Smartphone Sensors to Measure Individual Sleeping Pattern: Experimental Study

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Abstract: The wide spread of using smartphone sensors to measure several health parameters such as collecting and tracking individual activities, sleeping patterns and data, enables doctors to provide personalised treatment. This paper discussed the use of smartphone sensors to track insomnia. The SleepTracker app was developed to test the ability to track an individual's day to day sleeping pattern based on screen on/off events, its accuracy evaluated and further improved on.

1 INTRODUCTION

Sleep is a natural state of mind and body, about one-quarter to one-third of the human lifespan. Before the 1950s, sleep was considered a passive practice as a result of a reduction in some vital force (Rama et al., 2005). Physiologically, sleep is the complicated process of repair and renewal for the body and mind. While scientists do not have a conclusive explanation for why humans need sleep, sleep is thought to be valuable in some physiological operations including the mental processing of experiences and the consolidation of memories. It is therefore clear that sleep is essential, not just for humans but for nearly all creatures.

According to Deloitte's seventh annual mobile consumer survey, around 79% of young adults check their phones before going to sleep (Dewa et al., 2019). A further 26% of the survey respondents answer messages even after falling asleep at night while 89% of respondents use their phones within five to thirty minutes after they wake up(Dewa et al., 2019).

Technology may be a useful medium to detect sleeping patterns, and mental health deterioration before serious adverse events occur (Lin YH et al., 2019). This research contributes to the development of a mobile app that can be used to collect passive data and scalable at a public health intervention level. The app will be used to detect sleeping patterns and their relationship with anxiety and depression, especially among university students aged between 18 - 25 years.

2 RESEARCH PROBLEM

In November 2020, of the UK population are more likely to experience some form of depression and or anxiety, young adults age 16 – 29 years are found to be the highest; at about 31% and 29% respectively (Coronavirus, 2020). In 2014, 19.7% of people in the UK aged 16 and over showed symptoms of anxiety or depression - a 1.5% increase from 2013. This percentage was higher among females (22.5%) than males (16.8%).

When a systematic review was conducted to understand the impact of sleep quantity, quality, and regularity on mental health, the study found that sleep

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has healing abilities and a great effect on diverse mental health problems such as depression, bipolar disorder, anxiety, and suicide. According to Walker (2017), sleep deprivation has also impact on emotional moods among healthy individuals (Matthew Walker, 2017).

3 OUTLINES OF OBJECTIVES

The overarching aim is to test the feasibility of SleepTracker app to monitor and indirectly estimates sleeping patterns in young people. The app will detect changes in sleeping pattern that offer the opportunity to provide advice on improving sleep or signpost to early interventions for anxiety and depression.

4 INNOVATION

Previous studies by Z. Chen et al.(Ben-Zeev et al. 2015) and Min JK et al.(Min JK et al., 2014) had used multiple sensors in smartphones to understand sleeping patterns. However, the combined phone usage and usage of these smart phone sensors such as light, microphone, accelerometer can drain the smart phone's battery life.

Several other studies used the screen on/off events to track sleeping pattern. Lin's study of individuals' sleeping pattern based on a defined sleeping time window between 10.00 pm to 10.00 am disregarded the variation of sleeping time according to different individual's preferences(Lin YH et al., 2019).

In another similar study, an app called "iSenseSleep" was developed using the same screen on/off events(Ciman and Wac, 2019). By considering the longest time period where the phone is unused as the sleeping time, this app estimates and predicts the individual's sleeping pattern by collecting data over two days. This may not reflect the reality of the changes of individual's sleeping pattern according to any changes in circumstances.

Having identified the shortcomings in other studies and a possibility where individual may not touch the phone even when they are awake, it is therefore imperative to focus on the accuracy of the sleep duration and patterns.

