Technical Challenges to Deliver Sensor-based Psychological Interventions Using Smartphones

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ABSTRACT

Research in the development of tools to successfully deliver psychological interventions through smartphones is growing rapidly. As the research body grows towards more cutting-edge solutions that utilize the smartphone's advanced technical capabilities, various challenges are uncovered to successfully and efficiently deliver safe interventions in critical scenarios and situations. We present the SyMptOMS platform, a configurable set of tools that allows therapists to specify, deploy and follow-up location- and sensor-based assessments and interventions for various mental disorders, run and delivered remotely via the patient's smartphone at any place (ecological) and time (momentarily). From our experience in developing and running experiments with SyMptOMS, we overview and discuss technical challenges and open research questions involved in sensor-based interventions using smartphones.

CCS CONCEPTS

• **Human-centered computing** → **Ubiquitous and mobile computing**; • **Applied computing** → *Health care information systems*; *Health informatics*.

KEYWORDS

Ecological Momentary Assessment; Ecological Momentary Intervention; Mental Health; Mobile Health; Mobile Health Challenges

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1 INTRODUCTION

In his seminal work on Ubiquotous Cumputing, Weiser stated that the most profound technologies weave themselves into the fabric of everyday life until they are indistinguishable from it [12]. Modern embedded sensing technologies have virtually achieved this status: they are integrated in our mobile and wearable devices, invisibly and - virtually unconsciously to us - collecting a wide variety of context and physiological data. Among others, the use of these technologies has been extended to monitoring physical activity [3], health [6], social behavior [4] or psychology [8]. In the latter, there is still a significant amount of work left, and additional research in sensor-based solutions in psychology is particularly welcome, given prevalence of mental health problems. For example, the World Health Organization estimates that approximately 4% of the population suffers from anxiety or depression [13] (2017), with the latter costing the global economy US$ 1 trillion a year in lost productivity. The introduction of advanced analysis and sensing capabilities could help to make psychological treatments available to more people and get treatments where and when they are most needed.

Ubiquitous computing has been one of the main drivers for two key developments in technology-based mental health treatments: Ecological Momentary Assessment (EMA) [11] and Ecological Momentary Intervention (EMI) [5]). The ecological part, operating in the real environment of the patient, and the momentary part, doing it at the right time, fit perfectly within the context of ubiquitous computing: using (invisibly) available sensing technologies embedded in already present mobile/wearable devices and the environment to naturally assist a user in coping with mental health issues. However, in related literature, the technical capabilities of mobile and wearable devices are hardly exploited to their full extent [2]. This paper shortly presents the SyMptOMS platform, an ecosystem of Web and mobile tools that allows therapists to configure and personalize context-aware, sensor-based smartphone applications for mental health assessment and intervention. Based on our experiences developing and using SyMptOMS, we subsequently generally discuss the technical challenges and open research questions which arise when developing this type of systems. We hope our considerations may be useful for other researchers and generate further discussion in regard to balancing therapeutic value and efficacy with technical feasibility.

2 THE SYMPTOMS PLATFORM AND ITS OPERATIONAL PHASES

The SyMptOMS platform provides ubiquitous, timely and flexible tools for mental health treatments. It was designed and developed as an ecosystem of client-side applications and server-side services aimed to perform assessments and deliver interventions to patients under psychological treatment, anywhere (ecological) and at the most suitable moment (momentarily). Contrary to most existing solutions found in literature, SyMptOMS is not a dedicated solution targeting one particular disorder. Instead, it is aimed to be a flexible configurable platform, suitable for therapists to customize and personalize an assessment and/or intervention to be run on the patient's smartphone. The assessment is done mainly based on the collection and analysis of smartphone and peripheral sensor data, while interventions are delivered through the smartphone. Given the fact that therapists are often not skilled in coding and developing such apps, SyMptOMS offers a flexible and user-friendly Web interface that allows the configuration of the assessment and interventions, abstracting from low level and technical details, and without the need for programming knowledge. Hence, with our work in SyMptOMS, we answer Regli's call for *toolsmiths* [10]: developing tools and algorithms to accelerate research and experimentation in the field of mental health assessment and intervention.

