# Tools to Support Health and Well-being with Personal Data

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## ABSTRACT

Personal data can be instrumental for health and well-being. While it has become easier to obtain such data, realizing its benefits remains challenging. People overburden themselves by collecting too much data yet they may not *collect the relevant data*, especially as their needs evolve. They cannot usually *handle the complexity* of the data or they fail to *connect the data* to their needs. They additionally struggle to *translate data insights* to actions. My research addresses these challenges through 1) using technology probes around tools that help individuals understand their personal well-being, 2) building data-driven behavior planning systems that facilitate health behavior change, and 3) designing computational methods that characterize and quantify the impact of social adversities on mental and emotional state.

## CCS CONCEPTS

• **Human-centered computing → Interactive systems and tools**.

## KEYWORDS

personal informatics, health tracking, behavior change, ubiquitous computing

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## 1 INTRODUCTION

Personal data can be instrumental for health and well-being. It can not only support increased understanding, awareness and control of one's health, but also motivate and empower behavior change [4, 5]. It can also facilitate communications with health providers [3]. While it has become easier to obtain personal data, achieving the above benefits remains challenging [2, 9]. For example, people overburden themselves by collecting too much data yet they may not *collect the relevant data*, especially as their needs evolve. They cannot usually *handle the complexity* of the data or they fail to *connect the data* to their needs. They additionally struggle to *translate data insights* to actions. In the absence of tools for effective collection and use of data, the potential of personal data is not realized. Instead, people's efforts end in feeling overwhelmed and frustrated.

My research addresses these challenges through **human-centered design and development of tools to obtain and make sense of personal data and use it to inform health behavior change**. This involves building systems, designing interactive techniques, and devising computational algorithms that **improve the collection and use of personal data**. Specifically, I have worked on: 1) **technology probes** around tools that help individuals understand their personal well-being, 2) **data-driven behavior planning systems** that facilitate health behavior change, and 3) **computational methods** that characterize and quantify the impact of social adversities on mental and emotionl health. I combine theories and frameworks with formative qualitative and quantitative studies to understand needs and considerations in obtaining and using data for health. I then use this knowledge in designing, building, and evaluating tools that support well-being. I also use controlled observations as well as in-the-wild deployments to examine and study the use of these tools. Below, I describe past and planned pieces of work along these lines. These projects pertain to the broad classes of problems that fall under the research questions below.

## 2 RESEARCH QUESTIONS

My research broadly considers the following research questions: **(RQ1)** What interaction frameworks, and techniques better support the collection, interpretation, and use of personal data? **(RQ2)** What new insights can we obtain from personal health and behavior data? **(RQ3)** What computational methods can surface data insights and enable data interactions?

## 3 UNDERSTANDING PERSONAL WELL-BEING

Use of personal data can improve well-being by enabling health understanding and facilitating communication of one's needs and expectations to care providers, family members, and other stakeholders [2–4]. There are, however, challenges in the way of realizing this potential: it is hard to decide on relevant data and to make adjustments to it over time, it is non-trivial to make sense of the data, and it is difficult to discuss this data with the others to benefit from their expertise or cooperation [9]. **My research explored frameworks and interaction techniques that can help individuals in planning, collecting, and interpreting their personal data.**

I **examined the framework of goal-directed self-tracking** in a longitudinal deployment study with a technology probe in the context of migraine tracking where the above challenges are especially pronounced. Schroeder et al. [9] proposed the goal-directed framework to mitigate these challenges through scaffolding the tracking setup around what people want to gain from tracking; i.e., the tracking goals. They showed doing so better supported migraine


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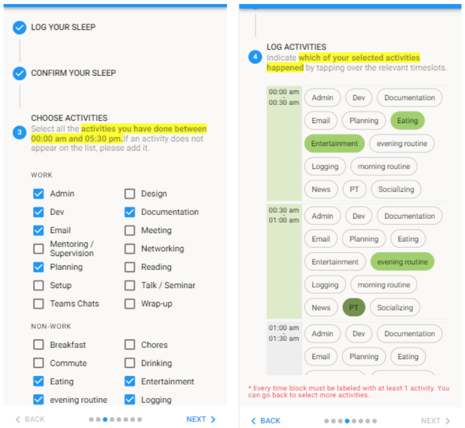


Figure 1: WoNoB Data Collection.

