Designing Context-Aware Cognitive Behavioral Therapy for Unipolar and Bipolar Disorders

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Abstract
This position paper presents our preliminary design of context-aware cognitive behavioral therapy for unipolar and bipolar disorders. We report on the background for this study and the methods applied in the ongoing design process. The paper ends by presenting and discussing different design options. We hope this will be useful input for further discussion at the workshop.

Author Keywords
Mental Health, Depression, Bipolar Disorder, Cognitive Behavioral Therapy, CBT, Context-Aware Intervention, Recommender System

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

Introduction
Unipolar disorder (depression) and bipolar disorder are common mental diseases with lifetime prevalence of 15-20% and 1-2%, respectively [14]. Depression imposes a very high societal burden in terms of cost, lost productivity, morbidity, suffering, and mortality [20], and is a leading cause of disability and disease burden worldwide [8]. According to EU, depression is among the most pressing public health concern today, and account for more than 12% of

Figure 1: The MONARCA system in use.

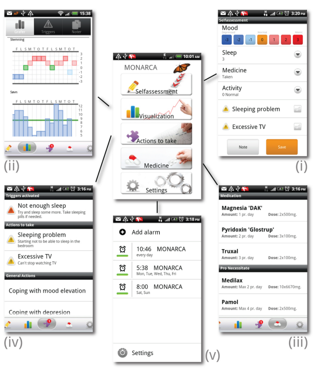

Figure 2: The MONARCA user interfaces for self-assessment.

all estimated ill health and premature mortality in Europe, only exceeded by heart disease and cancer [11]. According to WHO, mental health is the fastest growing chronic disease and is one of the leading causes to disability [18]. Together unipolar and bipolar disorders account for nearly half of all morbidity and mortality due to mental and substance use disorders [22], and burdens society with the highest health care costs of all psychiatric and neurological disorders [17].

Although psychiatric treatment in many countries has shifted from inpatient treatment to outpatient treatment during recent decades, costs to psychiatric hospitalization is still a major burden and typically comprises two third of all direct costs in psychiatry in Denmark. Patients with affective disorders are more frequently hospitalized than any other patient group, counting more than 10.800 patients in 2013 and 20% of all psychiatric hospitalizations.

Treatment of unipolar and bipolar disorders applies a variety of methods, including anti-depressants, mood stabilizers, psycho-education, and cognitive behavioral therapy (CBT). However, depression and bipolar disorder are often under-diagnosed and it might take months or years for the illnesses to be identified and treated [13].

It is the aim of the RADMIS project[1] to design, develop, and provide clinical evidence for the use of a smartphone-based monitoring and intervention technology, which has the potential to reduce the rate of re-admission with 50% and improve health outcome, quality of life, and empowerment for patient with unipolar and bipolar disorder. As part of this project, the goal is to research, design, implement, and evaluate CBT intervention technology, which is the topic of this paper.

[1] http://www.cachet.dk/research/projects/RADMIS

Background

Prior research done in the MONARCA project[2] have developed and tested a unique smartphone-based system for treatment of bipolar disorder [3]. The MONARCA system collects subjective self-assessment data and objective sensor data from patients on a daily basis, while allowing bi-directional communication between a clinician (typically a nurse) and the patient. In clinical trials with patients, the system has proved to be highly usable and useful, showed a high self-assessment adherence (>80%), and helped patients to better manage their disease [2].

Data analysis from several clinical studies have shown that automatically collected smartphone data reflecting mobility and social activity correlate significantly with the severity of depression and mania using blinded assessed scores on the HDRS-17 and YMRS rating scales [7]. A randomized controlled trial (RCT) have shown, that electronic daily self-monitoring including the two-level feedback loop to clinicians via the MONARCA system improved manic symptoms but had no effect on depressive symptoms [6].

Based on these studies, we have concluded that a smartphone-based monitoring system seems effective in recognizing and allowing for intervention on early warning signs of hypomania/mania, but less effective in relation to early warning signs of depression. However, since 80% of all bipolar episodes are depressive [12], emphasis on depressive symptoms should be a high priority including mechanisms to reduce the negative processing bias and depressive rumination [16].