The SyMptOMS platform consists of two client-side applications (one for patients and one for therapists) and a set of server-side services (see Figure 1). For patients, an Android-based smartphone application (SyMptOMS Mobile App) has been developed to monitor the patient both passively (collecting built-in and external sensor data) and actively (collecting explicit patient feedback, e.g., questionnaires), and to deliver interventions based on actionable information extracted by analyzing the collected data. For therapists, a web application (SyMptOMS Web App) allows to remotely configure the Mobile App, in terms of data of interest that must be collected (e.g., sensor data to collect, questionnaires to perform, etc.) and interventions that must be performed, together with necessary configuration data (e.g., frequency of data collection, intervention delivery conditions based on the analysis of collected data along with the current context of the patient). Next to configuration, the SyMptOMS Web App also provides the means for therapists to monitor patients' progress through chart- and map-based visualizations. Finally, the server-side services provide the core functionality of the platform: authentication, data storage and analysis.

Next, we describe the operational flow, while a patient is under treatment, of the different components of the platform.

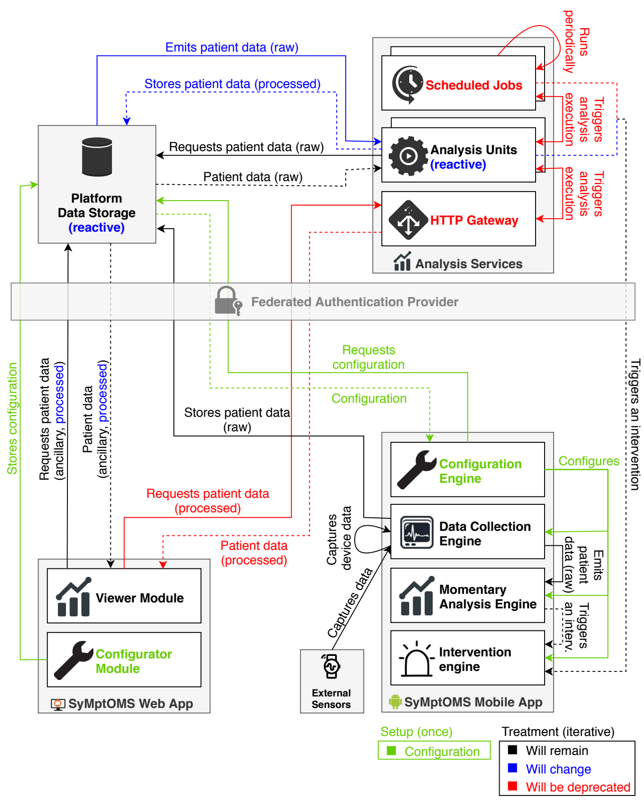

Figure 1: SyMptOMS platform components and their interactions, current status and future work.

Setup phase

After an initial screening, a therapist envisions and creates a customized configuration adapted to the treatment according to diagnosis. The configuration setup flow (in green, Figure 1), begins at the Configurator Module of the Web App where the therapist specifies the information that he/she wants to obtain from the patient and, based on it, to determine the conditions that must be met for intervention and content delivery. The information can be obtained passively (from smartphone internal and/or external sensors) or actively (interacting with the mobile app, e.g., filling in a questionnaire). The therapist does not specify the source for passive data collection (i.e., GPS, accelerometer, heart-rate monitor, etc.); instead this is inferred by the platform itself based on the type of processed information that the therapist seeks (e.g., number of times of home exits, time spent at a certain kind of place, anxiety level, etc.). Based on the selection of the therapist, the configuration engine in the Mobile App determines which data collection modules need to be activated and configured (e.g., GPS, heart-rate meter), along with other app components in charge of on-device data analysis and intervention delivery.

