 Background of the Idea

Major Depressive Disorder (MDD), is characterized by persistent sadness, negative thoughts, anhedonia, irregular sleep, unhealthy eating patterns, and in severe cases suicidal ideation [3]. It has been estimated that more than one in six people across EU countries had a mental health issue in 2016, equivalent to about 84 million people. Unfortunately, mental health issues have been raised with the recent COVID-19 pandemic. Currently, MDD is typically treated with antidepressant medication and therapy, which is not effective for every patient.

An idea that emerged in the research community is to use available technology to help MDD patients to get the most suitable treatment as fast as possible by monitoring their response to the their current treatment remotely. In this regard, the technological developments appearing in the domain of portable health monitoring, using devices such as smartwatches, smartphones, generally named as the internet-of-things (IoT). Specifically, a proposed idea to have more success treating MDD patients is giving the practitioner (psychologist, neuroscientist, etc.) an ability to monitor daily activities, to facilitate recovery and propose a personalized treatment. Yet, a daily monitoring of patients suffering from pathologies such as anxiety or depression is not straightforward for practitioners.

2.2 Previous Studies

A major study on the daily monitoring of MDD patients was recently published [4], which is used as a reference in this work, giving directions to the search for features required. Mohr *et al.* analyzed every day generated data and ML methods applied in this data, feature extraction and MDD correlation. In previous studies it has been concluded, that with use of all sensors present in people's everyday lives it is possible to collect and generate useful knowledge estimating users' behaviours, moods levels and clinical conditions.

In the many studies that Mohr *et al.* have been reviewing, it has been shown that with everyday life generated data, it has been possible to see correlation with depression, although as authors conclude that some of the studies have been mostly carried out with few participants and not much evidence supporting replicability. Data variability in hardware, environment, different platforms and lifestyles only contribute to challenges that were met. The other challenge is privacy: it is hard to de-identify some data, such as GPS trackings. In order to make the proposed methods accurate, a whole unified infrastructure must be built for continuous data collection and training.

3 Psycho-Physiological Bio-Markers of Major Depressive Disorder

3.1 Daily Activities

Our daily activities mirror what is going on in our minds. Posts and comments that we leave on social media, the amount of exercise we get, where we go during the day, and many other daily activities really are connected to our mood. Similarly, when we are suffering from mental health disorders, our daily activities are affected by the severity of the disorder or the recovery. Monitoring these daily activities can then serve as signs to predict mood disorders, using for instance machine-learning tools.

3.1.1 Levels of Physical Activity

A low, especially sedentary level of physical activity is strongly connected to MDD. This has been shown in [5], using wearable accelerometers tracking the physical activity of the participants. Because of this relation it is a matter of interest to define it as a feature e.g. by dividing into different levels of activity and explaining how these levels can be enumerated using sensors. [6]

Physical activity intensity can be qualified by monitoring one's heart rates. Together with accelerometers physical activity level and energy expenditure can be reliably calculated[7].

Physical Activity Categorisation The Physical Activity Level (PAL) is a way of enumerating the activity level of an adult through its energy expenditure. This parameter is calculated by dividing one's total energy expenditure (TEE) by resting energy consumption (REE):

$$PAL = \frac{TEE}{REE}$$

REE represents the energy consumed when at rest, most of it consisting of energy consumed by metabolism. Determinants such as age, gender, body size, body composition, ethnicity, physical fitness level and environment affect REE. TEE is comprised of many parts such as physical activity energy expenditure, the thermic effect of food and REE [8].

The typically PAL level of an adult is between 1.4 and 2.4: below 1.4 is considered extremely inactive (E.g. cerebal palsy patients), 1.4-1.69 sedentary (E.g. office workers getting little exercise), 1.7-1.99 lightly active (E.g. construction worker, if a person runs for one hour daily), 2.00-2.40 fairly active (E.g. person swimming for two hours daily or an agriculture worker) and greater than 2.40 as very active (E.g. competetive cyclist). PALs are usually estimated with a 24 hour precision. [9], [8]

Physical Activity Level Estimation Accelerometers are widely used in wearables. Here, the principle is to sense the direction of the acceleration (forwards or backwards) in the three dimensions, by clustering three accelerometers together. With some processing, it is possible to tell apart activities such as standing, running, climbing up and even vacuuming[6]. This has been shown for instance in [5], by using wearable accelerometers tracking the physical activity of the participants. Many wearables are capable of estimating energy expenditure to some extent, usually in calories. If a general REE is estimated based on body parameters then a relatively accurate PAL could be calculated as well. For instance a Fitbit Sense smartwatch estimates calories consumed by BMR (basal methabolic rate), or the minimal energy required to sustain life, which is slightly lower thatn REE. The smartwatch also estimates calores that are consumed in total, inlcuding BMR. [8] [10]

3.1.2 Calorie Intake-Outtake

The American Psychiatric Association has reported that lifetime rates of MDD in individuals with eating disorders are very high, ranging between 50% and 75% [11]. In additions, patients having both MDD and eating disorders are more likely to attempt suicide making it a dangerous combination[12]. MDD interacts with eating disorders making them more dangerous, by sharing common risk factors such as low self-esteem, body image dissatisfaction and low social support[13]. MDD and eating disorders have been proved to be partly influenced by common genetic factors. A person having MDD is more likely to get an eating disorder and vice versa: both scenarios are as common [14].

