Supporting Control and Alignment in Personal Informatics Tools

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ABSTRACT

Despite the abundance of diverse personal data and its potential for improving health, individuals struggle to draw value from it. A key challenge is difficulties in controlling the functionality of existing systems and aligning them with evolving needs. These systems commonly restrict what information is recorded and how, lack effective means for sense-making and decision-making, and fall short in supporting the translation of data insights into personalized actions. My research addresses these challenges through building prototype systems, designing interactive techniques, and devising computational algorithms.

CCS CONCEPTS

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

KEYWORDS

personal informatics, health tracking, behavior change, end-user data analysis

ACM Reference Format:
Yasaman S. Sefidgar. 2024. Supporting Control and Alignment in Personal Informatics Tools. In *The 37th Annual ACM Symposium on User Interface Software and Technology (UIST Adjunct '24), October 13–16, 2024, Pittsburgh, PA, USA*. ACM, New York, NY, USA, 4 pages. https://doi.org/10.1145/3672539.3686709

1 INTRODUCTION

Although it has become easier to collect large and diverse data with substantial potential for improving health, it remains challenging for individuals to achieve that potential and draw value from their data. A key challenge is difficulties in aligning existing systems with people's evolving needs. Firstly, systems commonly restrict what information is recorded and how, thus forcing collection of data that is irrelevant or poorly connected to an individual's needs. Secondly, systems lack effective means for sense-making and decision-making. For example, personalized data exploration and pattern discovery can often require substantial investments in developing highly specialized computational workflows. Off-the-shelf tools fail to meet the wide variety of personal needs that individuals bring to their data, but people also commonly lack the programming and analytics expertise that would be required to implement their own workflows. Lastly, existing systems lack support for translating data insights into personalized actions. Individually and in combination, these barriers undermine the potential benefits and impacts of personal health data. My research draws from principles of human-centered design and development to address the challenges of control and alignment in the use of data systems.

I build prototype systems, design interactive techniques, and devise computational algorithms to contribute frameworks, techniques, and architectures that mitigate these challenges. Specifically, I have worked on: 1) technology probes and novel architectures to augment people's expertise in using their personal data for well-being, 2) data-driven behavior planning systems with explicit scaffolding for data sense-making to facilitate health behavior change, and 3) computational methods to characterize and quantify the impact of social adversities on mental and emotional state. In these efforts, I have combined theories with formative qualitative and quantitative studies to understand user needs and considerations to then use this knowledge in designing, building, and evaluating data systems via controlled or observational studies and field deployments. Below, I describe my past work and future research agenda for supporting control and alignment of personal data systems.

2 UNDERSTANDING PERSONAL WELL-BEING

Personal tracking systems hold significant potential for improving health. However, there are challenges in realizing the potential of these tools: it is hard to decide on relevant data and data collection capabilities (e.g., 'what about diet to record and how?') or to make the necessary adjustments (e.g., 'why to always record calories?'). Moreover, it is non-trivial to make sense of the data. I examined if the explicit representation of why people track, i.e., their *goals*, and subsequent structuring of the tracking system around these goals can address these challenges. Specifically, I used MigraineTracker (Figure 1) as a technology probe to demonstrate this goal-directed framework can improve user control over the tracking tool and the alignment of its features to user needs [3]. MigraineTracker elicited goals then used the goal expressions to guide data collection consistent with the goals. Data presentation and review were also goal-centered. In a longitudinal deployment study, I showed that such scaffolding led to highly personalized experiences that helped individuals track data for multiple and evolving goals and make adjustments when needed. In addition to supportive evidence for the value of goal-directed framework, I contributed to the theoretical models of personal tracking (i.e., the importance of accounting for multiple goals and their inter-relations in the models) and highlighted key requirements for complex decision-support systems (e.g., alignment while accounting for evolution). This