Treatment phase

Once the initial setup is completed and the patient starts the treatment, an iterative workflow (in black, red -to be deprecated- and blue -planned-, Figure 1) starts, involving multiple processes such as data collection, analysis and delivery, and continuously runs until the treatment finishes. During this stage, the Mobile App collects data from the mobile device's built-in sensors and attached wearable devices (e.g., smartwatches or smartbands). The flow of raw collected data is stored remotely in a cloud database. The therapist can access the treatment-wide collected processed data (via server-side analyses) at any time through the Web App to obtain valuable information. An intervention is triggered when the result of a locally performed analysis (i.e., on the device) over captured data meets certain conditions (e.g., when the patient enters an area of interest for the treatment), or when a cloud scheduled job ends its execution detecting changes in patient's behaviour (via server-side analyses) worth triggering an intervention.

Foreseen improvements

Based on our experiences developing the initial versions of the platform, and on experimental case studies conducted with patients on-field, we identified several technical challenges and possible architectural improvements to make the platform more effective in terms of scalability, streaming and reactivity support, and ease of maintenance. We discuss the challenges in the next section, and the architectural improvements next.

Currently, the momentary analyses that occur on-device, i.e. on the Mobile App, have a reactive nature: when a new data observation is collected (in addition to being stored), it is locally processed to determine if an intervention should be delivered. This reduces the time between data collection (capture of an event) and the action taken. On the other hand, server-side analyses are performed as periodically scheduled jobs over treatment-wide data in order to detect behavioral changes of the patient in the long run. This however implies a time drift between an event happening and its detection, causing some latency (along with other technical challenges). Our immediate goal is to bring the same level of reactivity currently implemented in the mobile app to the analysis processing on the server-side. This is partly possible thanks to the reactive cloud database we are using (i.e., the Firestore database), which has the capability to notify other processes (server- or client-side) of changes made to the information stored within it. Correspondingly, the Analysis Units, which calculate relevant information from raw patient-collected data, need to be updated from a traditional query-based paradigm to an event-based reactive programming paradigm. Further implications of the shift to a more reactive platform are elaborated with discussing technical challenges (see Section 3).

3 TECHNICAL CHALLENGES

While developing SyMptOMS and testing it in different therapeutic scenarios, we identified several technical challenges in order to efficiently and successfully implement EMAs and EMIs. Even though encountered in the context of SyMptOMS, it is important to stress that these challenges apply to any smartphone-based EMA or EMI solution capturing data to assess the behaviour of the patient (assessment) and react to changes (intervention). Hereby, we expose and discuss an opinionated selection of these technical challenges.

The technical challenges are classified into sensing challenges, i.e. related with data acquisition and processing, and intervention challenges, i.e. related with treating patients anywhere and under different scenarios. Beyond where they influence technical challenges, we do not discuss psychological or clinical issues/challenges here, even though they are a fundamental part of any sensing-based mobile apps for the treatment of mental disorders.

Sensing challenges

Trade-off between battery usage and data collection strategy: An increasing frequency of data collection, along with the variety and number of built-in and external sensors potentially can improve the accuracy of detecting relevant behavioral patterns and changes. Nevertheless, this improvement occurs at the expense of increasing battery drainage. The issue is further complicated due to the high variability of devices and sensor types, battery capacity and usage, combined with the specific requirements of treatments to detect behavioral changes on a longer or shorter term. Smart software solutions, regulating the data sampling rate, seem key to reduce unnecessary battery use on one hand, and to reconcile battery usage with the necessities of the treatment on the other hand. For example, context-aware strategies for data collection may reduce sampling rate, e.g., if the smartphone remains stationary for a while (detected using accelerometer), or contrary, increase it when needed, e.g., when the patient shows initial signs of stress (e.g., using GPS and heart rate data). Or reducing computationally-intensive operations such as scanning for a home-placed sensing Bluetooth device if historical location data shows a patient cannot be at home at that moment. Similarly, another improvement on battery drain is for example not to try to read heart rate of a smartband that is not currently attached to the wrist.