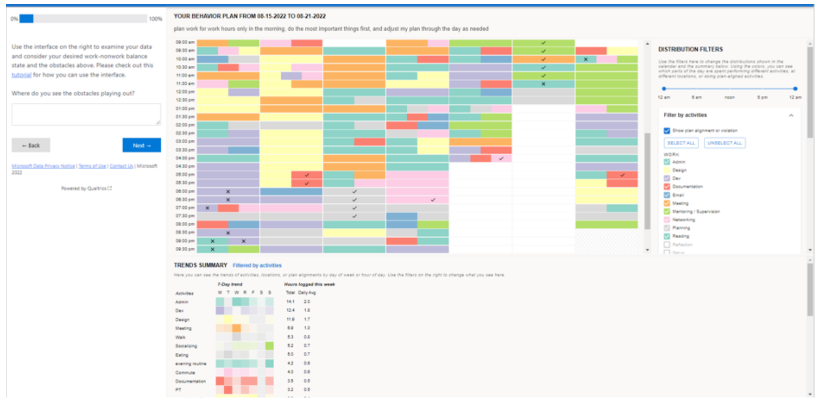

Figure 2: WoNoB Reflection. Instructions are on the left, filters on the right, visuals in the middle, and summaries at the bottom.

patients and their providers in their preparation for tracking. Preliminary analysis of 106 interview sessions of the longitudinal study I led with 10 migraine patients and three providers demonstrates the benefits of goal-directed tracking beyond the preparation and in later stages of self-tracking. It also highlights the needs and considerations in designing goal-directed tracking tools for these stages. Moreover, it points to unmet challenges that arise because of the flexibility and richness of goal-directed tracking. For example, data handling should be fully personalized to account for the nuances of each patient's appropriation of goal-directed tracking.

In a follow-up to the deployment study, I am building a system to **enable personalized data handling and interpretation of self-tracked data**. The system is designed to scaffold data exploration process by explicitly inquiring user goals and iteratively incorporating their nuanced understanding of data. Specifically, user goals seed a preliminary set of steps to prepare, analyze, and visualize the data. This set is built based on an existing bank of expert-user participatory analyses of self-tracking data across domains (e.g., migraine, work-nonwork balance, or shoulder pain). Users are next asked to clarify and modify the steps based on their unique knowledge of the data. I plan to evaluate whether the system can successfully elicit user input and improve data exploration and sense-making. This is an area I particularly welcome input / feedback.

## 4 DATA-DRIVEN BEHAVIOR CHANGE

People face a number of challenges in changing their behavior for improved health and well-being: they struggle to decide what behaviors to perform and how, they fail to stay on track with their behavior plans, or they cannot adjust those plans based on dynamic demands and resources. I **explored ways of using personal data to increase awareness, highlight opportunities for change, facilitate progress monitoring, and provide relevant resources to respond to changes**. These capabilities can help address challenges above.

Specifically, I designed the **WoNoB system [10, 11] for bringing data to the application of implementation intentions and mental contrasting**, two self-regulation techniques that help individuals overcome the challenges in planning and following through with behavior change goals [6]. Implementation intentions are if-then plans that help individuals think once about what, where, and how of achieving their goals and then act upon it. For example, an implementation intention plan to be more physically active may look like: "whenever I use the restroom, I'll do 10 squats." Mental contrasting asks people to think about their desired state juxtaposed with their current reality and identify the obstacles that are in the way of reaching their desired state. Combining the two strategies has been shown to be particularly effective for behavior change but relies on identifying key obstacles as well as the doable actions for addressing those obstacles. Both are non-trivial tasks that can be addressed by personal data. WoNoB system attempted to enable these tasks with personal data. It facilitated collection of (Figure 1) and reflection on (Figure 2) activity, whereabouts, and progress data. It combined multiple reflection design patterns that past work had identified as effective [1]. These included visualizations (time by weekday calendar and summary graphs), statistics (summary values), textual prompts and questions (instructions), and refining and revising different aspects of data (filters). The system allowed users to explore how and where they spent their time, examine how well their current behaviors matched their desired behaviors, and look into mismatches as well as opportunities to address them. During my internship at Microsoft Research, I evaluated WoNoB system in a three-week between-participant study with 43 information workers who used the system in the context of improving work-nonwork balance. We found evidence that reflection on personal data improved awareness of behavior plan compliance and rescheduling, which are important in realizing work-nonwork balance goals. We also observed the value of *micro-reflection*, reflection on limited data of the very recent past for implementation intention and mental contrasting.

