Sedentti: Improving Quality of Sedentary Lifestyle Using a Behaviour Guide App for Android Smartphones

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ABSTRACT

Sedentary behaviour causes various problems to our health. In this paper, we present a smartphone app capable of tracking users' activities. The goal of the app is to help people spend less time sedentary. It uses Google Activity Recognition API and Significant Movement Sensor to determine the activity. The app is developed with focus on the UI and UX and digital behaviour change interventions in order to motivate its users to follow a healthier sedentary lifestyle. The chosen way of implementation did not bring the expected change in the users' behaviour. The paper discusses the suggestions and potential improvements to the app.

Keywords

mobile sensing, sedentary job problem, sedentary lifestyle, activity tracking, digital behaviour change interventions

1. INTRODUCTION

People perform various activities through a day and spent significant part of time in a job. We consider activities that requires low energy expenditure as a sedentary behaviour [1]. Although this kind of behaviour appears mainly during our sedentary job, we may find other various situations in which it occurs. To give an example, it can be lying on a bed while reading or playing video games, travelling or driving, but also watching a TV [2]. All these activities may be so entertaining that we may lose a track of time.

What is more, people who spend more time sitting may have an increased risk of metabolic syndrome [3] which includes problems with diabetes, obesity and hypertension. Another researches concluded that there is a correlation between time spent sedentary and the risk of obesity [4, 5], cardiometabolic health [1, 6] and mortality [2, 7, 8].

In this paper, we present an Android application (aka. app) that helps people to sit in a healthier manner and mitigate problems related to prolonged sitting by implementing parts of the Habit Alteration Model (HAM) presented in [9]. The main aim of this app is to break a habit of having a long continual sitting period. Training self-control of a person through repetition makes a habit automated [10] after some time which is exactly what this app tries to achieve in users behaviour - to help him or her nonconsciously resist habitual impulses to keep sitting.

2. RELATED WORK

As we have already mentioned, there are various researches regarding the bad impact of sedentary behaviour on people's health. On the other hand, we are here interested in ways of collecting data about the user's sedentary behavior which is related to the technology development. The simplest way of monitoring is to ask people to self-report their behaviour on the paper. As sitting is highly habitual, a participant may forget to write it down, and thus this method can be subjectively influenced.

With advance of technology, we welcomed smartphones which are often carried with us. The smartphones have sensors required to track user's activity. The only requirement here is to have it with you for the whole time. There are various products, such as Apple Watch or Mi Band from Xiaomi, that track user's activity. These wristbands send notifications regarding prolonged sitting as well. These solutions are very effective, but not everyone owns such a device. Therefore, a smartphone app would be more convenient.

The research by Fahim [11] et al. shows that data from an accelerometer can be used to derive actual activity of the user. They compute features extracted from time and frequency domain of the data and use non-parametric nearest neighbour algorithm to determine the activity. Their app does not have statistics to be shown on a device, but rather sends the data to a cloud where they are being further analyzed. Therefore, we cannot talk about any interventions into user's sedentary behaviour. Another app by Bond et al. [12] shows performance statistics as an automotive dashboard and a fuel gauge depicting the number of sedentary minutes remaining until the next break. As stated there, showing such information motivates the users to follow the lead towards a healthier behaviour. The results show that the app helped its users to spend less

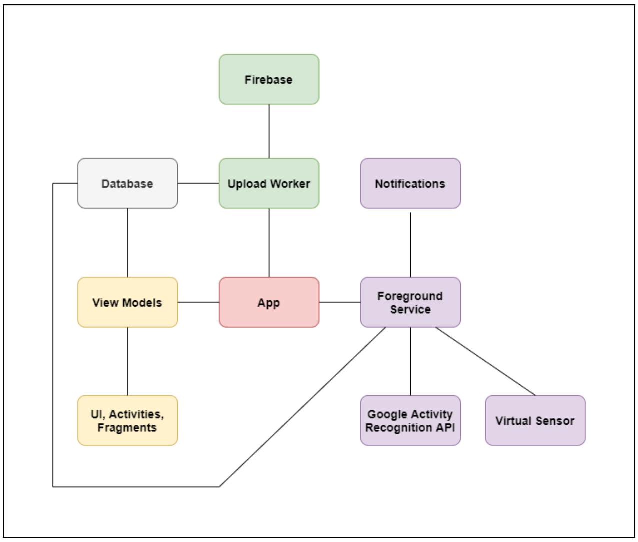

Figure 1: Main units that the app consists of

time sedentary. Moreover, 30-minute period of sitting followed by 3-minute break yields the most significant improvement.

