Providing Patient Context to Mental Health Professionals Using Mobile Applications

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ABSTRACT
The quantified-self movement entails self-tracking of physical activity, often using wearable devices and mobile applications. In parallel, mobile applications focusing on mental health are increasingly popular, and they often rely on active user input to track the user progress and to deliver feedback and motivation. In this paper we discuss the potential benefits of bridging these two distinct yet highly relevant application domains. We argue for the benefits of combining *explicit* (user-provided) and *implicit* (device-collected) data sources in the context of mental health care. We argue that this combination allows for improved methods to observe patients' lives, and thus provide a more in-depth overview of their progress. This may enable mental health professionals to establish more personalised and adaptive care plans.

Author Keywords
Quantified self; self-care; care trajectory; smartphone; wearable devices; ESM; EMA; depression; well-being; mental health

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

INTRODUCTION
Mobile applications aiming to improve users' mental health are increasingly popular. These applications claim how easy improving your mental health is by using slogans such as "*In just 12 weeks, you can lead the life you deserve*" [7], or "*86% of frequent users get happier in 2 months*" [15]. These applications typically follow the trend of self-cultivation, *i.e.* educating oneself on personal characteristics and habits to realise personal development. By collecting data on day-to-day activities, it is possible to achieve these insights into one's life.

Self-cultivation applications targeting mental health contain large similarities in both their approach and objective compared to the quantified-self (QS) movement. While the most popular QS applications seemingly focus on physical activity tracking, there are applications also tailored for collecting data and providing insights on other areas of life, such as finances or calorie intake. With an estimated 43.6 million adults facing mental problems in 2014 in the U.S. alone [4], it is important to explore the possibilities of these applications also in mental health care.

In contrast to the well-defined tracking objectives in QS (*e.g.*, distance travelled by bike, personal expenses), mental health progress can be more abstract and challenging to measure reliably [8]. Most popular mobile applications for depression and mental health focus on self-reporting (*e.g.*, [7]), but do not fully consider rich sensor data to complement the self-reports. Doing so could enable a range of possibilities for treatment and intervention, but also introduces the challenge of determining which sensor data to collect and which questions to explicitly ask patients.

In this paper we describe our design of a mobile application that uses the combination of rich sensor data together with self-reports from mental health patients to provide a comprehensive situational awareness for mental health professionals, *e.g.* psychotherapist, psychologist, counsellor. In many countries (including our own), such patients are typically under continuous treatment of a qualified mental health professional, with whom they consult on a regular basis. We discuss how our prototype can help mental health professionals to augment the patient's recovery process. We have not begun actual trials with patients yet in this context, and hope to now raise discussion especially on the potential limitations, long term pitfalls, and possibilities of our approach.

RELATED WORK
A rich literature from various disciplines investigates the correlation between a person's context and mental health. This work has revealed a variety of factors, both on an individual and community level. Individuals growing up in 'risky' families, characterised as aggressive and/or conflict-prone and with low levels of support, develop a different bio-behavioural profile (resulting, for example, in problematic emotional processing and increased likelihood of substance abuse) [13]. Also, depression severity has been shown to correlate strongly with that of friends and neighbours [14], extending up to three degrees of separation (friend of a friend's friend). Depression has also been

shown to effect interpersonal communication [17], resulting in lower levels of personal engagement, and experienced levels of discomfort during human-to-human interaction.

Diagnosis and analysis of depression through social network usage characteristics has recently attracted more attention. De Choudhury *et al.* [5] show that various aspects of an individuals' Twitter activity (*e.g.*, raise in negative affect, decrease in social activity) can characterise the onset of depression. Other work has investigated the use of social media to track multiple ailments and symptoms, including allergies, depression, and obesity [11]. As such, social media does not only allow for analysis of what is happening at this instance in time, but can also be used in the form of a digital diary to provide insight on past events.

Using mobile sensor data to support mental healthcare has been explored in various applications. Burns *et al.* [1] explore the use of mobile sensors to develop a context-aware system named *Mobilyze!*. This mobile application is able to detect when users need assistance and can directly offer support. Combining concurrent sensor values and machine learning techniques, the application achieves a 60% to 91% accuracy rate in predicting various categorical contextual states (*e.g.*, user activity, location). However, states rated on scales (*e.g.*, mood, emotions) did not attain high accuracy. Nevertheless, following usage of the application, the mental health of participants significantly improved. Ma *et al.* [10] developed *MoodMiner*, a mobile application aimed to collect a real-time, daily mood assessment using various sensors of the mobile phone including hardware sensors (*e.g.*, GPS, accelerometer) and communication channels (*e.g.*, SMS, phone calls). Over a 30-day experiment period (N=15), the researchers are able to achieve a 50% accuracy over the three recorded dimensions (displeasure, tiredness, and tensity) compared to user self-reports. Similar to [1], Ma *et al.* state that "*people show significant difference in daily behavior style and use pattern of mobile phone, making it difficult to build a model working well for anyone*" [10].

