Personal Informatics Tools Benefit from Combining Automatic and Manual Data Capture in the Long-Term

Nora Ptakauskaite
UCL Interaction Centre
University College London
The Alan Turing Institute
London, UK
nora.ptakauskaite.16@ucl.ac.uk

Mirco Musolesi
University College London
The Alan Turing Institute
London, UK
m.musolesi@ucl.ac.uk

Anna L Cox
UCL Interaction Centre
University College London
London, UK
anna.cox@ucl.ac.uk

Abhinav Mehrotra
University College London
The Alan Turing Institute
London, UK
a.mehrotra@ucl.ac.uk

James Cheshire
University College London
The Alan Turing Institute
London, UK
james.cheshire@ucl.ac.uk

Chiara Garattini
Intel
London, UK
chiara.garattini@phe.gove.uk

Abstract
Harnessing the research opportunities provided by the large datasets generated by users of self-tracking technologies is a challenge for researchers of both human-computer interaction (HCI) and data science. While HCI is concerned with facilitating the insights gathered from data produced by self-tracking systems, data scientists rely on the quality of such data for training more accurate predictive models, which can sustain the flow of insightful data even after manual self-tracking is abandoned. In this position paper we consider the complementary roles that manual and automated data capture methods hold and argue that interdisciplinary collaborations are vital for advancing long-term self-tracking, the research and intervention opportunities that come with it, and provide a concrete example of where such collaborations would fit.

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Self-monitoring; personal informatics; mental health; data science.

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

Introduction

Self-tracking technologies offer a wide variety of benefits to their users. The large amounts of data generated by self-tracking devices also provide an attractive and engaging research opportunity for experts in HCI, data science, machine learning, and psychology. These opportunities take many different forms, including, advancing the technology itself, improving user experience, bettering users' health and/or acquiring "cleaner" and "richer" datasets [19]. Addressing all these factors is important as they feed into one another, particularly, in mobile health interventions: better user experience prevents abandonment and promotes adherence; this in turn results in higher impact interventions for the users, which ultimately leads to higher quality datasets as the users are more engaged with the system [14]. However, working on these features in parallel can be challenging. This position paper discusses the dynamics of solving interdisciplinary problems in the context of data science and long-term self-tracking for mental health by reflecting on experiences gathered during a collaborative project involving computer scientists, data scientists and human-computer interaction researchers.

Background

Self-tracking (or personal informatics) technologies aim to provide individuals with knowledge about themselves, namely, their behaviours and factors that influence them. Computerised self-tracking tools facilitate this process through their ubiquity as data can be automatically collected, processed and visualised [6]. Tracking one's health across extended periods of time has the potential to offer insight into how the choices and actions made in the present influence specific outcomes in the future. This can be achieved by enabling users to interact with visualisations of their personal data, allowing them to discover trends and patterns in their past or even infer future behaviours and identify behaviour change opportunities. To realise this potential, interdisciplinary research teams need to come together to identify user needs associated with long-term self-tracking, and how self-tracking itself could be optimized to provide the most insightful and accurate information possible [4,14].

Aims and Contributions

The main aim of this paper is to discuss how views expressed by experts in data science and HCI may vary when deciding which specific features and functions are appropriate for a technology being developed. We also considered why it is important to integrate both perspectives to meet the needs of users and the researchers who work with the data that the technology collects. The paper concludes with an example of how effort made by experts from both fields could enhance and facilitate the research and development process.

Personal Informatics

Personal informatics (PI) refers to a collection of tools that enable users to collect, transform and reflect on their personal data for self-insight and/or behaviour change [6]. In theory, PI tools offer a viable solution for gathering behavioural insights and helping people to see important behaviour-health links, specifically those that emerge over longer periods of time. Existing self-tracking tools are well adept at supporting the monitoring of short-term goals, such as running distances or daily step counts; people can easily interpret such metrics at a glance and update their behaviour accordingly [3,16,17]. However, research has also shown that the use of most self-tracking tools

Sensor	Description
GPS	The individual is not exploring new locations, follow routine routes (work-home).
Accele-rometer	Physical activity levels go down.
Camera (Light sensor)	The person sleeps too much/too little, stays up late.
Phone usage data	Less text messages and calls are received or made.

Table 1. Data driven profile of an individual affected by depression categorised by sensor type.

is short-lived and goes through cycles of use and abandonment as users forget to turn on the app, report results or wear their self-tracking device [4]. Extracting meaningful information from incomplete datasets is particularly problematic as limited recorded occurances provide flawed or insuffienct insights upon which to make sound judgements [7]. One means of maintaining a stream of information without requiring active participation, is to use sensors incorporated into mobile smartphones for the continuous monitoring of user activity [10].

Such data can be used to infer behavioural patterns and trends [10], providing a potential solution to the use and abandonment issue mentioned above [4]. However, inferring users' behaviours through smartphones can also bring its own challenges related to both modelling [11] (concerns related to data science) and the absence of reflections inherent in automated information processing (concerns related to HCI), where reflection refers to the process of exploring personal data and using the gathered insights to decide whether any behaviour change is needed [5,7].