## 5 QUANTIFYING SOCIAL ADVERSITIES

Potential benefits of personal data can go beyond n-of-1 cases above where the focus is on a single person's data. The personal behavioral records in aggregate can *facilitate new understanding* of health and well-being. This understanding not only *expands the knowledge from smaller scale* laboratory studies but also generates insights in

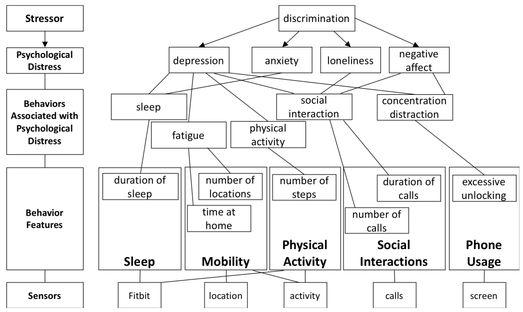


**Figure 3: Behavior Data Model of Discrimination Stress. Stress response to discrimination is linked to behaviors measurable by phone and wearables.**

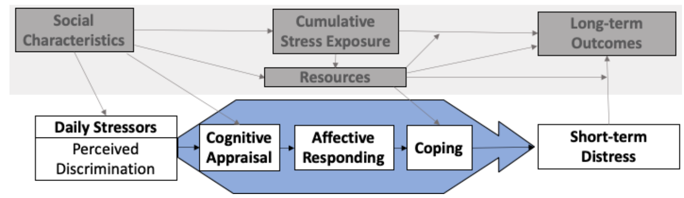


**Figure 4: Extended Stress Process Model for Short-term Distress and Long-term Outcomes of Discrimination. This extended model accounts for social, cognitive, affective, and behavioral factors influencing responses to everyday discrimination.**

domains where such *traditional studies are very hard* if not impossible. The detailed and situated records also make it easier to *project the large-scale insights* at the individual level which is important for personalizing interventions. **I explored the above possibilities for personal data in the study of everyday discrimination**, a pernicious social adversity that is common and consequential yet challenging to study in laboratory settings.

While the long-term physical and mental health outcomes of everyday discrimination is well documented [7], not much is understood about the pathways from short-term reactions to long-term effects [8]. Personal data can help elucidate this gap. Building on this promise, I first leveraged phone and wearable data to examine **behavioral changes associated with discrimination events [13]**. Given everyday discrimination can be considered a stressor, I operationalized behavior markers of stress response using passively-sensed location, screen use, calls, sleep, step, and physical activities (Figure 3). I found that time in bed decreased while number of calls, number of interactions with the phone, number of steps, and physical activities increased on the day of discrimination compared to other days among 209 college students who we followed for six months. These students also reported heightened frustration and depressive symptoms the day of the events. While elevated frustration and depression continued for another day, there were no change in behavior markers beyond the day of the events. I next interviewed 14 students who had encountered discrimination within 10 weeks of the interview session to further situate and interpret these findings [12]. Students described a number of emotional responses and coping behaviors that were aligned with our behavior analysis. However, they were typically affected by the incidents for longer than a day or two. While bounce back was quick for some, it took weeks for others. Some never resolved the situation. Analyzing participant accounts through social as well as cognitive, affective, and behavioral processing lens (Figure 4), I identified the **factors that explain the variations in experiences**. I found that everyday discrimination is more distressing if students face related academic and social struggles or when the incidents trigger beliefs of inefficacy. There were also distinct patterns of coping associated with ineffective resolution of the experiences. For example, different forms of continued avoidance behaviors prevented resolution.

Drawing from interview accounts, I studied the **changes in routine behaviors in relation to discrimination events**. To this end, I designed a novel routine extraction algorithm that leverages a new routine representation based on individuals' conceptualization of routines. It then uses this representation within an optimization scheme (submodular scoring with lazy greedy optimization) to find the best set of temporal regularities that comprise a routine. I evaluated this technique in terms of coverage, residual, and information gain metrics that I specifically defined for assessing routines as behavior summaries. I also demonstrated the utility of the algorithm in recovering well-known sleep patterns, namely sleep chronotypes and social jetlag. Moreover, I showed we can recover new sleep routine patterns in relation to mental health and academic performance. For example, students high on PSS stress score sleep with a distinctive irregularity pattern.

## 6 GOALS FOR CSCW DC

I would like to get feedback on the design of my final research project which I plan to complete over the next year. I am also looking for input on the framing of my work as one coherent body of research within HCI. Moreover, I welcome suggestions for promising future directions to take on based on my current work. In addition to getting feedback, I would like to connect to my my peers and experts in other areas. Bringing my own interdisciplinary background and getting to know others, I hope to further my understanding of different areas of research and opportunities for making contributions.

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