MOBILE MENTAL CARE PROTOTYPE

In collaboration with mental healthcare professionals, we have designed and developed the first version of our prototype as a plugin for the AWARE framework [6]. AWARE is a mobile sensing platform that makes collecting raw sensor data from Android devices easy, and the data can also be synced to a server in near real-time. Our goal is to allow for the simultaneous collection of self-reported mental states and sensor-collected data on Android devices.

We propose using machine learning to uncover relations in the data. As an example, consider the combination of location data and self-reported mental states, that together indicate a change in the patient's mental state at certain locations (similar approach as [3]). Interpretation of these classification results makes sense in the treatment process, and we plan to make this type of insight available to the mental health professional. It is then the professional's task to highlight and discuss these observations with the patient.

The technology required to achieve this is already available and, based on previous work [1], we are exploring to combine self-reports with the following sensors for further higher-level insights: *location*, *ambient light*, *accelerometer*, *mobile application usage*, and *physical activity*. Naturally, creating classifiers and refining data per each sensor type requires rigorous analysis and justification.

Information presentation

Healthcare professionals typically do not have the experience required to interpret mobile sensor data. Classifying and visualising data in a meaningful manner is challenging, despite the recent advances in making machine learning easier for the masses using cloud-based approaches. Furthermore, professionals are required to link the emerging insights to the patients' overall situation. This requires a thorough understanding of both the collected sensor data and the patient's mental states. To facilitate professionals in this challenging task, we have implemented a *dashboard* that allows the professional to configure and visualise the various parameters of the patient's (mobile) context. The dashboard is a component of AWARE [6].

Personalised data collection

The treatment plan of the patient should be continuously re-evaluated and updated to maximise its efficiency [1]. This is usually achieved following a consultation session between patient and clinician, or between clinicians alone. This process of continuous interplay is presented in Figure 1. The model follows a repeating process that fits well within the existing mental healthcare process, where patients regularly visit their counsellor. Information obtained from both the collected sensor data and the data submitted by patients will allow the mental health professional to either bring up or more accurately discuss relevant events, thoughts, and experiences of the past. In turn, the mental health professional can recommend adjustments to the data collection configuration, to obtain more relevant data for future consultation needs. These consultations help to determine the next steps in the patient's treatment, and can therefore possibly result in a change of the currently relevant metrics in the patients' treatment process.

Issuing the Right Question at the Right Time

The answers provided by the application users are key sources of information regarding their mental state. It is therefore vital that the questions issued by the mobile application are adequate and carefully considered. In our prototype, we use the PHQ-9 Patient Health Questionnaire [8], a validated scale consisting of nine question items – therefore allowing for relatively fast user input. PHQ-9 is used to track developments in the patients' mental state over longer periods of time. Since we rely on explicit input for the collection of this data, both the quality and quantity (*response rate*) of the answers depend on the users of the

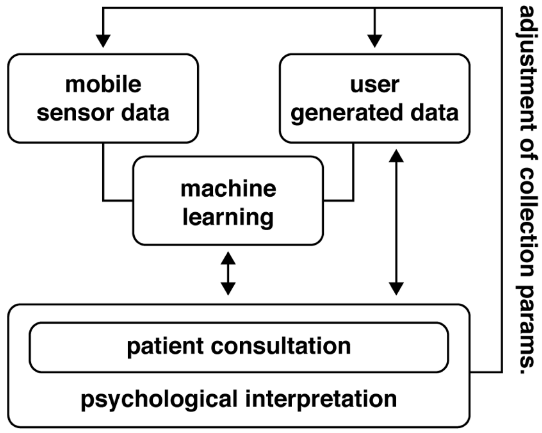

Figure 1. Model of mobile context in mental healthcare process with mental health professional

application. We discuss two elements of user-generated data collection that are of high importance, namely *timing* and *content* of the questions.

Originally we considered two main approaches to collecting user-provided data. The first approach, *active probing*, consists of notifying the user throughout the day to provide information. In this form, data collection is based on the Experience Sampling Method (ESM) [9] or similar methodologies. In the second approach, no probing takes place and users are required to *proactively* open the application and input information. We have chosen to utilise active probing, as it (in our case the ESM), allows us to obtain "*[...] reports about people's experience as it occurs, thereby minimizing the effects of reliance on memory and reconstruction.*" [9]. With active probing, asking questions at the right moment is crucial. Failing to do so can result in a reduced usefulness of the answer (out of context), no answer provided by the user, and increased level of user annoyance.

