Personal MobileCoach: Tailoring Behavioral Interventions to the Needs of Individual Participants

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Abstract
MobileCoach, an open source behavioral intervention platform, has been developed to provide health professionals with an authoring tool to design evidence-based, scalable and low-cost digital health interventions (DHI). Its potential meets the lack in resources and capacity of health care systems to provide DHI for the treatment of noncommunicable diseases. In the current work, we introduce the first personalization approach for MobileCoach with the purpose of identifying the needs of participants, tailoring the treatment and, as a consequence, enhancing the capability of MobileCoach-based DHIs. The personalization approach is then exemplified by a very first prototype of a DHI for people with asthma that is able to detect coughing by just using a smartphone's microphone. First empirical results with five healthy subjects and 80 coughs indicate its technical feasibility as the detection accuracy yielded 83.3%. Future work will focus on the integration of personalized sensing and supporting applications for MobileCoach.

Author Keywords
Open Source Platform; Behavioral Intervention; Public Health; Personalization; Machine Learning;

ACM Keywords
J.3 Life and Medical Science; I.2 Artificial Intelligence; K.3.2 Learning; J.4 Social and Behavioral Sciences; F.1.1 Models of Computation

Introduction
To support an individual to adopt a health-enhancing behavior has been the motivation for the design of effective and efficient health interventions. Based on behavioral health models [1, 9, 13, 17, 24] and techniques [1, 22], behavior change interventions have been the basis for several applications in the health domain and investigated thoroughly in the last decades. The existing bottleneck at resources and the capacity to provide behavioral health interventions for the treatment of noncommunicable diseases (NCDs) pose one of the greatest challenges for health care systems worldwide [27]. Furthermore, NCDs represented the leading cause of death in 2012 responsible for more than two thirds of the global deaths [5].
With respect to these shortcomings, Internet of Personal Health systems, in particular digital health interventions (DHIs), have the potential to play a crucial role in reducing the burden for an individual patient as well as for the whole health care system. Not only could they create the possibility of improving the effectiveness and efficiency of health interventions, but also reduce their costs [2]. In contrast to their potential, the design and implementation of evidence-based, scalable and low-cost DHI is sparsely empirically supported [23].

In this context, MobileCoach, an open source platform for DHIs, was introduced with the main objective "to give scientists, public and behavioral health experts a software platform that allows them to design evidence-based, scalable and low-cost health interventions." [8, p. 1] With a modular design, which enables developers of DHIs to extend and expand MobileCoach to their specific needs, it is the rule-based engine which monitors health states and triggers state transitions that lies at its heart. Moreover, MobileCoach bears the potential for the much-needed scalable and low-cost supply of DHIs to address the global healthcare insufficiencies, especially with regard to the previously mentioned NCDs.

Asthma, a chronic disease involving the airways and the lungs, ranks among the most prevalent NCDs. 30 million children and adults (less than 45 years old) suffer from it in Europe [10] and 3,630 people die from it each year in the USA [7]. According to clinical guidelines, asthma control, a term used to describe the course of the disease, can be assessed by symptoms such as wheezing, breathlessness, chest tightness and coughing. Coughing, particularly the amount of coughs per day or per night, is reported to provide an objective assessment which correlates with the standard measure of asthma control [21].

In addition to being used as a measure of asthma control, coughing, a common symptom for many respiratory diseases [15], is a well-recognized indicator for the improvement of diagnostics. As a consequence, many efforts have been made towards the development of objective audio cough monitoring systems, which can be traced all the way back to the 1950s [3]. Recent advances have been accomplished by employing machine learning to automatically detect coughs into a semi-automated [4] or fully automated procedure [19]. The latter is a smartphone-based solution that merely makes use of a smartphone's built-in microphone to record coughing sounds and to subsequently detect and count personal coughs.

In conclusion, a smartphone not only enables recording and monitoring of cough sounds in near real-time but also provides a low-cost and scalable scope for a sensing application which is able to trigger health interventions for people with asthma based on an objective assessment of asthma control. In this current work we elaborate on the development and design of the aforesaid application for the purpose of integrating it into the MobileCoach platform as a trigger for future behavioral health interventions. Furthermore, we want to enhance the capability of such a sensing application by using machine learning techniques for personalization.

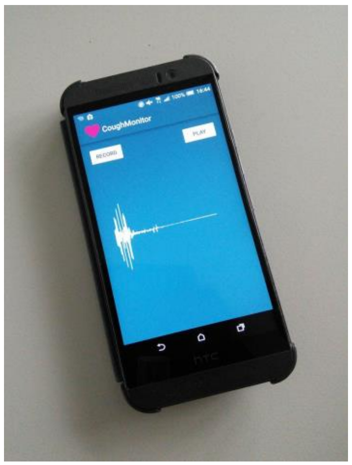

Figure 1: In this picture we show the coughing detection application, which makes use of the described algorithm. This application also enables a recording functionality, which was used in the test.