Calorie Logging Through calorie intake-outtake tracking, calorie consumption might be useful to screen against different eating disorders (e.g. too little calories taken showing anorexia, taking too much in short periods revealing binge eating, etc.). It can be an interesting feature to look at in future research, but must be used with caution as calorie tracking might cause more harm than good for individuals suffering from eating disorders, especially in combination with MDD [15].

Calorie intake logging could be done through an app: A participant would estimate calories taken whenever having a meal and calories spent can be approximated by wrist-worn watch sensory data approximation based on heart rate and accelerometer-derived physical activity calculation, just like in TAA estimation. REE should be considered as well, by calculating calorie expenditure based on person's height and mass, which can be done automatically.

3.1.3 Location Entropy

It has been discovered in a few studies that GPS data could be used in predicting depressive states. A number of location features were seen to be connected to depression. Surprisingly, the number of different places a person visits is not related at all, instead the variability in time spent in single locations is: the more time clustered around a few locations, the more likely one is to be depressed and vice versa more equal time distributions indicated lower depression results. [4]

Another feature measuring the periodicity of mapped movement, was firmly related to depression, proposing that disruption in the regularity of the movement is connected to severe cases of MDD symptoms. Especially in during non-workdays, when the movement is not forced by social expectations, these patterns were seen having an even more strong connection to depression [4].

Location Logging Location logging can be achieved most effectively through a smartphone app. It having constant internet connection could track the user's GPS location and simultaneously send GPS logs to a server. Here, additional data security and data anonymisation measures must be taken, e.g. by adjusting each participants GPS location by a random constant value.

3.1.4 Sleep Duration & Sleep Quality

Quality of sleeping is strongly linked to MDD. It is a key symptom of depression often driving patients to seek help. Among MDD patients, sleep disturbances, hypersomnia and insomnia, have been proven to be a risk factor for suicide [16]. Oppsitely, MDD diagnosis among patients not having symptoms of insomnia is rare and must be carefully considered [17].

Around 75% of MDD patients suffer from insomnia and especially in young adult patients hypersomnia, excessive sleeping during daytime is present in 40% cases [18]. When treating depression, if sleep disturbance remains even after other symptoms have been cured, it increases the risk that depression will recur, therefore sleep disturbances could be used as features predicting the outcome of MDD treatment and possible depression relapse and recurrence. [18]

Abnormal architecture of sleep patterns indicates depression, which can be seen physiologically: depressed patients wake up more often and when waking up during night they tend to stay awake for longer periods, whereas normal subjects fall asleep rapidly after waking. Sleep efficiency and total sleep periods are reduced, as well as rapid eye movement (REM) stage latency, the time required between falling asleep and beginning of the REM sleeping stage. REM stages themselves are shorter among MDD patients. [18]

Sleep Tracking possibilities Traditionally, sleeping stages are observed using electroencephalography of scalp and by looking at hypnograms, however modern techniques of using ML algorithms in combination with data coming from wrist-worn accelerometers and an optical pulse photoplethysmograph have proven mature enough to quite precisely detect sleeping stages [19], [20]. Remarkably, a single 3-dimensional accelerometer on a wrist could provide enough data for an ML model even for REM detection providing somehow accurate results [21]. Many smartwatches have sleep tracking capabilities up to REM sleep stage length estimation. Though the accuracy should be certainly tested, from what has been achieved in sleep stages detection looks very promising. With built-in accelerometers any movement during bed time can be logged, E.g. awakening or movement during sleep can be used for sleep quality assessment.

A smartwatch may be challenging for the user to wear without ever removing it, which is why alternatives can be put in place. With smartphone data (accelerometer, microphone, ambient light sensor, screen proximity sensor, running process, battery state, and display screen state) only, sleep periods could be estimated with 90% accuracy, especially in younger people, who use their smartphones to a greater extent [4]. With smartphone microphones, such features as snoring, ambient noise, body movement affecting long- and short-term sleep quality can be recorded. When enough data is collected, circadian-aware systems can be built detecting patient's chronotype or E.g changes in sleep patterns between workdays and non-workdays indicate how external pressure and social obligations driven waking differs from natural sleep, known as "social jetlag". These kinds of sleep disturbances have been proven to correlate with severity of MDD. [4]

3.1.5 Use of Social Media

With an increasing number of social media users, the use of generated data for judging on person's mental state is looking more and more feasible. The language used in posts, comments, discussions etc. on social media can be evaluated psycholinguistically, enabling a specialist to judge on writer's mood.