Therefore, to address depression both in bipolar and unipolar disorders, the goal of the RADMIS project is to extend the MONARCA system with support for cognitive behavioral

[2] http://www.monarca-project.eu

Behavioral and Cognitive Methods in CBT

Behavioral Methods

- Behavioral Activation & Registration
- Problem Solving
- Situation Analysis

Cognitive Methods

- Evening Therapy
- Cognitive Restructuring
- Inappropriate Habits
- Concern Parking
- Mindfulness
- Benefits & Drawbacks

therapy (CBT), which have shown to be effective in treatment of depression [21]. The aim is to design and clinically evaluate a smartphone-based CBT program that utilize the sensing, computational and communication capabilities of smartphones to continuously monitor an individual's context including physical activity, location and environment, and use this sensing information to deliver context-aware and personalized intervention.

Design Methods

The design of smartphone-based CBT has been done in a user-centered design process at the Psychiatric Center Copenhagen involving patients (3), psychiatrists (2), psychologists (2), and computer scientists (2). At the time of writing, this group has been meeting for two-hour design workshops on a biweekly manner for 4 months.

Figure 3: Discussion at biweekly design workshops.

As a frame for this design process, the Patient–Clinician–Designer (PCD) framework [15] has been applied. This framework outlines how the key principles of user-centered design — including user focus, active user involvement, evolutionary systems development, prototyping, and usability champions — can be applied in the context of designing for mental illness. The framework consists of four design phases: (1) understand the illness and its challenges, (2) sensitively involve patients in design, (3) mediate co-design with patients and clinicians, and (4) accommodate different evaluation goals. For each phase of the user-centered design process, the PCD Framework provides questions to be addressed and considered. See [15] for details.

Focusing more specifically on CBT, we did a complete survey of all existing methods applied in the clinic. CBT is not one method, but a general theoretical framework within which, several more detailed cognitive and behavioral methods have been developed. At the clinic they used four different behavioral methods and six cognitive methods, as listed in the sidebar.

At a more concrete level, we investigated in details how patients did CBT and what paper-based and electronic tools they used. As shown in Figure 4, two main types of artefacts were used; the self-assessment form and the activity scheduling and registration (ASR) form. The self-assessment form helps the patient to get an insight into his or her disease progression and was the subject for design in the MONARCA project, and will thus not be discussed here.

The ASR form is used in Behavioral Activation, which is a core behavioral method in CBT that has shown to have good effect and is often recommended to depressive patients [4]. The patient starts making a detailed plan of what activities to do every hour each day of the week. When the activity is done, s/he notes this down and provide it with a score on '*perceived mastery*' (i.e., how well did I do this?) and '*perceived pleasure*' (i.e., how pleasant was this activity to do?). The purpose of behavioral activation is to help the

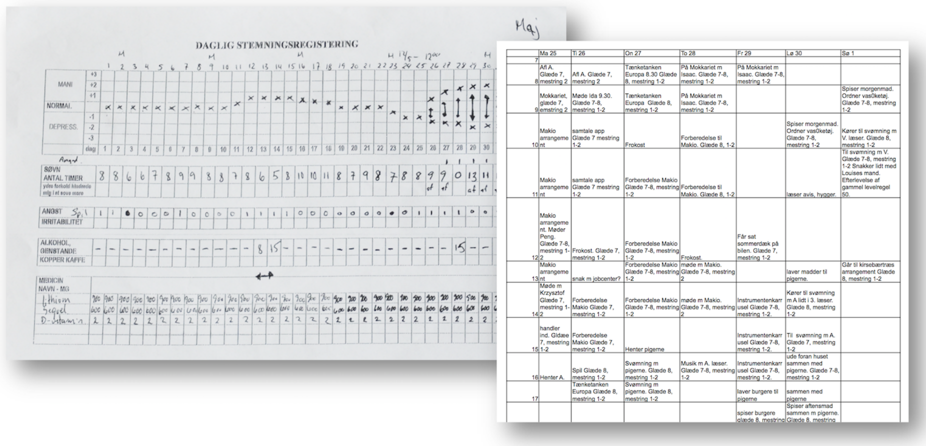

Figure 4: Paper-based tools used by patients today: Mood charting (left) and activity planning and registration (right).

patient to do activities that feels good and which s/he can accomplish. Patients are encouraged to implement their own ASR tool in whatever format they prefer. Hence, we saw different types of implementations, including paper-based diaries, Excel spreadsheets (as shown in Figure 4), and electronic calendars (also used on smartphones).