We are interested whether our solution is able to help people to lead a healthier lifestyle or not. In particular, we want to examine the amount of time that is spent sedentary. Our solution, as opposed to others, is based on activity recognition done by Google Activity Recognition (GAR) API [1]. The aim is to provide an app that successfully implements digital behaviour change interventions regarding sedentary lifestyle.

3. IMPLEMENTATION

We use GAR API to determine the user's activity. Based on activities types, they are converted into segments referred to as sessions which are stored in the local database. You can see the app structure in figure 1.

3.1 Session System

Sessions represent activities performed by a user through the day. We distinguish between *sedentary session* and an *active session*. We classify each activity under specific session separately according to its type. We consider a user being in a sedentary session when the received activity is of type *STILL*. Therefore, we are not able to distinguish between standing and sitting from the information we receive from GAR. Thus, the *STILL* activity may represent a user who is being in either sedentary or standing position. We tackle this problem by using another sensor which can be more read about in section 3.3.

An interval for a healthy sitting period ranges from 20 [13], 30 [14] all the way up to 60 minutes [15]. The 30-minute limits work the best regarding the user's motivation [12]. Nevertheless, we still provide a user the possibility to adjust this value in the app settings. The limit for an active session can be adjusted from 1 to 5 minutes. To break a habit of having a long continual sitting period, just-in-time notifications before the session limit is reached are pushed as a specific behavioural suggestions to help the user stand up before the end of session.

3.2 Google Activity Recognition API

Google Activity Recognition API (GAR) processes signals from device's sensors and determines user's activity with a battery consumption optimization. We take the advantage of it as we believe Google has a lot of data to train and optimize their heuristic. On the other hand, this method brings some cons such as a long delay to receive the activity or inability to distinguish standing from sitting position. According to our initial observations, the delay may take up to couple of minutes to sense the transition from one activity to another. Such a behaviour is not sufficient enough to sense small breaks between the sedentary sessions. We add another sensor as a consequence, explained later in section 3.3.

We want to point out that GAR API was changed in the May 2018. The old API offered a way to ask for updates in specified interval, on contrary to the new one when only the transitions are sent. We tried both to see which one works better for our app. We encountered a problem with the older API where newer versions of Android stop sending the broadcast messages once the phone is locked and *Doze mode* is activated. Google mentions this kind of behaviour in the specification [2]. For this reason, we stick to the newer version of GAR.

3.3 Significant Movement Sensor

GAR is unable to sense an immediate change in user's activity. Therefore, we implement another way of spotting these transitions. *Significant Movement Sensor* senses a sudden changes in position. Once the movement occurs during a sedentary session, we create an artificial active session. It can either end once its limit is reached or continue after an active activity is received from GAR. In the second case, the session is no more artificial, so it continues until the next sedentary session is started by GAR.

3.4 Foreground Service

The *Foreground Service* is a core processing unit of our app. It contains session system logic, maintains

[1] `https://developers.google.com/location-context/activity-recognition`

[2] `https://developers.google.com/android/reference/com/google/android/gms/location/ActivityRecognitionClient`

data persistence, receives broadcasts regarding new activity from GAR, listens for significant movement and also fires notifications. Therefore, it is required the service runs permanently. Unfortunately, this was not always the case due to various optimizations implemented by smartphone manufacturers[3].

3.5 User Interface

We put a lot of effort into designing an easy-to-use and intuitive user interface (UI). As stated in [16, 17], this may help the users to spend more time with the app and to check their performance and overview more often. Others add [17] to the importance of displaying the progress as simple as possible, for example using an image of a garden with growing flower showing progress [17]. The B-MOBILE app [12] uses a fuel gauge to show how many minutes are remaining. We decided to use a stopwatch-like design, because the user is already familiar with watch showing the progress and time (e.g. Google Fit[4] and Apple Watch Activity app[5]).

We divide the app into three fragments: Home (figure 2), History and Profile. Home fragment provides useful information (e.g. streak and success rate) to arise user's motivation. History fragment provides an overview of all completed sessions to reveal information that may be previously unknown to the user (e.g. time spent sedentary during the specific day). Lastly, profile fragment contains overall statistics and achievements of the user. We believe that the information displayed may help the user to achieve better results in terms of DBCIs.