Leveraging HCI and Data Science

This section provides an overview of the considerations that our team consisting of data scientists and HCI experts had to make when developing novel tools for long-term anticipatory mental health tracking. Even though our project's focus was on mental health, the challenges and opportunities that we encountered can be applied to the wider context of self-tracking.

The role of manual data capture

In their model of PI, Li et al [4] describe how individuals interact with their personal data through five stages: preparation (deciding what data to collect), collection (acquiring the data), integration (transforming the data), reflection (gathering insights from the data), and action (aka., behaviour change; acting on the previously made insights)[5]. The more engaging the process of exploring personal data, the more valuable the insights into opportunities for behaviour change will be [7]. Data exploration can be made more engaging by using varied types of data visualisations or by instructing individuals when and how to reflect on their data [3,5]. Importantly, reflection plays a key role in PI research, with some researchers arguing that automated sensing is not suitable, at least, not in all stages of self-tracking. This, in fact, seems to dominate or have dominated [4] the landscape of PI as a field in general [5,6]

The role of automated data capture

There are several reasons why people might decide to engage in self-tracking. As mentioned above, some strive to improve their health and achieve behaviour change, others may simply want to observe the trends and patterns in their behaviours [4]. In the future, however, medical professionals may ask their patients to self-track over extended periods of time to observe whether they are maintaining a healthy lifestyle and/or good mental wellbeing. The latter scenario leads one to consider whether it is realistic to expect that people will adhere to manual long-term self-tracking lasting years or even decades? This is exactly where sensor based, automated monitoring fits in.

Sensors integrated into smartphone devices can collect rich and insightful datasets that can be used to infer people's mental states. For example, Table 1 illustrates how sensor data could indicate whether a person is

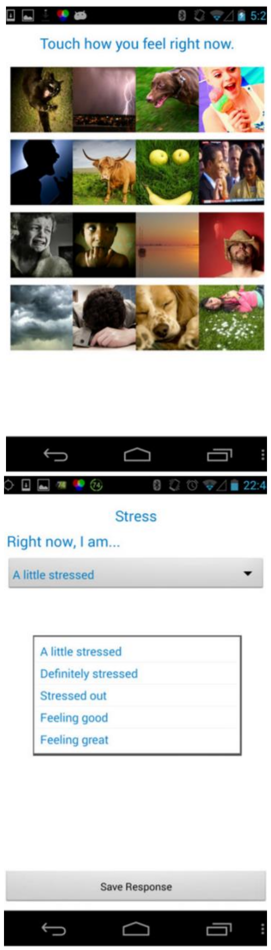

Figure 1. Examples of EMAs based on the Photographic Affect Meter (top picture) and text (bottom picture) [15].

becoming depressed [1,8,10,18]. Access to such data can help to administer early interventions, or provide a convenient way for medical professionals to monitor people suffering from a mental health illness [1]. For these tools to work, however, they first need to be trained by using human labeled data. This process involves using ecological momentary assessments (EMAs), where the user is asked to input their mood or other health-related measures, such as mood or stress (see Figure 1 for an example) multiple times per day on their smartphone [2,13,15]. The information collected is then used to label the data coming in from mobile sensors (e.g., GPS points). Higher quality data translates into more accurate models, improving the ability of the system to infer the user's mental states [11].

Finding a Balance Between Automation and Manual Logging for Long Term Self-Tracking

One of the main issues with this approach, as we discovered first hand during our project [11], is that few people provide frequent and/or reliable EMA responses [11,21]. As a result, our research team had to work with hundreds of thousands of unlabeled data points generated by the participants' mobile sensors, with only a few dozen EMA responses per participant available to label the remaining dataset. This made obtaining accurate inferences from mobile sensor-generated data extremely challenging [11]. Similarly, by providing only a small number of EMA responses the users also have fewer opportunities to reflect on their data, such as mood patterns and what might be influencing these. In this scenario, once the users abandon manual self-tracking, they are left with a poorly trained model generating unreliable inferences and they are also unaware of what reported health measures might be influencing the model's outputs.

Attempting to interpret and make inferences from incomplete datasets is a major challenge for both researchers advancing automated self-tracking and users of such systems in general [6,21]. This issue underscores an opportunity where both HCI and data science communities could benefit from collaborating. The use of methods such as gamification, better interaction design and applying intelligent notification systems to deliver EMAs at opportune moments may help to incentivise users to report more and higher quality data through EMA responses [9,20]. This could result in cleaner and larger datasets for making more accurate inferences and provide more opportunities for reflection when first commencing the use of the monitoring system. Over time, this would result not only in making the users more aware of the trends and patterns in their behaviour and what influences it, but it would also make it possible to train more insightful models capable of tracking and inferring behaviours with minimal intervention from the user. This can be particularly useful when the motivation to self-track is low, for example, when the novelty of a device or app wears off, or the user reports less due to mental illness [4,12].

Conclusion

Designing successful long-term self-tracking interventions is still an open challenge. However, the research and development process can be facilitated through the combined efforts coming from specialists in HCI and data science.

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