

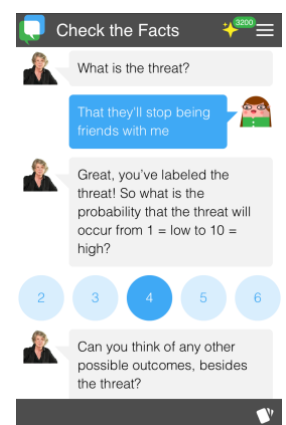
Many patients and health providers believe that health technologies, particularly those that incorporate self-tracking, have the potential to provide a more complete and accurate understanding of an individual's habits and overall health. Such an understanding could lead to more personalized care. However, current tools often fail to support the goals people have for health tracking and management, leaving this potential largely unrealized. **My research focuses on supporting people and their health providers in expressing and pursuing their multiple, distinct, and evolving goals to help them overcome barriers to personalized health management.**

My research approach draws on **human-computer interaction (HCI)** theories and techniques to examine supporting patients and providers in specific health contexts, including: 1) **formative work** to identify needs, challenges, and opportunities within that context (e.g., through surveys and interviews); 2) **iterative design and development** of novel methods and tools to support patients and providers (e.g., through prototypes and implementations); and 3) **evaluations** of those methods and tools to understand how patients and providers use and respond to them (e.g., through deployments with pre- and post-interviews and surveys). Throughout this process, **I consult and collaborate with health professionals** to draw on existing medical expertise within those contexts.

Using this approach, I have investigated three health contexts characterized by complex, chronic symptoms that require personalized interventions to address: 1) mental health disorders, in which I investigated support for dialectical behavioral therapy; 2) irritable bowel syndrome, in which I investigated support for personalized trigger identification; and 3) migraine, in which I developed *goal-directed self-tracking*, a novel method to help people and health providers express and pursue their goals. My research in health and self-tracking has been supported by a National Science Foundation Graduate Research Fellowship, received a Best Paper Award (CHI 2017) and two Best Paper Honorable Mentions (CHI 2017, DIS 2018), and directly informed grants from both the National Science Foundation (IIS-1813675) and the National Institutes of Health (R01-LM012810). In the following sections, I review my research in the three health contexts I have examined. I then discuss future opportunities for AI support in personalized health and wellness.

Supporting Dialectical Behavioral Therapy for Mental Health Management

Approximately 18% of US adults experience a mental health disorder each year [5]. Dialectical behavioral therapy (DBT) is an evidence-based treatment designed to help people develop concrete skills to solve problems, maintain relationships, and navigate negative events and emotions. I investigated fostering DBT engagement and mental health management with Pocket Skills, a conversational mobile web app designed to provide holistic support for DBT, including goal setting, educational components, skill practice, and self-tracking of positive and negative moods and behavior [12]. I joined the Pocket Skills project during a summer internship at Microsoft Research, working with a team of HCI researchers, clinical psychologists, and mobile app designers and developers to help translate the DBT Skills Training Manual and Workbook into app content. I then conducted a 4-week field study with 73 participants to assess the feasibility of Pocket Skills. Throughout the study, participants completed surveys consisting of validated scales that allowed us to assess their progress in terms of depression, anxiety, and coping skill use. The surveys also included open-ended questions asking what people liked and disliked about the app and whether and how it helped them. After the study, participants reported improvements that were both statistically and clinically significant (i.e., 50.0% of participants were “recovered” or



