Designing for Hourly Activity Sampling in Behavioral Activation

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Abstract
This position paper presents our preliminary design of a smartphone-based behavioral activation method for unipolar disorder. The method relies on extensive collection of patient generated data on hourly activity. We report on the background for the study and the methods applied in the ongoing design process. The paper ends by discussing the challenges associated with such detailed experience sampling.

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Mental Health, Depression, Activity Sampling, Behavioral Activation

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H.5.m [Information interfaces and presentation (e.g., HCI)]: Miscellaneous

Introduction
Of all registered mental diseases in Europe, unipolar disorder (depression) has the highest prevalence of 6.9% [15]. This large patient group imposes a large societal burden with re-admissions, lost productivity, and mortality [14]. The current treatment consists of pharmacotherapy, psychotherapy, or a combination [10]. The most popular method of psychotherapy for depression and many other mental disorders is cognitive behavioral therapy (CBT) [5] due to its

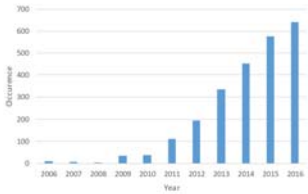

Figure 1: Amount of scientific papers published with keyword: "smartphone data".

Figure 2: Screenshots of the Moribus prototype.

short-term consultations and problem solving technique. However, in a large 16-week randomized trail [2] it was found that behavioral activation (BA) alone was as effective as pharmacotherapy and both treatments were significant better than cognitive therapy (CT). The treatment plan for BA starts with the patient reporting his/her activity every hour for several weeks [7]. This is done on a print-out of a week schedule typically between 8am and 11pm. The activity is provided with a score on '*mastery*' (i.e., the level of accomplishment) and '*enjoyment*' (i.e., how pleasant was the activity?). Together with a psychologist the patient then identifies activities that reinforces depressed and healthy behavior [7]. This information is then used to plan activities of the following week.

Limited clinical personnel together with a growing patient group, have fostered numerous smartphone based BA solutions (see [6] for a review). Smartphones used in behavioral studies and healthcare have been exponentially growing since 2010 (see Fig. 1) due to its passive sensor data and the ability to prompt users *in-the-wild*. This yields a powerful combination for behavioral change interventions [11].

Wahle et al. [13] have developed the most recent system targeting BA for depression. Passive sensors monitoring mobility and physical and social activity are guiding a recommender system to suggest activities. However, the system and other similar systems are based on a pre-made list of activities, usually in collaboration with a psychologist. This method creates a non-personalized behavioral change intervention that does not learn from the patients' behavioral traits.

Our aim is to make the BA personalized by leveraging patient generated activity data. To develop an automatic recommender of personalized activities, we first need to identify what activities sampled from the patient are reinforcers of respectively healthy or depressed behavior. Such a system would have the possibility to not only improve existing BA methods, assist inexperienced psychologists to locate possible reinforcers, but also provide the patient with a powerful data-driven psycho-educational insight into their own behavior.

Design Methods

To inform the design of the system, biweekly user-centered design meetings have been conducted over a period of 12 months at the Psychiatric Center Copenhagen, applying the Patient-Clinician Designer (PCD) framework [8]. The process has included patients (2), a psychologist (1), psychiatrists (2), computer scientists (2), and a biomedical engineer (1). An image from one of the workshops is shown in Fig. 3.

Figure 3: Discussion at a design workshop.

The system under development is named 'Moribus'[1]. The core design approach of the system is to support the BA method by building a patient-generated database of activities and help the patient to discover reinforcers. Hence, every hour between 8am and 11pm the patient provides

[1] Moribus is Latin for 'Behavior'.

Activity categories

Movement
- Running, biking, taking a walk, commuting

Sparetime
- Reading a book, watching TV, shopping mall

Work and education
- Updating CV, doing volunteer work, at the office

Practical-dos
- Vacuum cleaning, buying groceries, refurnishing

Daily living
- Sleeping, eating, taking a bath

Social
- Cup of coffee with a friend, cinema with mom, with guests

information on the current activity and scores it in terms of '*mastery*' and '*enjoyment*'.