UIST Adjunct '24, October 13–16, 2024, Pittsburgh, PA, USA

ACM ISBN 979-8-4007-0718-6/24/10
https://doi.org/10.1145/3672539.3686709

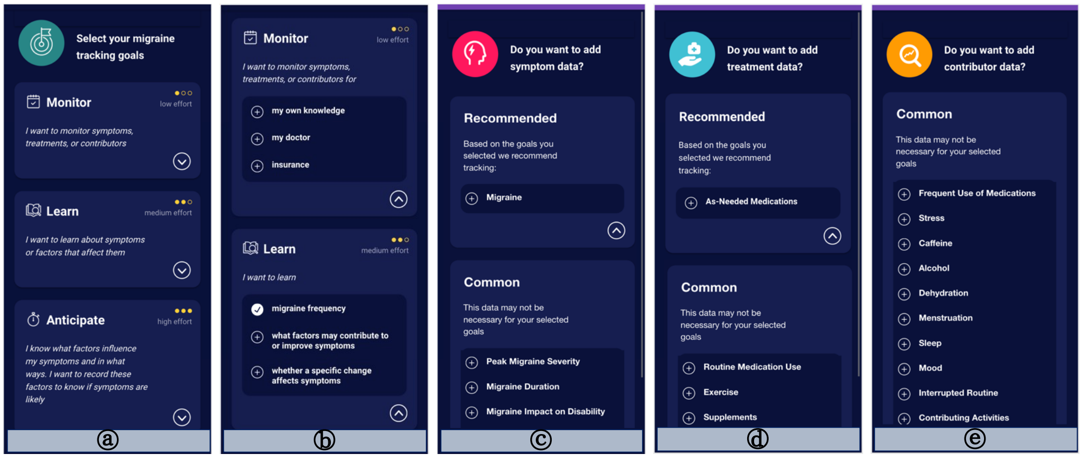

Figure 1: With MigraineTracker individuals can express (a) goals and (b) sub-goals then configure collection of (c) symptoms, (d) treatments, or (e) contributors.

work was recognized by a Best Paper Award in CHI 2024 for its quality and the significance of the contributions.

Personal data is inherently heterogeneous. People record different information, they record the same information differently, and one person may change their recording over time. No assumptions can be made for hard- or pre-coding analysis in the presence of high within and between variations in recording. Moreover, data is not neatly formatted contrary to the expectation of most analytics and visualization systems. Additionally relevant semantics are often hard to automatically infer and only known to the individual. Data heterogeneity thus poses a major challenge in data analysis particularly for end-users with limited analysis and programming expertise. Addressing this challenge, I developed a novel end-user analysis architecture that brings together computational capabilities and user expertise about their data [4]. This architecture is based on Analyticons ("Analytic Icons"), visual interactive objects that represent assumptions underlying goal-aligned visualizations and guide individuals in leveraging personal knowledge to satisfy those assumptions. Assumption satisfaction in turn transforms heterogeneous personal data and structures it into effective visualizations code-free. This architecture is compositional as different implementations can underlie exposing and satisfying assumptions (e.g., I leveraged Large Language Models (LLMs) in one implementation of the architecture). It is also extensible as new objects can be integrated to expand the system (e.g., the existing implementation includes Analyticons for core needs in managing chronic conditions such as migraines. New Analyticons can support other health needs). In addition to formally representing the analysis process to facilitate personalized and accessible data inquiry, this work demonstrates the benefits of using intermediate interactive artifacts in harnessing the power of computational tools (e.g., foundation models).

3 DATA-DRIVEN BEHAVIOR CHANGE

People struggle in leveraging personal data for behavior change due to challenges in planning changes, staying on track with their plans, and adjusting the plans given dynamic demands and resources. In collaboration with Microsoft Research, I built WoNoB ("Wanna Be") system (Figure 2) that draws upon goal pursuit strategies to scaffold sense-making and decision-making with personal data and to align these processes with individual needs and context [5, 6]. Specifically, WoNoB brings implementation intentions and mental contrasting (IIMC) to personal data. 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, "whenever I use the restroom, I'll do 10 squats." is an implementation intention plan to be more physically active. Mental contrasting asks people to think about their desired state against their current reality and identify the obstacles in the way of reaching the desired state. Using IIMC to structure reflection on personal data, WoNoB allowed individuals to more effectively explore how and where they spent their time, examine how well their

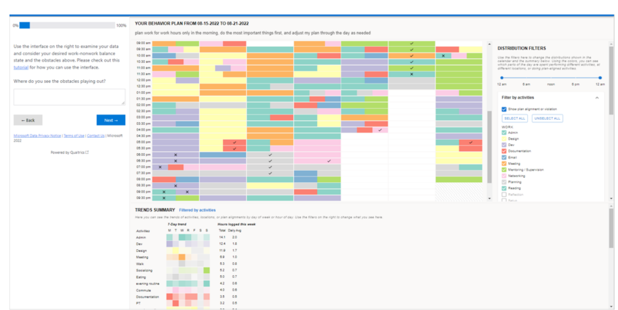

Figure 2: WoNoB system scaffolds data review and behavior change planning with the help of implementation intentions with mental contrasting.

current behaviors matched their desired behaviors, look into mismatches as opportunities for behavior change, and identify ways to address the mismatch. I evaluated WoNoB in a three-week between-participant study with 43 information workers who used the system in the context of improving work-nonwork balance, a key factor in workplace well-being. This study showed using IIMC with data improved awareness of behavior change compliance and the ability to reschedule behavior plans. Interacting with data without IIMC was confusing. These findings highlight the importance of explicit scaffolding techniques in bolstering user control over computational capabilities that would be otherwise opaque and hard to use.