By deconstructing the text, E.g. looking at word choices, their negativity or positivity, anger, sadness, relation to anxiety. Further, through psycholinguistic feature extraction, it is possible to classify processes contained in it, for example, affective processes describing emotions, or time-oriented processes, social context, biological processes describing if the process is sexual, body, ingestion or health matter, linguistic categorization, and many other. With these features a depressive mood detecting ML model can be built, some studies achieving 60-80% accuracy [22], 69% with real MDD patient validation [23] and as high as 91% in measuring signs of depression[24]. The accuracy depended and differentiated between used computerised text analysis software packages and ML methods.

3.2 Physiologcal Stress Detection and MDD

Psychologically, continuous exposure to stress and stressful (e.g. traumatic) life events, especially in early life, can proceed to the formation of dysfunctional cognitive schemes, resulting in biased cognitive processing of outside stimuli, making us cognitively and emotionally vulnerable, later increasing the risk of gaining depression in response to stress.

Physiologically, continuous exposure to stress and stressful life events have an impact on changes in the phenotype of the central nervous system itself, hyper activating hypothalamic–pituitary–adrenal axis, increasing levels of cortisol and corticotropin-releasing hormone, sometimes leading to molecular changes in different circuits creating molecular vulnerability to stress and stress-initiated depression. [25]

Psycho-physiological responses are controlled by the autonomous nervous system, sympathetic and parasympathetic. Results of physiological indicators discussed in sections below show that stress-depression relation has a connection to the parasympathetic nervous system, suggesting that MDD may be positively correlative to hyperactivity of it. Changes in physiological indicators have different sensitivities. For instance, finger temperature is very sensitive to depression and stress then comes skin conductance and heart rate is least sensitive.

Psychophysiological Stress Response and Depression Psychophysiological stress responses differ between normal people and MDD patients, increasing parasympathetic autonomous system responses: the more severe depression risk is, the more parasympathetic the physiological responses to stress were, whereas normal subjects stress responses were purely sympathetic. [26]

Measure stress with Skin Conductance Stress levels correlate with increased skin conductance, but show a negative correlation with stress responses in MDD patients, though among them skin conductance is increased generally in normal conditions. There are many solutions for skin conductance measurement on the market, though finding that feature on a consumer-level device was unsuccessful at the time of the study. Recently, more advanced wearables enable this measurement.

Measuring stress with Heart Rate Increased heart rate correlates with stress exposure, but shows a negative correlation to stress-related depression. As mentioned before, heart rate can be measured with a smartwatch or a smart ring.

Measuring stress with Finger Temperature Stress has shoved correlation to decrease in finger temperature and positive correlation to stress-related depression, showing significant affection by stress and depression interaction. Finger temperature could be measured with a wearable ring, E.g. Oura claims in its blog [27], that their smart ring is capable of measuring finger temperature with 0.1 degree accuracy.

3.3 Subjective Assessment

3.3.1 Retrospective Self-Reports

As the data mentioned above is subject to variability depending on the person, culture, time of the year, differences between devices, especially mass-market devices, some individual assessment is required in order to evaluate any correlation with passively collected data. With self-reports such data must be assessed subjectively. For example, a questionnaire on sleep quality can be given to participants, subjective stress assessment or features generated out of social media data could be assessed with mood questionnaires. [4]

3.3.2 Ecological Momentary Assessment

Ecological momentary assessment (EMA) was developed to get a better vision of affective and behavioural dynamics in daily life and is widely applied in mood disorders research. The term ecological stands for the environment of data collection, as data is collected repeatedly in real-world contexts. The term momentary refers to the way assessment is focused on the time of the experience.

With the development of smartphones and smart devices, EMA reports have become more and more easy and ergonomic for subjects to respond and the idea of it being ecological and momentary started making more sense, as assessment subjects can be automatically prompted to fill report questionnaires. EMA report data has also been successfully validated with smartphone embedded and wearable data, providing a new view on MDD in daily life contexts, which is much harder to accomplish with traditional methods [28].

Positive and Negative Affect Schedule A most widely used way of measuring mood states is positive and negative affect schedule (PANAS). PANAS scale consists of a number of words describing different feelings and emotions, which are supposed to describe participants mood dimensions, e.g. from positive valence (joy, enthusiasm, crush, etc.) to negative valence (anger, fear, anxiety, etc.). PANAS has been long validated in many fields as well as in MDD patients mood assessment [29], [30].