Context sensing can be used to not only passively infer in which context an answer was provided, or determine the timing of a question, but can also *actively steer* the question content. This way, the questions are in line with the current activity and/or location of the patient. For example, the mental health professional and patient might agree that increased physical activity would be beneficial to the patient. Based on the detected activity context, the mobile application is then able to ask questions predetermined to follow the physical activity. Furthermore, by storing user answers the number of questions asked to the patient can be reduced. For example, after asking the user to assign a label to the current location (*e.g.*, home, work), the location can be saved to the device and used to steer further questions.

DISCUSSION

Health professionals, including those working in mental health, benefit from a complete picture on the daily life and progress of their patients. Having such understanding has multiple advantages to the treatment process, including tailoring of the treatment plan, identifying potential barriers to treatments, patient compliance, as well as the ability to set goals that are appropriate to the patient's current (mental) state [1].

Since consultations in our environment usually follow a regular schedule (*e.g.*, weekly, bi-weekly, monthly), the picture that professionals can form regarding their patients' lives can potentially be improved using a more real-time approach: by leveraging the patients' personal mobile devices as the proverbial right hand of the mental health professional. Employing the context obtained through the users' mobile phone, it becomes feasible to obtain a much more accurate picture of patients' lives.

The widespread proliferation of mobile phones allows for new application possibilities that serve both individuals and the society. The popularity of mental self-care applications is just one example. Particularly in the mental health domain, we see potential in using mobile phones to collect data about users, without the need of constant appointments with clinicians. Further, phones can simultaneously collect other data about patients' lives, to provide new type of information to the care personnel. Using a reflective method (Figure 1), mental healthcare professionals are able to adjust data collection as they see appropriate, and thus benefit the patient.

Various applications offer the user notes of encouragement throughout the day (*e.g. Joyable* [7]). Though, as stated by Calvo *et al.*, "*much is yet to be discovered about how and when to provide mental health support*" [2]. Both the already existing self-care applications and the prototyped mental care trajectory application bear strong parallels to the QS movement. We should therefore be wary to fall for the same mistakes that threaten (long-term) usage of QS applications [16]. Figure 2 shows the different stages of a typical QS process. The process starts with an initial *question* and, ultimately, results in a certain *action* by the user. To accomplish this, the application should be able to construct a data cycle that leads from a user *need* to an *insight* provided to the user. As noted by Van Berkel *et al.*, "*a QS-tool needs to adapt to the users' dynamics of questions*" [16].

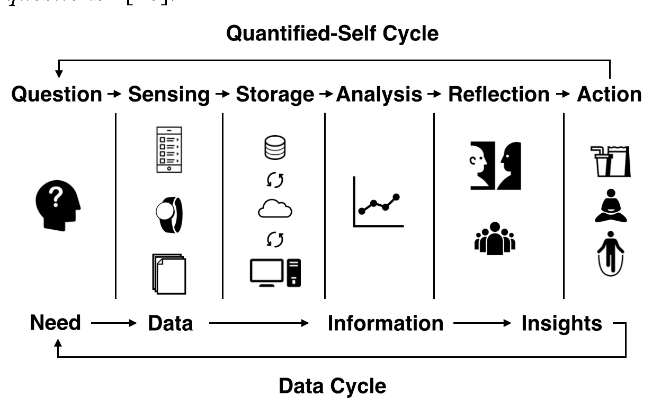

Figure 2. Stages of QS [16].

In the case of typical QS applications, these *users' dynamics of questions* are derived from a single user. By involving the mental healthcare professional, as proposed in this paper, the various stages in the QS process become shared between stakeholders. For example, the patient and clinician may come up with a certain question in consultation – but analysis of the collected data is performed by the clinician. User needs are therefore derived directly from the consultation between patient and clinician.

CONCLUSION

Following the popularity of mental self-care applications in the mobile market, we discuss the opportunities for mobile applications in the professional mental healthcare process. Through the use of context sensing, the mental healthcare professional is able to construct a better-rounded overview on the patient's progress. We have developed a mobile prototype application that can be used to collect this information, present it to a professional, and allow the professional to adjust the parameters of data collection. We stress the integration in the patient's treatment plan as a key to success. By integrating application usage with the ongoing treatment, the mental health professional can continuously (re-)configure the area of relevance for the application (Figure 1). This way, a continuous relevance of the collected data to the treatment process is ensured.

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