We implemented an algorithm to test the feasibility of detecting individuals' sleep duration unobtrusively and compare it with their sleep diaries, using the screen on/off event. With the result of 178 minutes of absolute mean difference, this algorithm was further revised and improved with added light and accelerometer sensors in the smart phones. This revised algorithm results to an absolute mean difference of 70 mins; an improved accuracy for the purpose of understanding sleeping pattern and detect insomnia.

5 TASK ANALYSIS

We had held a virtual focus group of 7 young adults; with the intent of discussing the feasibility of developing a "sleep tracking" app that runs in the background without user intervention and the frequencies of users' phone usage before and after bedtime.

The group indicated their preference for a user-friendly app that is non-user intervention and does not intrude their privacy such as the use of the phone's microphone or video camera. They are inclined towards such desired app that runs in the background that helps them understand their sleeping patterns and mental health.

As for phone usage, most of the focus group members checked their phones before getting up from bed in the morning. They gave a mixed response of waking up to phone alarms and on their own.

6 METHODOLOGY

We ran two field tests to ensure and improve on the accuracy of the SleepTracker app in detecting users' sleeping patterns.

The first field test was conducted over a 6-night period. It collects data from seven participants and calculated the sleep duration using an algorithm based on the screen on/off events.

With improved algorithm and additional movement and light sensors, the second field test was conducted over a 7-night period, collecting data and calculate individuals' sleeping pattern from a fresh set of six participants.

6.1 Field Test One

By calculating the time spent for mobile phone usage and estimating daily sleeping hours, we developed the SleepTracker app to estimate individual's sleeping pattern.

Due to the individuals' different sleeping time windows, the app defines a diurnal rhythm for which the users record their sleeping window (i.e., the times that they normally sleep). The app enables users to specify the earliest time they will sleep and the latest time they wake up. By the app being activated and running in the background only during the users' indicated sleeping time windows, it helps to reduce the phone's daily battery usage.

The algorithm was based on estimating the time spent using the phone during the sleeping time window. It then calculates the total time spent using the phone during this window. As example, if the user selects to sleep after 10 pm and wake-up before 8 am, the app stores all the screen on/off status and calculates how long the user uses the phone within these hours (Figure 1) in a firebase database. The algorithm records daily total sleep duration at the end of the daily sleeping time window.

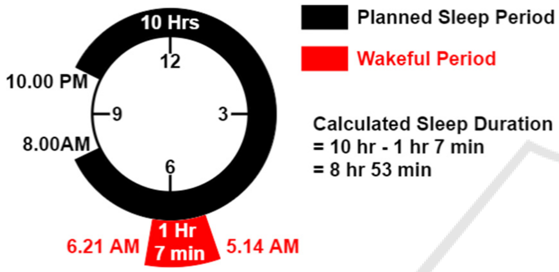

Figure1: Field test 1- Algorithm of SleepTracker App.

6.1.1 Recruitment and Sampling

We managed to recruit 9 young adults (5 females and 4 males) with an age range between 19 and 22 years old. Before these users were asked to use the app for one week, a step-by-step instruction manual for downloading, installing, and using the app was given to them; after obtaining their signed consent form.

6.1.2 Results

While this study was designed to track individual sleep duration, this field test one resulted to a noticeable variation between the app's recorded sleep duration and the participants' diaries. For example, a particular user recorded in his sleeping diary a total of 10-hour sleep (between 11.00pm and 9.00am); whereas the planned sleeping time window entered in the app was a 9-hour sleep between 11.00pm to 8.00am. In this instance, when the app is deactivated at 8.00am as per planned sleeping time window, the participant is still asleep. Any screen on/off events after 8.00am were never recorded.

Using absolute mean formula (Figure 2), the overall absolute time difference between the sleep diary and the app raised the issue of accuracy and that had led us to further improve the algorithm in the subsequent field test two.

