Personalized Models for Health and Wellbeing: Insights from an Ongoing Project on Unobtrusive Stress Tracking with Smartphones

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Abstract
Long-term self-tracking has promising applications in different fields. However, self-tracking is usually short-lived because of user abandonment. This extended abstract presents work on a tracking system that addresses several current challenges of self-tracking and provides opportunities for long-term tracking in wellbeing applications. The main concern we seek to address through our research is alleviating the burden on users by using a tracking system that is not adherence-based. We report on an ongoing project which involves an unobtrusive system that generates a time-series of a person's daily activities inferred from smartphone data. The aim of long-term tracking with this system is to generate N-of-1 models for health and wellbeing applications. We aim to generate discussion around the promises and challenges of long-term tracking from users' perspective, as well as technical and ethical perspectives.

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Long Term Self Tracking; Quantified Self; User modeling;

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

Introduction

Despite the plethora of ubiquitous activity tracking applications and wearables, the challenges associated with user adoption and abandonment of these technologies are widely recognized. For example, [7] examined why users adopt and abandon a wide range of wearables over a time period of two months. They enumerate several reasons why users take on and give up using wearables, but most importantly assert that unless the wearables align with people's daily routines, adoption remains short-lived.

Besides reducing user burden for tracking, it has been suggested that using tracking as "a means to an end" (i.e. providing value for the user rather than merely quantifying user data) can support long-term use of self-tracking technologies [2]. Long-term tracking can provide the unique benefit of being able to build personalized models, accounting for individual differences, thus creating value, such as effective health interventions, for users.

In this paper, we present motivation for long-term tracking. We then present our ongoing work on long-term comprehensive tracking for wellbeing (mainly stress) which address user abandonment and adherence issues and capitalize on the applications of long-term tracking in different fields. In contrast to efforts that aim to generate user models based on short term tracking data, this paper proposes ways in which long-term tracking can be implemented in real-world settings. Our work is focused on lifestyle applications designed to alleviate users' burden and enhancing the value of long-term tracking for users. Furthermore, we aim to generate discussion around the benefits of using long-term tracking data to build personalized models and the challenges arising from such implementations.

Motivation for Long-Term Self-Tracking

Lifestyle is an important risk factor, as well as an effective intervention, for several diseases. Evidence in the literature shows that lifestyle tracking can identify the risk of several diseases for an individual. Even before sensors and digital trackers became prevalent, a number of studies used non-digital long-term tracking of lifestyle to identify high and low-risk populations for several diseases. For example, [12] followed 84,129 women for 14 years and periodically updated information about their diet and lifestyle through surveys sent to the participants every two years. Similarly, [14] tracked 181 subjects for 14 years. Both studies found that long-term lifestyle tracking predicted coronary heart disease. Other studies have also tracked lifestyle over several years to predict obesity [9], type-2 diabetes [10], cancer [11] and depression [13]. With stress being associated with lifestyle diseases, there has been an increased interest in using self-tracking to detect causes of stress in daily events and activities.

Given the promises of long-term tracking for health studies, it is no surprise that literature on long-term self-tracking with digital technology often highlights the benefits of long-term self-tracking for wellness and wellbeing [6]. Tracking allows for a holistic approach towards health and wellness, taking not only biophysical metrics into consideration, but also physiological, contextual, and social factors. With longitudinal data, individual models can be built to take individual differences into consideration. Past research has shown that ideographic N-of-1 models are better predictors of stress and exercise behavior than one-size-fits-all, nomothetic models [1]. N-of-1 models are challenging because they require a large amount of historical data per user in order to study the relationship between tracked events and the dependent variables of interest for every individual.

Given that adherence and abandonment are the main challenges of personal tracking, addressing these issues can enhance the opportunities for collecting and using long-term longitudinal data which can eventually capitalize on the benefits of personalized models. Advances in sensors embedded in everyday devices enable continuous unobtrusive tracking without requiring extra effort from the user to input data, thereby addressing the major shortcoming of adherence and abandonment in self-tracking.

In our ongoing work described in the next section, we show how we use data from unobtrusive sensors that do not require user's manual input, and we describe our approach to build individualized models to study health and wellbeing from longitudinal tracking data in everyday life.