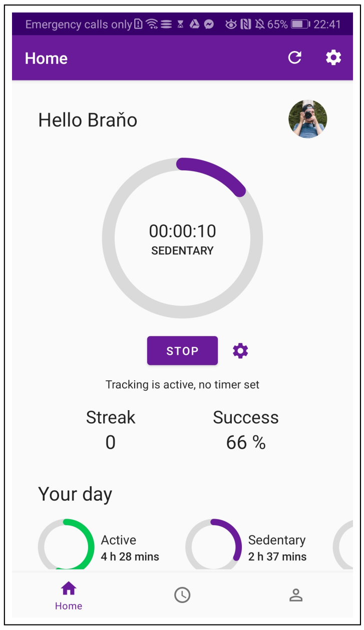

Figure 2: Home fragment displaying all crucial information that helps the user with motivation

4. DATA COLLECTION

We divide the data collection into 2 separate testing phases. Data are collected periodically throughout the duration of 1 week for each phase. Each phase has its own version of the app. The app is distributed by the start of each phase. We prepare a questionnaire to get an additional information which is not possible to retrieve from the app.

4.1 Testing Phases

The purpose of the first phase is to get a baseline data from the users. We ship a version of the app which has limited functionality where no DBCI components are present. The full app is provided with all of its DBCI components for the second phase during which the app also tries to motivate its users to perform better.

4.2 Questionnaire

To get a better insight into "how it actually feels like to use our app" we create a questionnaire. The questionnaire consists of 71 questions and it is divided into 7 categories. We include part about UI & UX design and System Usability Scale (SUS) which is the standardized way for evaluating the app's usability [6]. Although, this part helps us to evaluate functionality of the app, we add another questions regarding sessions and tracking with GAR. Another area of focus is DBCIs and motivation of the users. The questionnaire is sent to all participants after the second testing phase.

5. RESULTS

We divide the results section into two blocks. The first one provides the analysis of the app data collected from the 2 testing phases and the second one concludes the questionnaire.

5.1 Data Analysis

Our data collection within the app was split into two phases. In the first phase, 20 people enrolled and 18 installed the app. Only 11 people provided us with useful data. In the second phase, 11 people enrolled, 5 installed the app and 4 provided us with useful data. 489 sessions were recorded in total where 72.2% sessions were unsuccessful and 27.8% were successful. A sedentary session lasted for 80.35 minutes and active session lasted for 27,05 minutes in average from both phases. Table 1 shows even more details about duration.

Although we have data only from 4 users, we looked into success of sessions in each phase. The data are shown in figures 3 and 4. We calculate how many per-

[3] https://dontkillmyapp.com/
[4] https://www.google.com/fit/
[5] https://support.apple.com/en-us/HT204517
[6] https://www.usability.gov/how-to-and-tools/methods/system-usability-scale.html

Phase	Session Type	Success	Mean Duration [minutes]
1	Sedentary	-	74,8
		Yes	10,99
		No	131,67
	Active	-	23,35
2	Sedentary	-	85,90
		Yes	12,62
		No	140,28
	Active	-	30,74

Table 1: Table of specific duration according to phase and success

cents of sessions were successful. We compared each users separately and we found out that 3 users were less successful by 3%, 8.6% and 100%. Only one user was more successful in the second phase with 18% improvement. There was 23,4% decline in average. We explain this by a lack of participants in the second phase and poor functionality of the app that affected the users' interest to continue with the testing. On the other hand, the user that performed better claims that he had followed the received notifications and had stood up when he had been asked to do so by the app. Therefore, we can conclude that the concept of the app works.

We also look at average reduction of sedentary time through comparison of both phases. We used a formula by Bond et al. [12] as follows: (*% time spent sedentary in the 1st phase - % time spent sedentary in the 2nd phase*) / *average day tracking time from both phases / 100*. The data shows there was an increase - 31,32 minutes per day in sedentary time in the second phase when both compared. This increase emphasises what we have already said, that the app did not help the user to spend less time in a sedentary position.

