Context-aware notification management systems for just-in-time adaptive interventions

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***Abstract*—Just-in-time adaptive intervention (JITAI) is a framework used to provide personalized and context-dependent interventions to a user. To fully integrate a JITAI into a user's context, the intervention developer needs to ensure that the user is responding, while still being in the same context. Consequently, they need a context-aware notification management system (CNMS) to accurately time the sending of interventions. This research aims to study smartphone sensor based CNMS for JITAIs in a behavioral change and health context. In this work, we outline the various studies – completed or underway – from a smartphone based digital coach providing interventions and collecting passive sensing data. This data will then be used to train machine learning models, which are finally evaluated in a verification study in the field.**

I. Introduction

Just-in-time adaptive intervention (JITAI) is a framework developed by Nahum Shani et al. [1] used to provide personalized and context-dependent interventions to a user. In particular, interventions for behavioral change and health applications (e.g., quit smoking [2] or increase physical activity [3]), have shown promising outcomes using JITAIs. With their widespread adoption, mobile devices not only provide an ideal platform to deliver these interventions, but their built-in sensors are also a crucial source of information to sense the context and provide the foundation for adaptation of the content. While some researchers have deployed and tested JITAIs (e.g. [2], [3]), very few (e.g. [4]) have used a context-aware notification management system (CNMS) to time a push notification, ensuring the user is responding, while still being in the same context. Comparable research is using smartphone sensor data and machine learning models to reduce the burden of push notifications in general (e.g. [5]–[8]). However, Sahami et al. [9] have shown that the disruptiveness of push notifications is application dependent, consequently making general CNMS difficult to apply in a health or behavioral change context.

II. Methodology

The objective of this research is to investigate if a CNMS can reduce the burden of behavioral change and health related push notifications sent by an application using a digital coach (chatbot), who chats with users autonomously. To train and test these systems, we conducted three studies for collecting smartphone sensor data. The collected sensor output is then mapped to the point in time, when users responded to these push notifications, i.e., when they are receptive to act on an intervention.

Ally [10], our first data collection study was recently completed, with the data analysis currently underway. A total of 272 users participated and shared their data. Ally studies different mechanisms to promote physical activity among smartphone users by using a mix of financial incentives and digital coaching. The coaching is entirely done by a chatbot, which sends out push notifications, which then act as a ground truth for our data collection. Additionally, we have two more studies, OPTIMAX [11] and PEACH [12], currently in data-collection phase with 250 and 300 users, respectively. PEACH investigates the possibility to change personality along the big-5 [13] personality dimensions using a chatbot sending push notifications. OPTIMAX is a survey study to analyze the effect of a psychological anxiety intervention. The surveys are also delivered using a chatbot and act as an intervention with a heavy burden, as users get a 22-item survey five times per day. While the data collection phase of PEACH will end at the end of the year 2018, data from the OPTIMAX study will be collected until 2022. All three studies use the same collection module and the same chatbot system, called MobileCoach [14], [15]. Sensor data is collected 24 hours per day from both iOS and Android users and includes: GPS (every 10 min), WiFi (every 10min), Physical Activity, Battery state, Bluetooth devices nearby (every 10 min), Proximity and lock/unlock events. All the above sensor data are collectively known as the *contextual factors*, which may or may not change for each notification for each user. In addition, we also consider several *intrinsic factors*, which remain constant for a user throughout the study. These include general demographic (e.g. age, gender etc.) and personality traits (e.g. big-5 [13]) information.

In a first step every dynamic and intrinsic factor is analyzed individually for their predictive power towards the response delay, i.e., the time between receiving and responding to a push notification and the response rate, i.e., the number of responses divided by the number of push notifications sent out. Methods used for this analysis include generalized linear modeling, ANOVA and Tukey-Post hoc, which have all been used successfully before [6], [16]. After analyzing the individual prediction capacity of every factor, machine learning models are built and tested. Initially, established methods of predicting interruptibility such as AdaBoost, Bayesian net as used by

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Pejovic et al. [17] and hidden markov models (HMM) [18] are investigated. We further wish to investigate the efficacy of using RNN for detecting opportune moments, which has not been evaluated, yet. The best performing method will then be deployed and tested in a small validation study. In this study 50 students will use a light version of the Ally app with an active CNMS timing the delivery of these push notifications.

III. Preliminary Results

An extensive literature review and meta analysis [19] covering more than 1600 articles showed that only few studies have tested their models in the wild. Further we found that there is evidence to increase the response rate, but little support to decrease the response delay. Preliminary results from the Ally dataset support the literature findings that many intrinsic and contextual factors have the capacity to predict the response rate, additionally, we also found some interesting effects on the response delay. However, the effects on the response rate and the response delay are small, which is in line with previous research [19]. For the intrinsic factors in particular the device type (iOS vs. Android) was found to be statistically significant. Android users had both a higher response rate and a lower response delay. Further, neurotic, conscientious and more agreeable users were associated with a higher response rate. Other intrinsic factors such as gender or age did not have an effect. The contextual factors show a temporal pattern that users respond more frequently during the day, as compared to being at home or somewhere else. Further we found that users are not likely to respond when the battery is full.

IV. Conclusion

In this project we aim to develop a CNMS for JITAIs. After conducting an extensive literature review and meta analysis including more than 1600 articles, we ran several data collection studies and have found preliminary results. Our results support findings from our literature review and expand the field by investigating different device types and including more factors than were investigated before. Finally, we will conduct a verification study to test the performance of our models in the field.

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