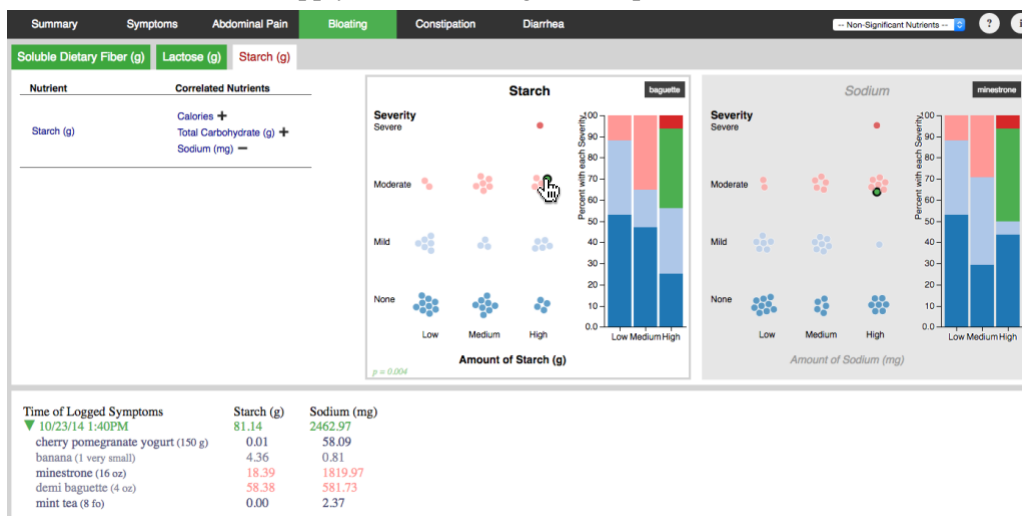
Pocket Skills supports people in learning and practicing skills which they then implement in their daily lives.

“improved” in terms of anxiety, 26.4% in terms of depression, and 19.4% in terms of DBT skills use, with details of these scales and definitions in [12]). I also contributed a model of how participants felt Pocket Skills supported DBT, finding that the app helped them *engage* with their DBT and *learn* and *practice* skills that worked for them, which enabled them to *implement* those skills in their daily lives, see *concrete results* of using the skills, and *increase their self-efficacy* to manage their mental illness.

However, although many participants reported progress towards their goals using Pocket Skills, the app did not explicitly support an individual’s goals: skills were taken directly from traditional DBT and not tailored or suggested based on the individual using the app. We ultimately envision the app intelligently *recommending* skills that are likely to be feasible and effective for a particular individual. I therefore performed a quantitative analysis of the feasibility study data to examine the relative effectiveness of specific skills, developing data-driven design implications for translating evidence-based treatments into mobile applications and identifying opportunities to provide personalized skill recommendations [13]. The analysis revealed the importance of considering an individual’s in-the-moment environmental, emotional, and personal context when suggesting skills to reduce distress. We next plan to investigate how to apply these human-centered artificial intelligence guidelines to produce ethical, useful, and contextually-appropriate insights to better support an individual’s goals for their therapy.

Supporting Personalized Trigger Identification for IBS Management

Irritable Bowel Syndrome (IBS) symptoms can often be triggered by certain foods, but different people have different triggers. Providers often recommend patients keep food and symptom journals to attempt to identify their personal symptom triggers [1], but both patients and health providers struggle to interpret resulting data (e.g., describing data as overwhelming, making biased and inconsistent recommendations). I investigated supporting people and providers in identifying personalized IBS triggers using food and symptom journals. Working as part of a multidisciplinary team of health and HCI researchers, I first developed analyses using food and symptom data to identify correlations between specific food nutrients an individual consumed and their subsequent IBS symptoms [14]. I then designed and developed interactive visualizations to help people explore relationships between the foods they eat, the nutrients those foods contain, and the symptoms that correlate with those nutrients [9]. I evaluated those visualizations in a feasibility study with 10 pairs of patients with IBS and health providers. I found that collaboratively reviewing the visualizations helped patients and providers interpret the data, communicate and apply their knowledge and expertise, and build mutual trust.