Work in Progress

Unobtrusive stress tracking with smartphones
Researchers have explored different ways of quantifying information about a person's lifestyle and daily activities. With smartphones carrying more information about our lives than ever before, it has become possible to draw a picture of a person's lifestyle solely from smartphone data. Our colleagues have developed a mobile application that can be downloaded on smartphones to collect multimodal data streams from smartphones [8]. The multimodal data streams are then put together to make inferences about an individual's environmental and social conditions to generate a "personicle", i.e. a personal chronicle: a time-ordered list of a person's activities.

Our current research project uses the personicle to understand events that trigger stress and how users cope with stress. We use the personicle mobile application to collect the following data streams: (1) using the phone's GPS, we infer user location based on mapping the geolocation with the Google Maps API that provides location type (e.g. restaurant, school), (2) using the phone's accelerometer, data on physical activity is collected and activity type is inferred (e.g. walking, driving), (3) using the phone's calendar, information about the current activity is extracted (e.g. work meeting), (4) data about apps used are collected and the category of the apps are recognized through the app market API (e.g. Messenger app, category: communication). Collecting these streams of information can be done unobtrusively, without interrupting the user or requesting input. Our project aims to extract meaningful features from the personicle to build a machine learning model that predicts stress. Currently, a proof-of-concept study is underway wherein participants download the mobile application and wear a stress tracking device (GSR sensor). Once the model is built for predicting stress, the stress tracking device would be no longer needed as the system would be able to predict stress from the personicle mobile application alone. The goal is to eliminate the need for extra wearables to measure stress thus reducing user burden. Long-term tracking in this project is essential to get a holistic understanding of stress, and is possible because the system is not adherence-based, hence avoiding issues of user abandonment.

The temporal information about a person's daily activities inferred through has several important applications for health and wellbeing. Future work will build personalized stress interventions based on contextual data from the personicle. Future work can also look into the personicle of users with certain lifestyle diseases such as obesity and type 2 diabetes and identify opportunities for effective lifestyle interventions.

Open Questions and Challenges

Based on insights drawn from our ongoing work and prior literature, we pose a few challenges for long term self-tracking to stimulate discussion around open questions.

Technical Challenges

Models need to be continually improved and evolved. A personalized model may be less accurate a few years later with lifestyle changes. To address this problem, an approach called "active learning" in machine learning can be used, where the model can query a source to label new data. With long-term tracking, the models we build will need to be continuously updated taking into account new patterns in tracked data, which might pose a technical burden.

Even with unobtrusive tracking systems that do not require direct user input or an extra wearable device, there could be user burden resulting from exhausting resources of the user's device. For example, tracking using the smartphone consumes storage space and battery life which can interfere with users' regular use of their smartphones. This inconvenience can cause abandonment [7], which poses the question of whether it is possible for a tracking system to be entirely unobtrusive given the limitations of consumer technologies.

Ethical Challenges

To our knowledge, privacy implications of long term tracking remain to be fully understood. The implications of tracking user's everyday activities in terms of their privacy needs impact not only users and designers, but also legal and ethical regulatory bodies. How could we incorporate perspectives from all stakeholders to inform and shape decisions in long-term tracking going forward? How can the expected benefits and expected privacy challenges be quantified and balanced?

Another ethical challenge for long-term tracking is user agency. Users should have agency over their data, making informed decisions on what to track and share [5, 3, 4]. An example of user agency over their personal data is implemented by Amazon's Echo device, where users can view data collected by the Echo and shared with developers. Users of Amazon's Echo can also delete any data they do not wish to be recorded and shared with developers. The problem with this approach of user agency is the resulting incomplete and missing data. In our ongoing work, we inform users of what data is being tracked on their smartphones and they can opt-out of one or more components (e.g. calendar events or activity tracking). We hope that with personalized models and long-term tracking, missing data can be compensated for, either by building models without the features containing missing data, or by imputing missing values based on historical data.

Finally, a broader issue around the quantified self is the possible loss of subjective information. What happens when we objectify (i.e. quantify) subjective experiences? How can the community use the opportunities provided by tracking technologies to improve people's health and wellbeing without undermining the value of people's experiences?

Unobtrusive long-term life tracking and personalized models are the future of health and wellbeing. It is therefore imperative that HCI researchers drive collective interdisciplinary efforts to guide the future of long-term tracking technologies utilizing the wealth of knowledge and insights of user experiences with technology. With insights from our ongoing work that is aimed at alleviating user burden and ensuring long-term tracking, we provide promising evidence for the applications of long-term tracking. We also describe the challenges and raise questions to spark discussions that could lead to the formation of future research agenda.