PANAS alternative Though PANAS is widely used, it has been criticised for the validity of its theoretical conception of using only two mood describing dimensions. As an alternative for PANAS, EMA report questionnaires can be for instance conducted by measuring three trivial mood dimensions: valence, calmness, energetic arousal. A proposed scale has two items per mood dimensions. EMA report participant responds to questions about how they currently feel choosing corresponding value on a scale having mood describing adjectives as endpoints. The proposed negative-positive endpoints are tired — awake, full of energy — without energy (energetic arousal); agitated — calm, relaxed — tense (calmness); content — discontent, well — unwell (valence). A mean value of two bipolar scales is then taken to describe participants mood per dimension (calmness, valence, energetic arousal). [31]

3.4 Electroencephalogram Validation

Electroencephalogram (EEG) is a non-invasive brain activity measurement that records highly random electrical activity of brain signals, widely used by physicians and researchers to study the function and connectivity in health and disease. EEG is a reliable method to study MDD due to its ease of use, requiring only simple placement of electrodes, and showing a good temporal resolution. MDD typically indicates some dysfunction in the brain, which can be seen (not visually) in measured abnormal EEG signals as variations in brain rhythms and connectivity patterns of the patient and EEG is dependent on biotic activities of the brain for the accurate detection of signal abnormalities.

EEG can detect five different brain rhythm signals with their own bandwidth (alpha, beta, theta, delta and gamma). Generally speaking, alpha and beta waves represent conscious states and theta and delta unconscious states. Gamma rhythm is responsible for sensory perception.

Depression affects three brain parts: hippocampus, prefrontal cortex and amygdala. Hippocampus holds memories and controls cortisol hormone production, which is excessively produced during depression. Long term exposure to cortisol causes slower production of new neurons and causes the hippocampus to shrink leading to memory problems. Excessive cortisol levels also shrink the prefrontal cortex, which controls our emotions, makes decisions and creates memories. The amygdala, which is responsible for emotional responses on other hand enlarges due to cortisol exposure causing sleep disorders and other activity patterns. In normal patients, cortisol levels are high in the morning and low during night but in MDD patients cortisol level is higher during the night. [32]

MDD mostly affects the frontal brain and asymmetry of frontal theta waves can be used as a biomarker of depression: MDD patients tend to have less asymmetry. Gamma waves can also distinguish MDD (but only under certain disorders) as alpha waves by looking at its frontal asymmetry and power.

EEG Validation With biomarkers described above (on a very general level) and many other biomarkers that Yasin and his colleagues describe in their study on MDD detection with neural networks over EEG scans [32], depression can be reliably diagnosed with EEG. There are ready-made EEG datasets which with neural networks can reliably (up to 99.5% accuracy) give an MDD diagnosis. Many of these datasets are public. [32] Such high accuracy and ease of use of non invasive electrodes makes sense to use for validadion. Even wearable EEGs are in developmend[33], but wearing such a device constantly would cause too much discomfort to a patient, therefore EEG MDD validation must be done clinically, providing even more accurate data points.

3.5 Summary of the findings

Based on previous sections it is possible to say that MDD is trackable psychophysiologically. These features of interest and proposed ways of measurements and tracking are summarised in Table 1.

Table 1: Data of Interest

Indicator		Motivation [reference]	Proposed devices [reference]
Group	Name		
Daily activity	Physical location (in/out, home/away)	Activity levels impact general mental health[4]	Smartphone location sensors (GPS, etc.), phone log analysis (calls, texts, etc.) [Ea]
	Calories intake/ outtake, physical activity	Activity levels impact mental health[4]	Movement sensors in smartphone or wearable survey for calorie intake[Ea] [Fw][Or]
	Use of social media	Can be used to infer mental state[4]	smartphone data analysis[Ea] (*not targeted in this work as considered too intrusive*)
	Sleep duration / sleep quality	Sleep impacts mental health[34]	Wearable with sleep monitoring or by default phone activity, ambient light[Ea][Fw][Or]
Outside conditions	Temperature	Outside conditions impact general health/ mood[4]	Temperature sensor, location data[Ea]
	Ambient light		Light sensor, correlation with location[Ea]
	Heart rate		Measured with wearable[Fw],[Or]
Physiological	Speech	Used to infer stress[4]	Microphone (*not targeted in this work as stress can be also monitored through skin response*)
	Skin moisture and temperature	Skin state related to stress level and mental states[26]	Galvanic Skin Response sensors with wearable or with hospital measurements if not available
Subjective assessment	Retrospective self-report	Correlation with other measurements[4]	Collect participant's data through smartphone[Ea]
	EMA reports	Grasps affective and behavioral dynamics in daily life[28]	Collect participant's survey data through smartphone[Ea]
Brain activity	EEG	Brain activity can be assessed through electrodes[35]	Headset with on-chip classifier (*not targeted in this work initially, headset considered too intrusive*) [36]
			Hospital measurements (*not remotely monitored*)

[Fw] — Fitbit smartwatch, [Ea] — Ethica app, [Or] — Oura ring (not tried out).