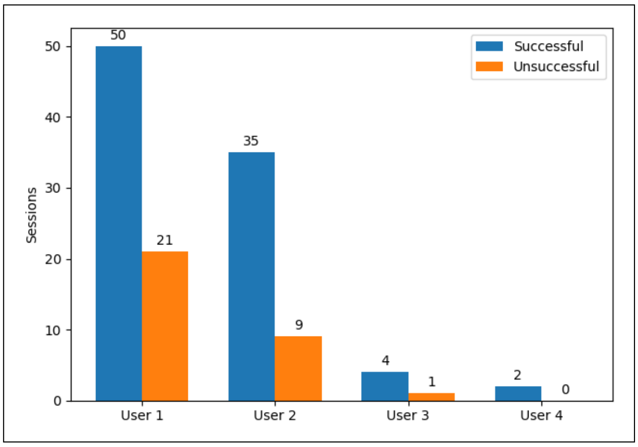

Figure 3: Sessions by users in testing phase 1

Lastly, we look at the distribution of sessions during the day to see if we can confirm the hypothesis that the app should be used mainly during working hours. As it can be seen in figure 5, the users are the most active in terms of tracking from 11 AM up to 7 PM. This figure needs to be interpreted with the questionnaire data where we found that all users are students, so their daily schedule is shifted from a normal 9-to-5 job.

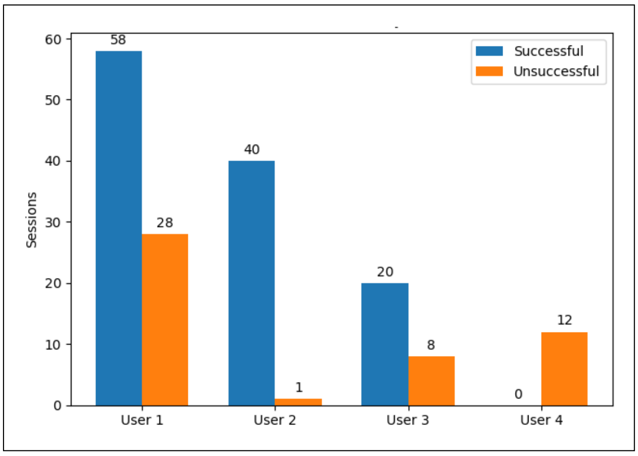

Figure 4: Sessions by users in testing phase 2

5.2 Results From Questionnaire

We received 7 answers from questionnaire. These answers help us to better understand who the users of our app are. All 7 participants showed an interest in the healthy lifestyle and were aware of the fact that sitting can cause health related problems. All of them were students and 2 had jobs too. Regarding the sent instructions at start of each testing phase, we see that the participants were not able to fully understand the instruction about turning the tracking on/off in the app or when the right time for using the app was.

Next part was UI & UX of the app. The app scored 85 points in the SUS evaluation. We discuss the score being that high (68 is average[7]) and note the app is small and the whole concept is not overwhelmingly complex what is reflected in the score. The participant felt confident about the navigation inside the app and understood the purpose of each fragment. The abstraction of the session system was understood well, but the stopwatch style of showing the progress was not as self-explanatory as we expected. The users were not aware of the limits of the session, although they did know that they can adjust these limits in the app settings.

When it comes to functionality, we can confirm that the app itself was stable. On the other hand, the session did not always correspond to the reality and duration of the session was not accurate as well. Moreover, the

[7] `https://www.usability.gov/how-to-and-tools/methods/system-usability-scale.html`