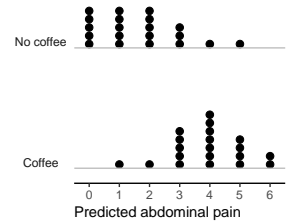
I developed interactive visualizations to support exploration of a patient’s food and symptom data, displaying which nutrients were significantly correlated with symptoms and which foods in their diet contained those nutrients. My feasibility study revealed that such visualizations can enabled patients and providers to individually and collaboratively interpret and reflect on the patient’s data.

My interactive visualization helped people *form hypotheses* about which nutrients may trigger their IBS symptoms. However, as the underlying data was correlational, it was insufficient to establish causal patterns. I therefore collaborated in a project to design, develop, and evaluate a system that supports *hypothesis testing* by guiding people through personalized self-experiments to examine whether a nutrient causes symptoms [6]. I also characterized nuanced and personalized goals people often want to pursue *beyond* simply identifying whether a certain nutrient triggers IBS symptoms (e.g., cost-benefit analyses to determine whether to avoid a nutrient in a particular context). In a follow-up study investigating personalized health goals [10], I proposed Bayesian methods to analyze self-experimentation data and produce representations that can better support these additional goals. I also adapted my visualizations in a collaboration to design and evaluate a mobile photo-based food and symptom journaling app, finding that photos can support identification of straightforward food-symptom relationships while my analyses and visualizations can support identification of more complex relationships [3]. In an ongoing project, I am mentoring a junior student examining how Bayesian network learning could provide more understandable and actionable analyses of symptom and trigger data.

Supporting Goal-Directed Self-Tracking for Migraine Management

My research in mental health and IBS examined supporting common goals patients and providers often have within those contexts and revealed opportunities to support more nuanced and personalized goals. Informed by this prior research, my work in migraine has focused on *goal-directed self-tracking*, a novel method to help people and providers express and pursue their specific goals. Goal-directed self-tracking aims to support people and their providers in: 1) understanding each other's tracking goals; 2) tracking exactly and only what they need to track to achieve those goals; and 3) interpreting resulting data relative to their goals. I am collaborating with the UW Headache Clinic to examine this method in the context of migraine, a condition characterized by debilitating symptoms that can be caused by the accumulation of a variety of personalized contributors [7]. To identify challenges and opportunities in migraine tracking, I first conducted a formative study in which I surveyed 271 people with migraine and conducted follow-up interviews with 13 survey respondents and 6 health providers [8]. Unpacking an overall management goal of reducing symptoms, I found four distinct categories of tracking goals that people often bring to migraine: 1) learning about their migraines; 2) predicting and preventing migraines; 3) monitoring migraines over time; and 4) fostering motivation and social recognition. Each goal category has different needs for data, analyses, and visualizations to support migraine-related tracking.

Building on this work, I iteratively designed and developed a goal-directed self-tracking system that supports people in deciding *what*, *when*, and *how* to track toward specific goals, and in interpreting the resulting data given those goals [11]. I first reanalyzed the formative study data to develop scaffolding for each goal category. Using a paper prototype to present these design ideas, I then conducted interviews with 14 people with migraine and 5 health providers. My findings indicate potential for such a system to: 1) help people define and develop tracking and management goals; 2) encourage people to consider and prepare for all stages of self-tracking; and 3) contribute additional expertise in patient-provider collaboration. I also found pitfalls people may encounter when relying on a system's expertise or attempting to define appropriate goals. Based on these findings, I am currently implementing my goal-directed self-tracking system, both to continue to develop and evaluate my ideas and to convey a specific example of how a goal-directed perspective can inform future tools. Implementing and evaluating this system will allow us to investigate how goal-directed self-tracking can help people collect, interpret, and act on their data and achieve their migraine-related goals.



Using Bayesian modeling to generate predictive distributions, we can display predicted symptoms if an individual consumes (bottom) or avoids (top) a nutrient, supporting cost-benefit analyses.

The image shows a mobile app interface with a light blue background. At the top, it asks 'How would you categorize your migraine tracking goal?'. Below this, there are three sections: 'LEARNING', 'PREDICTING', and 'MONITORING'. Each section provides a description, an example, and a likely effort level. At the bottom, there are 'Back' and 'Continue' buttons.