4 Application

4.1 Smartwatch and Server API

A Fitbit Sense smartwatch has been selected for use as a wrist-worn wearable. Having all basic tracking capabilities existing on the market, at the moment of decision it was the only smartwatch offering electrodermal stress tracking, which was seen as a huge benefit. In contrary to more professional, medical-grade devices, the cost of consumer-level devices is much lower, both in terms of equipment and data collection. For future research purposes, where a numerous amount of research participants would have to be provided with a wearable, with the possibility that some of them would already have this device available or would be familiar with usage of the device. It is also a matter of curiosity to review the possibility to use mass-market devices in MDD assessment. Another valuable feature is its open API (Application Programming Interface) capabilities. Indeed, it is possible to make remote hypertext transfer protocol (HTTP) get-requests to a Fitbit server and receive processed health data, which can be then exported to a database at a very low cost. For instance, the Fitbit app also offers such features as calorie intake and exercise logging. Especially calorie logging proved very useful, as Fitbit watch continuously estimates calorie expenditure.

Figure 1: Fitbit Sense Watch

Photo source: fitbit.com

4.1.1 Consumer-level Device Limitations

Choosing to use a consumer-level device appeared to have several limitations. The greatest disadvantage is the lack of any medical or technical documentation on sensory or feature-related measurements, e.g. their accuracy, how certain features are estimated or calculated. Generally, the API documentation manages well to explain the structure of sent data in javascript object notation (JSON) format, how to request it and how authentication works, but it fails to explain the meaning of returned measurements. Though Fitbit indirectly advertises itself in research use and supports third-party applications development, it fails to document the data it generates: for instance, Fitbit proclaims that it is capable of estimating the wearer's stress, providing a certain stress score. What that score really stands for, stays unknown. Similarly, the wearable measures activity level but doesn't explain what it means. It could be expected that activity level may correspond to PAL, but Fitbit provides no evidence except having a similar classification. A related issue holds in sleep stage detection as well. Nevertheless, the data gathered by such device seems to be somewhat accurate and is still valuable.

4.1.2 Smartwatch Data Extraction

Several scripts were written to extract smartwatch data. The software handles secure authentication, makes HTTP requests and exports received data to .csv files, which can be then moved to a database. The software was made with future research considerations, making multiple research participant management easier and can be found on GitHub (see attachments section).

Physical Activity Level & Steps By making a physical activity level request Fitbit sends data with up to one-minute precision. The physical activity level itself is not as precise and is shown as an integer 0 to 3 (0 meaning sedentary, 1 - lightly active, 2 - fairly active and 3 - very active). The classification and naming is similar to PAL's but as mentioned before, Fitbit provides no evidence about it.

An example of physical activity level data gathered during one day is shown in Figure 2, in which physical activity level resolution might seem as small, but it should be enough to calculate the physical activity level for 24 hour period, which is a general practice in PAL. From the graph, it can be observed that in middle of the evening the physical activity increased as wearer was running at that time. The same pattern can be seen in figures 4 and 5 as an increase in calorie expenditure and heart rate. Steps can be counted as well, with per-minute resolution, showing the same pattern of increased steps when running (Figure 3).

Calorie Expenditure Like in physical activity levels, the time resolution of calorie expenditure is high and requested accuracy can be varied (e.g. one minute, 15 minutes, one day...). Based on given biometric values (body mass, weight), Fitbit calculates calories required by basal metabolic rate consumption, i.e. energy spent on basic life-sustaining functions like breathing, blood circulation, heat maintenance, etc and

Figure 2: Physical Activity Data (physical activity level / minute)