Small, context-based improvements definitively count towards saving battery usage. Smart software may also select a sensor that consumes less energy, in case multiple are available, or perform the selection based on current battery availability in case of multiple devices (e.g., smartphone vs. smartwatch GPS). Finally, specific treatment needs (e.g., need for time-sensitive interventions in case of gambling addiction versus less pressing intervention for alcohol addiction) may dynamically determine the increase or decrease of data sampling rate.

Real-time versus batch data processing: in a system in which decisions, such as the delivery of an intervention, are made autonomously and are based on contextual information, the choice of software architecture and programming paradigm [1] may greatly influence responsiveness and complexity of data processing tasks.

At one end of the spectrum, batch data processing allows for traditional and simpler periodical pull-based (query-driven) data processing, while, at the other end, real-time data processing requires a more complex, reactive programming style, in which data is processed as it arrives and analysis results are progressively updated. The latter is more scalable and has the potential to provide almost immediate responsiveness (e.g., independence of the time the treatment is running, versus increasingly lagging analysis time for batch processing), yet it has the disadvantage that it may lack sufficient information to be accurate, it requires a more complex architecture and complicates analytic functions (i.e., continuous query processing over streaming data is an ongoing research topic), particularly to detect changing patterns over time. For example, determining when a patient leaves his home can be easily and quasi immediately done using reactive (stream) processing, yet may lag when using batch processing. Conversely, detecting alterations of a patient's usual mobility pattern is inaccurate when trying to immediately calculate it (due to lack of data) and it is significantly more complex and costly as patterns change over time. If analyses are implemented to work in real-time a design decision that should be taken is to agree in the minimum unit of aggregation. For example, does the aggregation of data in 1-hour time buckets cover all treatment scenarios? This is an open question. What is clear is that the minimal aggregation unit should be higher that the minimum reporting frequency of the data collection mechanisms. As often, the happy medium may be most suitable, depending on the needs of the psychological treatment: performing some analysis in real-time depending on the complexity and need for (near) real-time response, while running other in batch mode. A mixed, balanced strategy seems to fit a wide range of situations, e.g., doing real-time pre-processing and more complex, sophisticated data processing in batch mode, or real-time (naive) processing (e.g., calculate deviations from currently known mobility patterns) based on current knowledge, with batch processing to periodically re-calculate mobility patterns.

Data storage challenges: as the mobile app collects sensor data passively, depending on the amount of patients, the amount of time they are under treatment, the amount of sensors collecting data, and the data collection frequency, the size of the collected data may grow significantly. Furthermore, the collected data can be quite heterogeneous, not only in terms of sources (sensor data, location data and human-provided input) but also in structure, granularity and scale. Here, specialized technical solutions may come to the rescue. Big data storage solutions are specifically designed to handle large amounts of data in a scalable way, yet they do not take into account the peculiarities of the data at hand. In addition, time-series databases usually have time-based indexes and are prepared to dynamically create horizontal partitions based on the time dimension (i.e., time in which a data record gets collected), and are thus particularly suitable for periodically collected sensor data. As another example, spatial databases are specifically designed and optimized to store and query geospatial data. The challenge here is to reconcile the various data storage technologies, possibly replicating (some) data in various storage media, given the wide variety of gathered data and according to the needs of the specific usage scenarios.

Data security and privacy: moral and ethical implications must be taken into account (i.e., to which extent does improving a patient's mental health outweigh giving up part of his privacy), while legal requirements must be addressed as well. Technically, a balance between authentication, data encryption and possibly data obfuscation (in case of potentially identifiable data, such as location data) particularly if the data will be shared (e.g., for the sake of science) is vital but challenging. Therefore, a balanced strategy to meet the previous requirements without putting hard constraints on the analysis processes that run on the data should be reached.