Personalization is known from the web customization process in which organizations determine the needs of the users and provide them advertising services, shopping services and filtering without the users having to ask for it explicitly [28]. In the context of MobileCoach, personalization may first help identifying the needs of the participants in the intervention more precisely and therefore develop a more sensitive trigger for DHIs, second it may help to tailor DHIs themselves, hence enhance their capability. With regard to the sensing application for cough monitoring this could mean that the system recognizes when it may lack the capability to monitor the participant's coughing rates precisely and therefore start on its own behalf to adapt the system's model by learning from the participant' individual coughs.

The remainder of this current work is organized as follows. We briefly outline a novel personalization approach for MobileCoach. We then describe coughing detection by means of a smartphone, present first empirical results from a technical feasibility study and describe how it can be related to a personalized MobileCoach DHI. We conclude with a summary and an outlook on future work.

The personal MobileCoach

In order to add personalization to the current MobileCoach, we illustrate its conceptual design first. The MobileCoach system as it has been introduced [8] follows the sequential logic of a state machine, where the state transitions are determined by intervention rules. The state corresponds to an aggregation of all significant variables, which are relevant to the intervention progress of the participant. Whenever a state transition is triggered by an intervention rule, significant participant variables are changed and therefore a change in the state machine occurs.

In particular, a participant registers himself / herself to the system by filling out an online baseline assessment (e.g. nickname, age, mobile number, intentions and the like), the consequence of which is the assignment of an initial state. By this action a fully automated dialog between participant and system commences. This dialog is executed over a text message service and consists of questions with pre-defined answer schemes. Depending on the participant's answer, state transitions are triggered and states are changed, based on the intervention flow formalized as rules, to lastly tailor the follow-up communication between participant and system.

It is just this exchange of information between participant and system over a longer period of time that we want to utilize to personalize MobileCoach. The more communication occurs and information is exchanged, the more evidence we have to possibly derive a comprehensive picture of the participant's needs. With regard to the conceptual design described above, the implications are that state transitions can no longer be triggered by taking into account only the last answer of the participant and the system's current state. In fact, in addition to the participant's answer, the current state and all the previous states have to be considered before a participant-specific behavioral health intervention can be triggered. With this in mind, a personalized MobileCoach would not only be able to recognize the interventions that had the biggest impact on the intervention progress of the participant, but also omit the ones that had less and lastly determine the treatment that is most efficient for the participant. Finally, different forms of personalization have been used in different fields. Among the most prominent, web search personalization, where the goal is to tailor search queries to a particular individual, based on her interests and preferences [16]. With regard to mobile application, personalized training periods have been exploited to infer the mood state of an user by analyzing communication history and application usage patterns of a smartphone [20].

The personalized cough detection module for MobileCoach

As described in the previous section, personalization should occur over time. For machine learning based cough detection, this could look as follows: After each night, the application detects and counts coughs and possibly triggers DHI based on the amount of coughs. Additionally, the application may choose a number of recorded sound sequences, preferably sequences which have been on the verge of being detected as cough sounds or being ignored, respectively. These chosen sequences are then queried to the participant to be labeled as coughs or non-coughs respectively. Alternatively, this data could also be judged and labeled by a third party such as cough experts or on-demand workers (e.g. [12]). Finally, by continuously integrating this new labeled data in the model learning process, personalization is achieved. This special case of supervised learning is known in literature as active learning and is characterized by its queries [25].

Results

The subject of the current work has been the development of a coughing detection module for MobileCoach to provide personalization as described above. The developed module is based on classification of spectral features from the audio signal of a smartphone's microphone. The system pursues a similar implementation as in [6]. However, support vector machine classification was used instead of simple decision-tree classification, which proved to generate better results in terms of sensitivity, specificity and accuracy with respect to our settings. A first test included a population of 5 healthy subjects (2 female, 3 male, mean age: 27, SD: 2.55), recorded by means of a bespoke app running on Android 6.0 OS on a HTC M8 smartphone. In this first test, 16 intentional coughs were recorded instead of natural coughs. The participants were instructed to intentionally cough while being recorded by the aforesaid smartphone. Analogously, the participant was asked to read for a limited amount of time. These recordings build the coughing data and non-coughing data, from which a predicting model was learned. The evaluation of the test yielded 86.7% sensitivity and 81.0% specificity, with an accuracy of 83.3%.

Future Work

We emphasized in this work the expendability of MobileCoach towards personalization and a new sensing module for smartphones. In the matter of asthma, further sensing modules for MobileCoach can be thought of as for instance, smartphone-based spirometry. Spirometry is the mainstay for measuring lung function and reports suggest that its functionality, namely the measurement of instantaneous flow and cumulative volume of exhaled air, may be reproducable by means of a mobile phone [11, 18]. Even beyond sensing, we can consider supportive DHIs. For example, wind instruments have been used in music therapy to improve the skill of asthmatic patients to attack asthma [14]. This finding can potentially be exploited by a smartphone-based wind instrument application [26] and be embedded in a behavioral DHI. Against this background, we want to extend MobileCoach with various sensing and supporting DHIs in our future work: not only to provide a broader toolset to intervention experts, but also to design efficient and effective interventions, which are tailored to the needs of the participants and provide objective (physiological) data on therapy adherence.

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