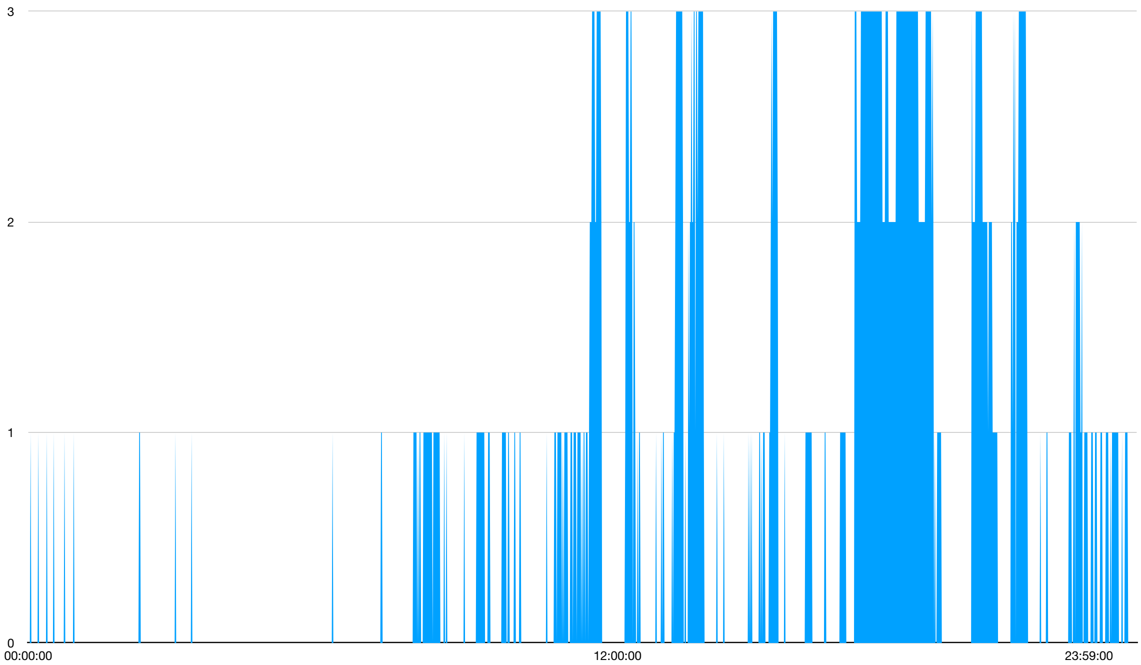
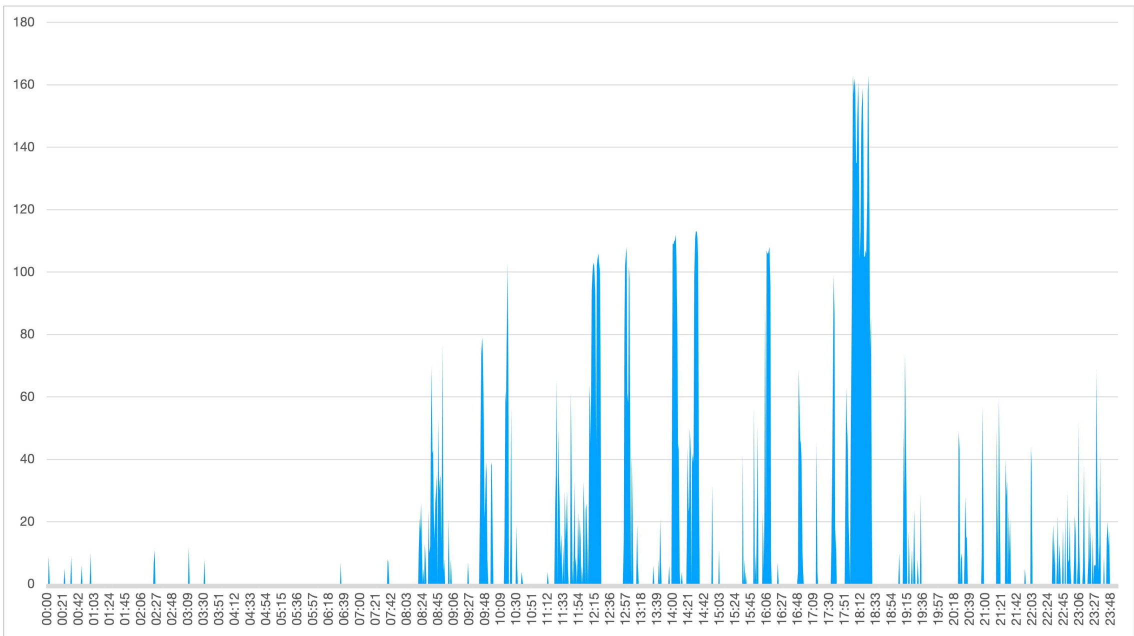
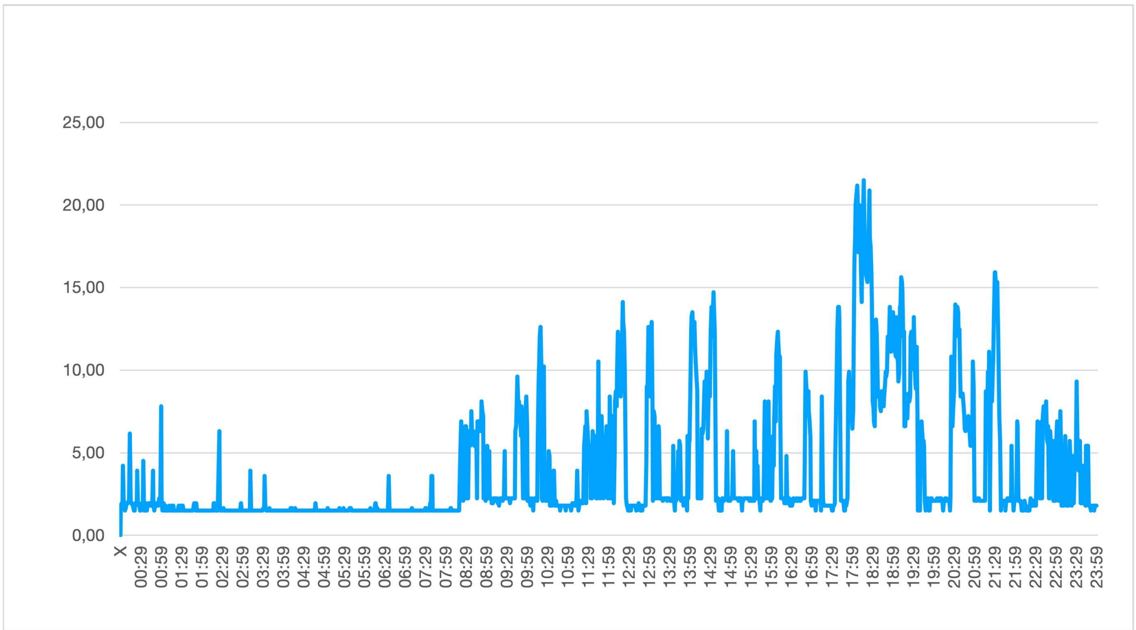