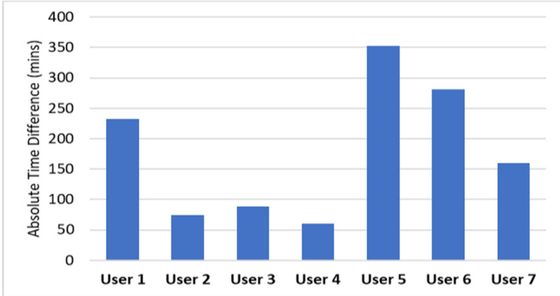

Figure 2: Absolute mean differences among the participants.

6.2 Field Test Two

The SleepTracker app, developed and deployed in field test one, was upgraded. The upgrades include a revised and improved algorithm, and the inclusion of additional two built-in device sensors that are:

- Ambient light sensor: To detect usage of light during normal sleeping hours.
- Accelerometer sensors: to detect the use of the phone during normal sleeping hours.

The revised and improved algorithm included collection of the data from the above two said sensors as variables for a more accurate calculation of results. This improved algorithm was designed to determine whether the utilisation of the additional two sensors would improve the measurement of sleep duration.

The sleep duration is calculated by considering the longest non usage period of the phone. The app activates at the start of the sleeping time window and commences collecting screen on/off events that indicate phone usages of 5 minutes or longer. Any phone usage that is less than 5 minutes is considered to be part of the sleep duration. Marking the end of the sleep duration, the app shall recognise the screen on event, on or after the planned wake up time of the sleeping time window. The longest period between screen off and screen on in the next day is considered as the sleep duration (Figure 3).

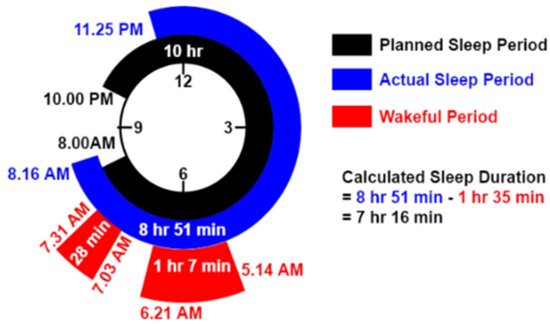

Figure 3: Field test 2- Algorithm of SleepTracker App.

6.2.1 Recruitment and Sampling

Of 16 new young adults invited to participate in our study, 9 had signed up and of which, only 6 participants (2 female and 4 male) completed. The participants' age range between 18 and 25.

Prior to a video demonstration and link for the app download, installation and usage, the participants gave a signed consent form to allow us to collect and analyse the data that is collected over a consecutive trial period of 7 nights. In addition to the collected data, the participants were required to provide us with their sleep diary at the end of the trial period.

6.2.2 Results

Apart from the app, data relating to the participants' sleep duration were collected from their submitted sleep diaries to establish whether they were awake during the sleep time window without using the phone or woke up in the morning and not touching the phone. This data are used to compare and analyse with the data collected by the app.

As compared to the absolute mean difference of 178 minutes in field test one, field test two showed better accuracy in the tracking sleeping pattern with an absolute mean difference of 70 minutes (Figure 4). This pave way for the next phase of this study; tracking sleep disturbances and provide signposts as early detection of insomnia.

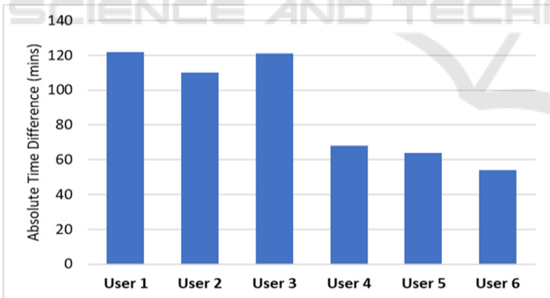

Figure 4: Absolute mean differences among the participants.

Figure 5 shows data sample collected from the devices' sensors of light, accelerometer, and screen on/off. Despite no activities in the device movement sensor and screen on/off sensor, a noticeable trend is the light level meters that keeps changing during the sleeping time window.