REFERENCES

1. Y Cheung, M Qian, S Yoon, L Meli, KM Diaz, J Schwartz, IM Kronish, KW Davidson, and others. 2017. Are Nomothetic or Ideographic Approaches Superior in Predicting Daily Exercise Behaviors? *Methods of Information in Medicine* 56, 6 (2017), 452–460.

2. James Clawson, Jessica A Pater, Andrew D Miller, Elizabeth D Mynatt, and Lena Mamykina. 2015. No longer wearing: investigating the abandonment of personal health-tracking technologies on craigslist. In *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing*. ACM, 647–658.

3. Sunny Consolvo, Katherine Everitt, Ian Smith, and James A Landay. 2006. Design requirements for technologies that encourage physical activity. In *Proceedings of the SIGCHI conference on Human Factors in computing systems*. ACM, 457–466.

4. Sunny Consolvo, David W McDonald, Tammy Toscos, Mike Y Chen, Jon Froehlich, Beverly Harrison, Predrag Klasnja, Anthony LaMarca, Louis LeGrand, Ryan Libby, and others. 2008. Activity sensing in the wild: a field trial of ubifit garden. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, 1797–1806.

5. Kathrin M Cresswell, David W Bates, and Aziz Sheikh. 2013. Ten key considerations for the successful implementation and adoption of large-scale health information technology. *Journal of the American Medical Informatics Association* 20, e1 (2013), e9–e13.

6. Rebecca E Grinter, Katie A Siek, and Andrea Grimes. 2010. Wellness informatics: towards a definition and grand challenges. In *CHI'10 Extended Abstracts on Human Factors in Computing Systems*. ACM, 4505–4508.

7. Amanda Lazar, Christian Koehler, Joshua Tanenbaum, and David H Nguyen. 2015. Why we use and abandon smart devices. In *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing*. ACM, 635–646.

8. Hyungik Oh and Ramesh Jain. 2017. From Multimedia Logs to Personal Chronicles. In *Proceedings of the 2017 ACM on Multimedia Conference*. ACM, 881–889.

9. John J Reilly, Julie Armstrong, Ahmad R Dorosty, Pauline M Emmett, A Ness, I Rogers, Colin Steer, and Andrea Sherriff. 2005. Early life risk factors for obesity in childhood: cohort study. *BMJ* 330, 7504 (2005), 1357. DOI: http://dx.doi.org/10.1136/bmj.38470.670903.E0

10. Matthias B. Schulze, Kurt Hoffmann, Heiner Boeing, Jakob Linseisen, and et al. 2007. An Accurate Risk Score Based on Anthropometric, Dietary, and Lifestyle Factors to Predict the Development of Type 2 Diabetes. *Diabetes care* 30, 3 (03 2007), 510–5. https://search.proquest.com/docview/223028104?accountid=14509

11. Mingyang Song and Edward Giovannucci. 2016. Preventable incidence and mortality of carcinoma associated with lifestyle factors among white adults in the United States. *JAMA oncology* 2, 9 (2016), 1154–1161.

12. Meir J Stampfer, Frank B Hu, JoAnn E Manson, Eric B Rimm, and Walter C Willett. 2000. Primary prevention of coronary heart disease in women through diet and lifestyle. *New England Journal of Medicine* 343, 1 (2000), 16–22.

13. Hisashi Tanaka, Yosiaki Sasazawa, Shosuke Suzuki, Minato Nakazawa, and Hiroshi Koyama. 2011. Health status and lifestyle factors as predictors of depression in middle-aged and elderly Japanese adults: a seven-year follow-up of the Komo-Ise cohort study. *BMC Psychiatry* 11, 1 (07 Feb 2011), 20. DOI: http://dx.doi.org/10.1186/1471-244X-11-20

14. JWR Twisk, HCG Kemper, W Van Mechelen, and GB Post. 1997. Tracking of risk factors for coronary heart disease over a 14-year period: a comparison between lifestyle and biologic risk factors with data from the Amsterdam Growth and Health Study. *American Journal of Epidemiology* 145, 10 (1997), 888–898.