Category	Description	Example	Effort Level
LEARNING	about your migraines or related factors May be a good choice if: you're new to migraine tracking or you're making a change	"I want to learn what factors may contribute to my symptoms", "I want to learn whether starting an exercise routine will improve my symptoms"	medium
PREDICTING	whether you're at risk for a migraine May be a good choice if: you know what factors affect your symptoms, and are willing to track often so you know when those factors are accumulating	"I want to know whether I'm likely to experience symptoms today"	highest
MONITORING	your migraines and related factors May be a good choice if: you just want to keep track of migraine-related data	"I want to keep track of how often I exercise", "I want to know how often I experience symptoms"	lowest

By explicitly asking *why* a person wants to track migraine-related data, I aim to 1) help them track exactly and only what they need to achieve their goals and 2) present goal-appropriate analyses and visualizations of their resulting data.

Future Opportunities for Data and AI in Support of Personal Health and Wellness

In my PhD research, I have focused on developing novel methods and tools to help patients and health providers better understand and manage chronic health conditions based on their personal data. In the future, I plan to continue to investigate new methods and tools to help people understand, manage, and improve their health and wellbeing. I am particularly interested in investigating opportunities to incorporate artificial intelligence into health and wellness tools. I am excited to pursue this research in an industry context, because I believe doing so will create the greatest impact in the world.

I see many parallels between supporting self-tracking towards an individual's health-related goals and incorporating artificial intelligence into health technologies. Based on my prior work, I believe that insights provided by artificial intelligence in health and wellness technologies must be *actionable*, *personalized*, and *interpretable* to ensure the resulting systems are feasible, ethical, and useful.

Ensuring *actionability* will require formative user research with stakeholders to understand what insights will be most feasible and useful in a given context. For example, DBT often includes self-tracking of negative moods. At first look, one might therefore think people would benefit from algorithms that can automatically track those moods. However, the act of self-tracking those moods can itself promote mindfulness and awareness that is beneficial. Instead of just automatically tracking, a better system might sense a negative mood and recommend in-the-moment interventions to ensure people are mindful of their mood and help them choose a positive coping mechanism to improve it.

Although ensuring *actionability* within a given context is important, my prior work has also emphasized the need for tools to also be *personalized* (i.e., tailored to an individual's preferences, characteristics, and in-the-moment context). For example, although a DBT system that detects distress and suggests an actionable skill may be generally helpful, some common DBT skills may be inappropriate for particular individuals (e.g., suggesting that someone who cannot walk should go for a walk) or specific contexts (e.g., suggesting that someone who is at work should take a cold shower). Similarly, some people may not be comfortable with an app automatically sensing their distress, so people should be able to personalize its behavior to instead rely on self-reports of distress. Research into tools that support personal health will therefore need to examine how to take this wide range of personal and contextual data into account, both in the machine learning models those tools employ *and* in the interfaces they present.

Finally, I believe *interpretability* is critical for data and artificial intelligence in health. In my work, I strive not to just tell people what to do, but to support them in identifying and implementing strategies they can use to independently manage their health by making decisions that are most beneficial for them in a given context. These decisions often involve a more holistic understanding than is feasible for a system to sense on its own. For example, caffeine is common trigger for people with IBS, but even with knowledge that drinking a cup of coffee is likely to cause symptoms, sometimes people need to do so to be sufficiently alert for important events. A system that supports interpretability could help people understand likely consequences of certain action, helping them plan and implement the best decision for their overall lives based on that information.

Overall, intelligent systems have the potential to be transformative in supporting personalized health, because they could help people in collect and interpret data and identify patterns they may otherwise have overlooked. But careful research is needed to ensure that these systems are feasible, ethical, and useful. I look forward to investigating how data and artificial intelligence can best support people's health and wellness goals.

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