Figure 3: Steps Taken (steps / minute)



is slightly lower than REE. Whenever Fitbit smartwatch doesn't sense any or senses very little physical activity, it logs estimated basal metabolic rate.

Figure 4: Calorie Expenditure (calories / minute)



Heart-rate Unlike in other, hear-rate per-minute time resolution offers measurements at a maximum of five-minute intervals or an average heart-rate can be requested with 24-hour intervals. Both of these intervals seem to be good enough.

Sleep There are two different ways that sleep data can be recorded: either estimating if the wearer is asleep, restless or awake or as a summary of time spent in different sleep stages. An example is seen in Figure 6 with gather data listed in Table 2. Here, sleep stages do not refer to actual "sleep stages", like different stages of non-rapid eye movement and REM itself, instead, Fitbit has four own sleep stage classes: deep sleep, light sleep, "REM" and awake. Again, consumer-level device limitations are faced and poor documentation does not explain the exact meaning of the classification. This is unfortunate, as a user or a researcher can never be sure whether "REM" actually means actual REM sleep, nor there is any information about the accuracy of supposed sleep stage detection. A study, which had clinically assessed another Fitbit smartwatch device resulted in proving that Fitbit is not accurate enough in sleep stages detection compared to clinical devices, and should not be used in clinical or research use [37].

Figure 5: Heart Rate (heart beats / minute)

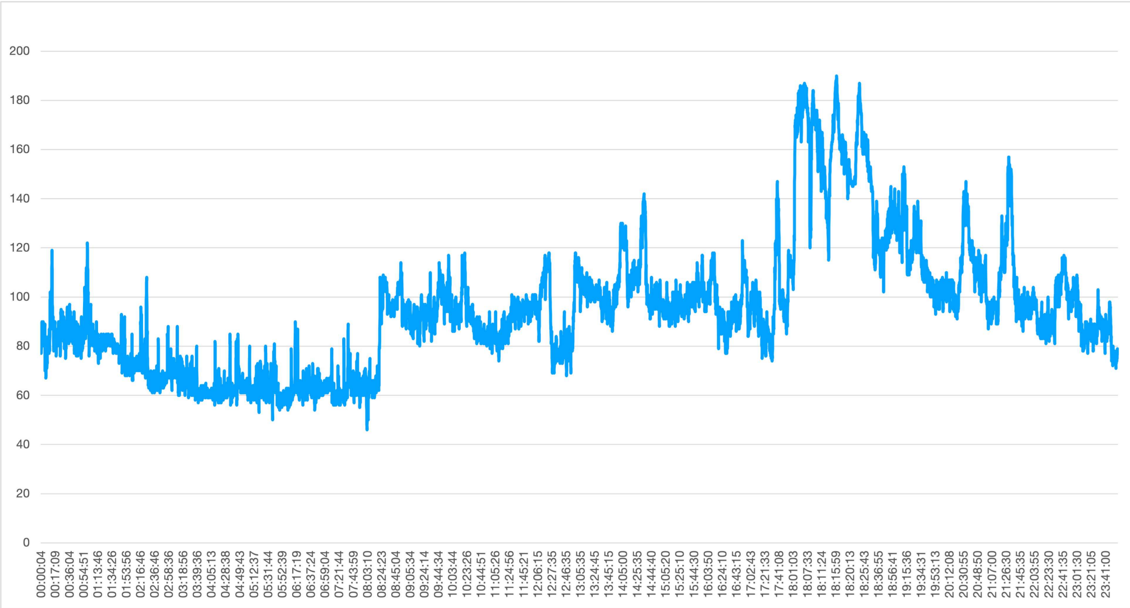
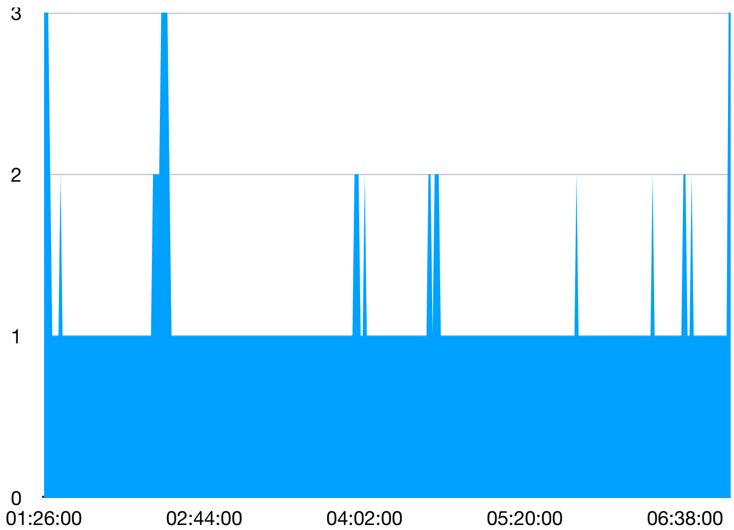