Context-Aware CBT

The specific approach in this research will be to make the smartphone-based CBT program context-aware and personalized. The novel functionality is an intelligent engine that provides personalized suggestions by learning about the patient's behavior in terms of physical, social activity and other behavior traits. This means that the CBT system will know about the patients 'context' including what s/he is doing and take this into consideration when suggesting CBT methods and content, which is personalized to the patient. For example, the system would do long-term monitoring of sleep patterns of a patient. This can help suggest activity planning and monitoring on good sleeping behavior, and provide these suggestions at the time and place (i.e. context) where it is relevant, e.g. when watching TV in the evening. These suggestions are personalized to patients depending on sensed behavior and preferences.

This intelligent suggestion engine can apply well-known decision theory models and potentially develop new models. As suggested by Mashfiqui et al. [19], recommender models can be used to dynamically learn from user behaviors and suggests actions that maximize the chances of reducing affective symptoms. Maximization is achieved by strategically suggestion a combination of frequent and infrequent CBT methods that may lead to healthy behavior – such a sleeping regularly. For example, there is evidence that physical activity like going for a walk is a fundamental behavioral method that helps lift mood in depressive episodes. Likewise, evening therapy is a fundamental cognitive methods used to think about all the positive things that has happened during the day. If, then, the patient makes a 20 minute walk 4-5 days a week but rarely enters into evening therapy, then the system would more often suggest to go for a walk while also occasionally suggest to increase evening therapy. The assumption is that walking to work is more regular and will be lower-effort to adopt while also pushing towards less-used CBT methods. Prioritizing frequent behaviors also means that these behaviors are practiced and therefore the user is likely to be good at those actions (i.e., users have mastery and pleasure). However, gradually accomplishing more demanding and potential unpleasant tasks (e.g., paying the bills) is equally important in CBT. Hence, the recommendation should provide a prober balance between different types of activities. Finally, as also suggested by Mashfiqui et al. [19], a core function of the

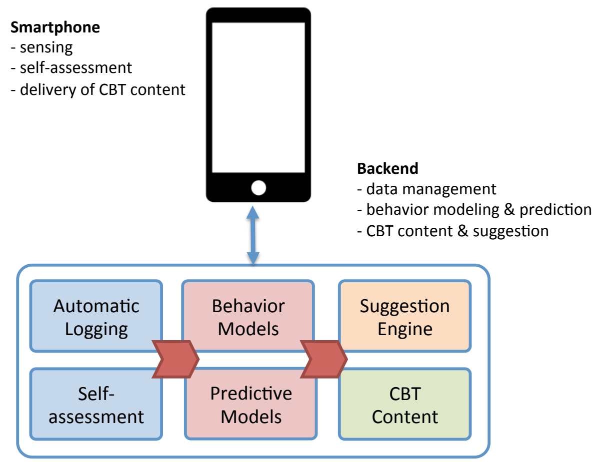

Figure 5: Core components of the context-aware CBT architecture.

system is to keep users in the loop by giving users control to prioritize and personalize suggestions that they prefer to follow. User preferences are then balanced with the machine generated suggestions.

Figure 5 shows the core components of the proposed context-aware CBT system. The smartphone is used to collect self-assessment data, sensor data, and to deliver the CBT content. The backend collects sensor and self-assessment data (blue components) and use this to build features representing behavior (such as mobility, physical activity, social activity, sleep, mood, etc.) and to train a machine learning model that can predicting upcoming affective episodes (depression and/or mania)[3] (red components).

[3] Some preliminary research have shown that affective episodes in bipolar disorder may be predicted using machine learning methods [9, 5, 1, 10]

The recommender engine (yellow component) will take as input these behavior and predictive models and use this to suggest CBT content adapted to the current context (including behavior) and upcoming affective state. The CBT content component (green component) will contain different CBT methods, as outlined above in the sidebar.

Open Issues

So far we have reported on our initial research and design of a context-aware CBT system for affective disorders. There is, however, still a range of open issues to be addressed in this line of research, which we shall shortly introduce below. We suggest this as input for a more detailed discussion at the workshop.

What are good examples of 'context'?