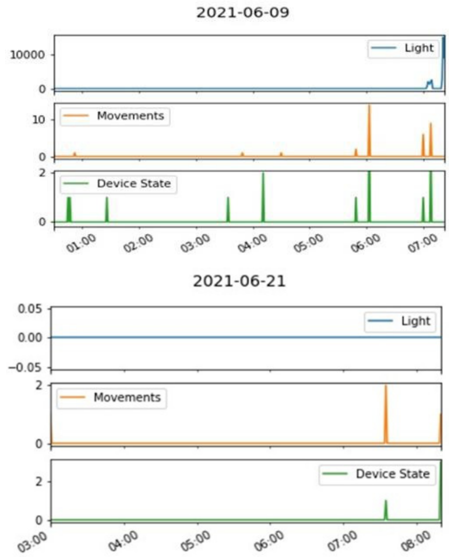

Figure 5: Sample of participants' data containing the light, accelerometer, and screen on/off events to measure sleeping pattern.

7 DISCUSSION

Through recording the screen on activity on or after the wake-up time, as per entry plan by the user, and any phone usage activity of more than 5 minutes, the improvised algorithm in SleepTracker app produces better accuracy in calculating sleep duration. The algorithm calculates and recognises app activation in the background at the commencement of the user sleeping time window or the start time of long non-usage period and the screen on event the following morning as the overall sleep duration; before deducting any phone activity of more than 5 minutes. The only possible drawback could be a situation where the user continues sleeping after waking up and uses the phone for more than 5 minutes.

A brief comparison table was drawn up against previous studies done by Z. Chen et al., Min JK et al., Lin and iSenseSleep. Critical variables were identified and compared against SleepTracker app (Figure 6). From the comparable table, we draw significance to the sustainability of battery life, adaptable individual sleep duration, period of trials and tests and the accuracy of the SleepTracker app.

While higher accuracy results were shown from an absolute mean improved from 178 minutes to 70 minutes, the accelerometer sensor had shown positive indicators of furthering the SleepTracker app's accuracy.

In order to help users detect insomnia and provide early intervention, this app can be further developed to detect sleep disturbances that occur during the sleeping time window by the usage of in built screen on/off and accelerometer sensors.

	Z. Chen et al.	Min JK et al.	Lin's	M.Ciman et al.	SleepTracker
Accelerometer Sensor	Y	Y	N	N	N
Light Sensor	Y	Y	N	N	N
Screen on/off	Y	Y	Y	Y	Y
Battery	N	Y	N	N	N
Microphone	Y	Y	N	N	N
Sleep Timing Window Defined by the app	N	N	Y	N	N
Study Period (days)	7	30	14	2	7
Accuracy, Absolute Mean Test (minutes)	42	49	83	17	70

Legend:
Y Yes
N No

Figure 6: Comparison Table of Sleep Pattern Studies.

8 EXPECTED OUTCOMES

In this study, we implemented an algorithm in field test one and improved this algorithm in the subsequent field test two. While the aim of this study was to calculate sleep duration using the screen on/off events, we upgraded the app by utilising additional in-built mobile phone sensors such as accelerometer and light that collected data relating to an individual's sleeping pattern.

The collected data from field test two showed better results of accurate absolute mean differences measurement, pointing to us that movement sensors can better help track sleeping patterns. In the foreseeable future, we plan to use screen on/off and accelerometer sensors better help in our further study to track insomnia and provide early intervention if depression or anxiety is detected.

9 STAGE OF THE RESEARCH

This current stage of this research is centered on the accuracy of the SleepTracker app in monitoring sleep patterns and durations. The next phase of this research shall be the study to measure sleep disturbances and its impact on mental health.

In the following phase, over a period of 2 months and a larger group of participants, we aim to conduct observational study to test the acceptability of the SleepTracker app and track symptoms of insomnia, depression, and anxiety. The app shall be used to collect data on the frequencies of nocturnal phone usages that are above five minutes and movements during the users' planned sleeping hours at night.

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