Intervention challenges

Online versus offline: even though online access has become virtually ubiquitous, reliable smartphone-based psychological treatments should also work in case of disconnectedness (e.g., in a remote area, in a plane). In these situations, data analysis performed only on the server-side prevents the correct functioning of interventions, as triggers (interventions) may not be fired, although the required data may have been captured (e.g., heart-rate collected from a wearable device to detect anxiety of a patient flying). To get things worse, performing analysis on the device further strains battery life and generally limits the power and possibilities of the analysis. The challenge here is thus to find a balance between less powerful, battery-intensive client-side data caching and analysis, versus more powerful, battery-conserving and server-side analysis.

An ideal solution could be to keep the middle ground, by running all the analyses on the server while the phone has connectivity (reducing battery consumption) and running all, or at least certain critical analyses, locally on the device when it loses connectivity. However, foreseeing to also run analyses locally increases the complexity of the software, as duplicate storage and analysis modules need to be written (i.e., client and server side), and a synchronization component needs to be in place. Despite some analysis functions could be shared, yet this would highly depend on the storage technologies, programming and data processing paradigms used (see *Sensing challenges*). Furthermore, complex analyses may simply be unfeasible on a mobile device such spatial analysis over historical data.

Other intermediate solutions and trade-offs may be envisioned. For example, to run only relatively simple analyses (e.g., requiring only one or few data samples) on the mobile device, regardless of the connectivity status. This can increase response time and offers offline functionality, yet only for interventions based on simple analysis (possibly omitting critical interventions). In summary, a balanced but advanced symbiosis between server- and client-side analysis could for example allow the mobile app to regularly download server-side real-time calculated partial analysis results (e.g., stream processing), only requiring to update them while offline. Obviously, such scenarios imply significant extra complexity and programming effort.

Delivery paradigms: while this may be regarded as an issue of less technical importance, paradigms and strategies for improving delivery content are vital. Unfortunately, it is still unclear how the delivery paradigm of psychological treatments influences their usefulness and effectiveness. Think for example of traditional mobile apps versus virtual or augmented reality apps, games, and so on. Even within a single app, different and timely interaction styles (e.g., mobile phone notifications, smartwatch vibration, chat bots) and user input methods (e.g., text-based, voice-based, video input) may have an effect on the performance of an intervention [7, 9].

Furthermore, we believe that one solution probably does not fit all, and the mental disorder at hand, the patient's characteristics and social, environmental and cultural factors definitively play a determining role. For example, the patient's profile may determine the best gamification technique to apply in an intervention to avoid treatment attrition [8]; younger patients may prefer games (or gamification elements in traditional smartphone apps) or be comfortable with virtual reality apps, while older patients may prefer traditional apps using voice or video input (rather than chat-style conversational bots). Much remains to be explored in innovative methods formats and strategies for content delivery.

4 CONCLUSION

In this work we have presented different technical challenges and open research questions in the development of smartphone-based ecological momentary assessment and interventions, based on our experience developing and carrying out experiments with the SyMptOMS platform, an ecosystem of tools that allows therapists to assess and treat patients remotely at any time and place. It does so by means of a configurable smartphone app that collects built-in and external sensor data of the patients and is used to deliver interventions. This mobile app is configured and customized by the therapists through a web application, which also allows them to monitor and view the processed patient data and analysis results.

We split the presented challenges in two categories: sensing and intervention challenges. The sensing challenges include issues such as battery consumption vs data collection strategies, real-time vs batch data analysis, data storage challenges, and data security and privacy. On the intervention side, we have presented challenges involving executing analyses on the device vs server-side, and issues related to usability and efficiency of delivery paradigms with respect to psychological interventions.

In summary, we think sensor-based psychological assessment and interventions delivered using smartphones are only in their infancy, and a wide range of technical challenges have yet to be explored and solved before more advanced, efficient and safe solutions become available. Even though we focused on these technical challenges in this article, it needs to be emphasized that these are only one piece of the puzzle. Further multidisciplinary research between psychologists, providing underlying theoretical foundations and exploring technology-based novelties, and computer scientists, realizing technically advanced solutions, are a must.

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