Clearly, identifying relevant context triggers is core to a context-aware system like the one suggested. It is, however, at the current stage of the project not at all clear exactly what kind of context is relevant and what the relevant context triggers are. Different types can be identified, including:

- Physical – location, time, temperature, ...
- Behavioral – mobility, sleeping, walking, running, watching TV, ...
- Social Activity – on the phone, texting, talking, being together, social relations, ...
- Cognitive – mood, stress, happiness, excitement, ...
- Disease-related – depressed, manic, medicine compliance, hospitalized, ...

Before designing a context-aware recommender CBT system, we need to understand what kind of context is relevant, how to collect and model information about it, and identify recurrent examples of it.

How to select the right CBT method?
As outlined above, a wide range of behavioral and cognitive methods exists, and more are being designed. Different therapists have different preferences, and so have patients. In analog CBT, behavioral and cognitive methods are selected and adjusted based on a wide range of paramenters, including:

- The therapist – experience, training, preferences, theoretical stance, ...
- The patient – gender, age, preferences, fitness, specific symptoms, socio-economical status, educational background, IQ, ...
- Clinical evidence – from the clinic, related case studies, randomized clinical trials, systematic reviews.
- Phase of disease – during hospitalization, when discharged, during outpatient treatment, GP care, self-care.
- Resources – spouse, supportive relatives/parents, network of friends, employed, ...

Hence, making the 'right' selection of a CBT method is difficult and takes into consideration many parameters, even for a trained therapist. Automating this choice will prove to be difficult. Hence, it is important to design the system in a way to take into consideration the experience of a therapist, while automating other things. In particular, we are currently focusing on designing a method for therapists to 'configure' the CBT system for the patient by using e.g., profiling.

How to accommodate different disease phases?
As outlined above, the CBT methods are selected and adjusted based on the phase of the disease. The kind of behavioral and cognitive methods useful for a patient is highly dependent on the phase of his or her disease. Some methods are pretty basic and are often used as the initial one. These include the ASR methods, whereas cognitive methods like restructuring are much more advanced. Hence, CBT should be adapted to the different phases of the disease, starting with the simple methods during discharge while proceeding to more advanced methods later. We plan to investigate machine learning models used in games for this purpose, since we view this as to being similar to progressing though 'game levels' in a computer game.

What is the role of medicine in treatment?
Treatment of affective disorders applies a combination of both drugs, including anti-depressants and mood stabilizers, and psychotherapeutic methods, including psycho-education and CBT. As such, medication plays an important role in treatment and should be addresses in parallel with CBT treatment. The current MONARCA design supports the patient to see his prescriptions (as done by the psychiatrist) and to track his or her compliance. It is, however, unclear what role medication should play in the design of the context-aware CBT module. Information about medication is, at least, an important context information. For example, non-compliance to prescriptions of an anti-depressant drugs would help us to understand a depressive state, which might not be addressed by any CBT method. But whether the suggestion engine should engage in suggesting medication, is a very open question.

What is the best feedback style?
Feedback to the patient is core to the design of this system. It is, however, quite unclear what 'style' is most fitted for this domain. A common strategy in many personal health technologies have been to use a metaphor, such as a garden, a fish bowl, or aquarium. Prior experience from the MONARCA project has taught us, that when approaching health applications (rather than general-purpose wellness applications), 'foolish' or 'game-like' metaphors can be per-

ceived as inappropriate by patients. On the other hand, however, adding an aesthetic design that may help patient get an overview of the progression of their disease and deliver CBT content in an easy-to-understand manner is still important design parameters. In particular, we're currently trying to create a design which can reflect the progression of the mastery and pleasure of the patient, while doing the different behavioral and cognitive methods. So far, the group of users and designers have not been able to come up with a convincing design, but this work will continue.

Conclusion

This position paper has outlined our current research on designing a context-aware cognitive behavioral therapy (CBT) smartphone-based system. This system will suggest personalized behavioral and/or cognitive methods to the patient, which is adapted to the current context and state of the patient. Context information is based on data collected from the smartphone — both self-assessment data and automatically collected sensor data — which are used to build behavioral and predictive models.

There is still a range of open issues related to this design, including identifying relevant context, selecting appropiate CBT methods, accommodating different disease phases, incorporating the role of medicine compliance in the design, and designing an appropriate feedback style. We hope to discuss these issues at the workshop.

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