Figure 6: Sleep Status Data (Sleep status / 5 minutes)



1 - Asleep, 2 - restless, 3 - awake.

Table 2: An Example of Raw Sleep Summary Data Gathered in a CSV File

totalMinutesAsleep	totalSleepRecords	totalTimeInBed	date	stages.deep	stages.light	stages.rem	stages.wake
425	1	516	2021-10-12	-	-	-	-
423	1	474	2021-10-13	-	-	-	-
421	1	473	2021-10-14	-	-	-	-
527	2	571	2021-10-15	64.0	283.0	62.0	51.0

No data is shown as dashes. In the last row, where stages detection was successful, time spent in different sleep stages can be observed.

4.2 Smartphone Data & research participants management

For smartphone data collection a system made by Ethica Data was examined. Ethica Data provides a ready-made environment for setting up studies with multiple participants, it offers study participant managing, cloud data processing, phone-generated data collection and survey pushing. Sending surveys and smartphone-generated data collection is possible through an Ethica app, which is customisable.

Survey pushing can be triggered by different conditions and a research participant would get a notification. Using third-party software makes it easier to set everything up and reduces the workload on researchers, it would also move away legal and data protection considerations from the researcher team.

Ethicadata offers even higher customisation, e.g. for studies following this work : the use of their server API would make remote monitoring easier through automation and make it possible to integrate smartwatch data collection into the study.

4.2.1 Smartphone Data Extraction

Different data that could be considered beneficial for the study is shown in Table 3. Due to sensors differentiation in different smartphones, some variability was seen in measurements. Most of the features worked well on Android but did not work with iOS. Surveys are designed well in Ethica. Users get an automatic notification if needed. User input can be limited to numeric values, scales or text.

Table 3: A Review of Data Collectable With Ethica App

Type of Data	Ethica Description	Usability
Motion Activity Recognition	The type of activities the user currently is involved in. E.g. stationary, walking, biking, or on vehicle.	Limited (3)
Ambient Temperature	Measures the ambient room temperature in degrees Celsius.	None
Pedometer	Counts the steps taken.	Full (1)
Accelerometer	Measures the acceleration force applied to a device,including the force of gravity (Unit: m/s2).	Full (1)
GPS	Measures the precise location of the device using GPS, with minimum battery usage (∼10% per day).	Partial (2)
Screen State	Records the time that the screen turns on or off.	Partial (2)
Light	Measures the ambient light level (illumination) in lx.	Full (1)
Linear Acceleration	Measures the acceleration force in m/s2 that is applied to a device, excluding the force of gravity.	Full (2)

(1) data varied between different devices. (2) Worked well on Android, but poorly with iOS, (3) the collected data was not accurate

4.2.2 Limitations

While on Android mobile operating system smartphones Ethica app seems to work flawlessly, on iOS it was found that the app had troubles collecting data whenever the app itself was not running or after some time it was left running in background. This is might be due to iOS's higher security features.

5 Results & Summary

A literature survey has been carried out to find out possible features in daily-used devices generated data that can point to MDD and its development (Table 1). Based on these findings, methods of collecting the features mentioned have been proposed and usability of a Fitbit Sense as a wearable and Ethica as a data collecting smartphone app and research participants management platform have been reviewed.

As a result, it has been shown that background data collection is possible to implement with a consumer-level device, though with great limitations: lack of documentation made data interpretation hard, unexpected changes in the API and its low flexibility. As the industry of consumer-level wearable trackers is young, there are no widely used standards that would make working with multiple different devices possible by impelling wearables to return standadised data. With Ethica, on other hand it has been found out that smartphone data collection is not as straightforward — some data collection failed and data collection on an iOS smartphone did not work in the background.

Whether this data, considering these limitations, is capable of building a successfully working ML model is yet to be proved in a continuing study.

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Attachments

GitHub repository github.com/AleksiSupikoski/Fitbit-Biometrical-Data-Gatherer
A GitHub repository with software used for data gathering.