Figure 2 shows screenshots of Moribus based on the design ideas generated from the biweekly meetings. Fig. 2(i) shows the main overview of today's planned activities with a pie chart showing the distribution amongst activity categories. Inspired by Moerch et al. [9] we developed six distinct activity categories to cover all types of activities as listed in the sidebar. Fig. 2(iii) shows a calendar to be used for weekly planning (typically on Sundays). By pressing an empty slot, the patient can plan an activity as illustrated in Fig. 2(iv). The patient selects one of the categories and optionally writes a small text input. Every hour the patient is prompted by a notification as illustrated in Fig. 2(ii), with the option of confirming that the activity listed in the calendar was done as planned or to dismiss it. In the latter case the patient gets redirected to Fig. 2(iv) to detail what activity was done. In both cases, the patient is asked to score the activity in terms of '*mastery*' and '*enjoyment*'. If no calendar entry was planned for the past hour, the patient can either select that he/she did 'the same' activity as the prior hour, or select 'new', in which case he/she can specify the details, as in Fig. 2(ii). At the end of the day, the patient enters a daily mood score.

The application is built on top of SENSUS, an open source system for mobile sensing [16]. The combined data from the activity sampling, daily mood score, and phone sensor data will be synchronized from the phones storage to an Amazon S3 storage when a Wi-Fi connection is available. In addition, patients will be wearing the MISFIT SHINE armband and this data will be synced daily as well.

Activity tracking

Moribus is an example of a system for collecting patient generated data (PGD) on activity. The end goal is to design a fully automated solution for BA therapy, which helps to restructure the patient's activities with recommendations based on own prior activities and activity patterns. The initial goal of the system described in this position paper is to collect the necessary data to identify healthy behavior recommendations. The amount and context of the recommendations should be in close connection with the patients self-assessed mood, which have shown to be highly correlated with the typical depression score questionnaires [4].

Several studies have shown a significant correlation between sensor-based smartphone data and depression scores (see e.g., [3, 12, 1]). Therefore, Moribus is also designed to collect sensor data. Furthermore, the mobility data from the smartphone (GPS, cell tower, Wi-Fi signals) combined with e.g. the Foursquare API[2] can be used to provide the user with semantically understandable location information, which can be used as context information for the collected activity data.

Current challenges

In our design, we have identified a set of challenges to collection of detailed PGD on activities, which we would like to discuss at the workshop.

Tedious manual input

A core challenge to most PGD application is the danger of overloading the user with tedious manual input. In the case of Moribus, prompting patients every hour – particularly patients with a mood disorder – is putting on a large data entry burden on patients. At the workshop, both patients agreed that only "*...if the activity sampling can be done with*

[2] As done by Zhu et al. [17]

few taps, it will be acceptable". Our current design tries to meet this request, but there is still much to consider on this issue.

PGD – for us or for them?
In Moribus, the user has the option to enter a small text description to each activity category. We don't plan to use the descriptive text since freely written text imposes large challenges such as misspells or custom abbreviations. It could be combined with the phones GPS signal in case of *Movement* entries, but social entries would require extraction of names or relation from the text. Maybe Bluetooth proximities could be useful. Any input on this matter is highly welcome.

What is the ground truth in PGD?
When designing 'intelligent' systems that can recognize or even recommend activities to patients, a common approach is to consider PGD as the 'ground truth'. For example, when a person says he or she is bicycling, we take this to be the ground truth and train our classifiers accordingly. However, in the case on Moribus, the activities collected from the patients might not be the ground truth in terms of recommendation. For example, if a patient specifies that 'eating cake in front of the TV' gives him or her high mastery and enjoyment, this might not be a wise recommendation when planning next week's activities. To compare or evaluate the future classifier of reinforcers for healthy behavior we probably need a psychologist to do a normal BA consultation with the patients, and use the outcome of that as the ground truth. This method is ideal but highly time consuming. Is there any other way of evaluating the classifier?

Workshop participants

Darius Adam Rohani (DAR) is a biomedical engineer, currently doing a PhD at the Technical University of Denmark (DTU) in association with the Copenhagen Center for Health Technology (CACHET). Before this, DAR worked at the Center for Lifespan Changes in Brain and Cognition, University of Oslo, Norway. Here he was analyzing biomedical signals and applied several machine learning methods. DAR can contribute with methods to process PGD.

Jakob E. Bardram (JEB) is a computer scientist who has been researching, designing, building, and evaluating healthcare technologies for decades – lately within mental health. He can help moderate and organize the discussion at the workshop, and potentially help organize follow-up workshops or other research activities.

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