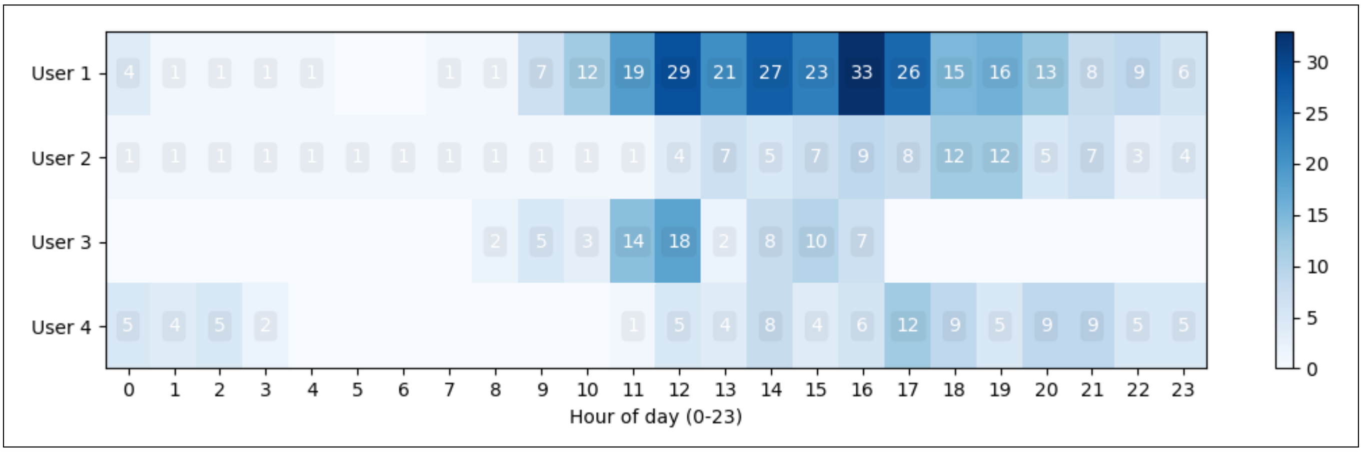

Figure 5: Most active hours during the data collection with the number of sessions performed during each hour of the day for each user

change in the activity was not always perceived by the app according to the answers. Therefore, we conclude that the GAR does not offer sufficient data about the user's activity for this kind of app. Neither the significant movement sensor helped to mitigate this problem. We conclude that the functionality of this app has to be re-implemented and other approach needs to be used. We spot that the activity of the participant decreased as time progressed and we believe the main reason of this is the poor functionality, although this does not explain the high score in SUS well.

Lastly, the questionnaire offers an insight into DBCIs and user's motivation. We need to note here that only 2 participants from 4 noticed the notification that advised to stand up once the sedentary session was about to reach its limit. These 2 participants claim they felt more motivated to stand up after the notification. In general, the app did not motivate its users to sit in a healthier way. The users' attitude towards information shown in the home fragment was neutral. Moreover, the users would appreciate more content that suits their personality such as personalized notifications. They would also feel more motivated if the app had more accurate notifications (3 answers), a widget (1), health recommendations about sedentary lifestyle (1) or notification with flashing LED (1). It is clear from the results that this area offers a great space for improvements in terms of DBCIs and functionality. Both would increase the user's retention and that could have a desired impact on the sedentary behaviour.

6. DISCUSSION AND FURTHER WORK

We developed an app capable of tracking user's sedentary behaviour with an unique session system. Although the idea of the app seems very promising, both the poor implementation of functionality due to chosen procedure and technology, and the number of participants limit the results. The results show us that the GAR API is not an appropriate solution for tracking the activity as it has a long delay which means the duration of the session are not accurate. GAR is not able to differentiate standing and sitting and some changes in the activity are not perceived at all. Moreover, the chosen implementation with the foreground service happened not to be the best solution as newer versions of Android kill even these kind of services if they consume too much resources. We advise to look for another approaches when developing such kind of apps. We suggest to use custom machine learning techniques with data from an accelerometer or use new virtual sensors in Android 10. It includes *Tilt detector* and *Step detector* sensors which are capable of sensing the movement immediately. It is clear from the questionnaire that the users see the potential in the app and that the app helps with raising awareness of the sedentary behavior problem.

7. CONCLUSION

In this paper, we present an app as a solution to the sedentary behaviour problem. We developed the unique session system which transforms data from Google Activity Recognition (GAR) and significant sensor. We implemented various digital behaviour changes interventions and focused on providing a good UI and UX. All to motivate users more to lead a healthier sedentary lifestyle. The results show us the potential of the app and also that the chosen implementation with GAR is not sufficient for this kind of an app. This paper confirms that if the app works correctly, it can help users to spent less time sedentary.

8. CONTRIBUTIONS

Branislav Puzder - UI, Google Activity Recognition, questionnaire and presentation. Samuel Pitoňák - DB model and in-app data manipulation, Firebase, app data analysis. Both worked on the report and on the implementation in general.

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APPENDIX

System Usability Scale[8]

SUS is standardized reliable tool for measuring the usability. The questionnaire includes following questions:

- I think that I would like to use this system frequently.
- I found the system unnecessarily complex.
- I thought the system was easy to use.
- I think that I would need the support of a technical person to be able to use this system.
- I found the various functions in this system were well integrated.
- I thought there was too much inconsistency in this system.
- I would imagine that most people would learn to use this system very quickly.
- I found the system very cumbersome to use.
- I felt very confident using the system.
- I needed to learn a lot of things before I could get going with this system.

[8] `https://www.usability.gov/how-to-and-tools/methods/system-usability-scale.html`