4 QUANTIFYING SOCIAL ADVERSITIES

There are unprecedented opportunities for using human behavior data to expand knowledge in domains where traditional methods of inquiry are very hard if not impossible to use. The objective is to first align data with relevant concepts from qualitative observations of a phenomenon or theories explaining it, then quantitatively examine these concepts, and finally generate new insights at scale to advance our understanding of the phenomena. I developed computational infrastructure and methods to study and quantify the impact of everyday discrimination, which is common and consequential for mental and physical health yet poorly understood in terms of short-term reactions and their pathways to long-term effects. Limited relevance of laboratory studies complicates observations. To address this gap, I aligned passively-sensed data from phones and wearables to theories of emotional and stress response and defined behavior markers associated with discrimination events [8]. Numerically characterizing an invisible phenomena, these markers showed changes in sleep, social interactions, phone use, and physical activity on the day of discrimination events among 209 college students who were followed for six months.

Further situating and interpreting these findings, I interviewed 14 students who had encountered discrimination within 10 weeks of the interview session. Students' emotional response and coping behaviors typically aligned with passively-sensed patterns. However, the emotional response often lasted longer than a single day [7]. While bounce back was quick for some, it took weeks for others. Some never resolved the situation. Building up on these observations, I designed a novel routine extraction algorithm that allowed a more complex and nuanced alignment of data with subjective reports of disruptions and changes in behaviors following discrimination events [9]. This algorithm leverages a new user-centered routine representation with an optimization scheme to find the best set of temporal regularities that explain a person's behaviors. I assessed the algorithm's performance in recovering known regularites under various levels of disruption and noise, demonstrated its utility in recovering well-known sleep patterns (sleep chronotypes and social jetlag), and discovered new stress-linked behavior patterns.

5 FUTURE RESEARCH

My goal is to build systems that allow individuals to control the power of computation and seamlessly align it with their needs. Some of the future directions I would like to take are as follows:

Goal-Directed Design. My work demonstrates the potential of explicit goal expressions for guiding interactions with data systems in complex self-tracking tasks [3–6]. Forms of scaffolding that leveraged goal expressions allowed individuals to control systems and align their capabilities with their needs. However, there is much left to explore in this space. What would it mean to leverage goals in other tasks, including online discourse, information work, or software development? In what ways can we effectively elicit goal expressions? What other forms of scaffolding are relevant, especially as goals evolve? How to take advantage of the interrelations among past and present or the concurrent goals?

Personalization and Collaboration in AI Systems. Supporting control and alignment can be key to personalized interactions with AI systems much like data systems (e.g., as in [3]). They can also be critical in Human-AI collaboration. The need to address challenges due to lack of control and misalignment is becoming increasingly important as we see the potential of foundation models and surge in their application across tasks and domains. It is thus critical to further study and understand the various manifestations of these challenges and the requirements they pose to then inspire solutions. For example, what scaffolding techniques might be relevant? How to support verification and adjustment? What interaction techniques and/or interactive objects can mediate user input across tasks? This last question calls for particular attention as foundation models are more broadly applied. It is not uncommon that specifics of a domain can be leveraged in interactions for increased efficacy and comfort. For example, in my work on end-user programming of robots [2, 10], I defined a tangible interaction paradigm which was more consistent with needs for programming tasks in the physical world and thus significantly reduced barriers in program understanding, expression, and debugging.

Connecting Small and Big Data. Realizing the unparalleled opportunity for the scientific study of such phenomena as human behavior at scale hinges on tools that make it possible to align observational and theoretical concepts with the data and offer computational methods to examine the relations among these quantified concepts. Techniques such as machine teaching have already shown promise as intuitive means for simple end-user concept definition (e.g., as in [1]). Can we leverage this same technique for defining more complex concepts? What other techniques would enable domain experts to take small-study observations to scale in a way similar to my own work on everyday discrimination [8, 9]? What computational methods are relevant given the observational nature of most big data corpses?

6 CONCLUSION

My work aims at designing tools for augmenting human expertise with computational power through better mechanisms for control and alignment. I study needs and challenges in human interactions with computational systems and design and evaluate solutions to combine human and machine expertise.

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