Personal Health Oracle: Explorations of Personalized Predictions in Diabetes Self-Management

Pooja M. Desai*
Columbia University Teachers College
New York, NY
pmrinmayidesai@gmail.com

Elliot G. Mitchell
Columbia University Medical Center
New York, NY
egm2143@cumc.columbia.edu

Maria L. Hwang
The Fashion Institute of Technology
New York, NY
maria_hwang@fitnyc.edu

Matthew E. Levine
California Institute of Technology
Pasadena, CA
mlevine@caltech.edu

David J. Albers
University of Colorado Medicine; Columbia University Medical Center
Aurora, CO; New York, NY
david.albers@ucdenver.edu

Lena Mamykina*
Columbia University Medical Center
New York, NY
om2196@cumc.columbia.edu

ABSTRACT

The increasing availability of health data and knowledge about computationally modeling human physiology opens new opportunities for personalized predictions in health. Yet little is known about how individuals interact and reason with personalized predictions. To explore these questions, we developed a smartphone app, GlucOracle, that uses self-tracking data of individuals with type 2 diabetes to generate personalized forecasts for post-meal blood glucose levels. We pilot-tested GlucOracle with two populations: members of an online diabetes community, knowledgeable about diabetes and technologically savvy; and individuals from a low socio-economic status community, characterized by high prevalence of diabetes, low literacy, and limited experience with mobile apps. Individuals in both communities engaged with personal glucose forecasts and found them useful for adjusting immediate meal options, and planning future meals. However, the study raised new questions as to appropriate time, form, and focus of forecasts and suggested new research directions for personalized predictions in health.

*Asterisk (*) denotes equal contribution by authors

CHI 2019, May 4–9, 2019, Glasgow, Scotland UK

ACM ISBN 978-1-4503-5970-2/19/05…$15.00
https://doi.org/10.1145/3290605.3300600

KEYWORDS

Personal informatics; predictive modeling; diabetes; self-management; user experience; technologies for health

ACM Reference Format:
Pooja M. Desai, Elliot G. Mitchell, Maria L. Hwang, Matthew E. Levine, David J. Albers, and Lena Mamykina. 2019. Personal Health Oracle: Explorations of Personalized Predictions in Diabetes Self-Management. In *CHI Conference on Human Factors in Computing Systems Proceedings (CHI 2019), May 4–9, 2019, Glasgow, Scotland UK*. ACM, New York, NY, USA, 13 pages. https://doi.org/10.1145/3290605.3300600

1 INTRODUCTION

For centuries people and cultures have been intrigued by the possibility of predicting their futures. While historically anticipating the future often fell into the domain of unscientific and occult, the rapid growth of data coupled with developments in machine learning and computational data analysis has advanced prediction generation to be well within the realm of the scientific and conventional. Forecasting solutions in fields such as meteorology and weather, financial management, and transit and traffic have helped individuals navigate novel situations, make informed choices, and prepare for anticipated outcomes [3, 18, 20, 21].

As predictive analytics has gained traction in several domains, one of its most significant applications has been within medicine and healthcare. For example, new computational approaches have synthesized the data within Electronic Health Record (EHR) systems to deliver insights and enable practitioners to provide more tailored, accurate, and effective medical care [23]. Furthermore, analytic tools have been used to communicate risks of prognoses, help patients build mental models of disease, and encourage preventative and diagnostic measures [4, 21, 38]. Other studies have demonstrated the value of prediction in facilitating informed decision-making by enabling patients to explore how possible treatment outcomes could affect their health and quality of life [19, 21].

One area where predictions of health outcomes may be particularly impactful is chronic disease self-management. One such disease, type 2 diabetes, is among the most common chronic diseases in the United States and affects over 30 million Americans [16]. Individuals with type 2 diabetes are often required to carefully monitor their blood glucose (BG) levels, diet, physical activity, and other daily routines to prevent BG spikes or drops that may lead to dangerous complications [10, 36].

For these individuals, anticipating the impact of daily choices on blood glucose (BG) is an essential part of self-management. However, given the complex nature of BG dynamics, individuals often struggle to anticipate glycemic impact of common activities, such as exercising and eating meals [18, 27]. With advances in the computational modeling of BG dynamics [1], there are new opportunities to develop solutions that may inform individuals' actions by predicting the impact of these choices on BG levels.

Yet, thus far, little is known about how individuals perceive, understand, and act on personalized predictions regarding the anticipated impact of daily activities on their health. Further, there exist few guidelines for designing interactive systems incorporating personalized prediction in such contexts. While a rich body of research in personal informatics has investigated how individuals engage with logging and reflecting on personal data [13, 21, 22, 27, 35, 38], there have been few studies that have explored how users engage with computationally generated personalized predictions. In one example, Hollis et al. explored personal predictions in mental health and found that anticipating changes in future moods can have a positive impact on one's emotions and moods [21]. However, many questions remain as to how to apply lessons learned from predictions in mental health to the management of other chronic conditions.

To explore these questions in the context of diabetes, we developed a smartphone app, GlucOracle, which provided users with personalized mealtime forecasts of anticipated changes to BG levels in response to meals. Using GlucOracle, users estimate the macronutrient content of a planned meal, record pre-meal BG level, and receive a personalized forecast for BG after eating the meal [1]. Further, GlucOracle can provide users with accuracy feedback on their nutritional assessment of meals generated by Registered Dietitians (RDs).

We pilot-tested the feasibility of our app with two different populations: five knowledgeable and technologically savvy members of an online health community (termed experienced adopters throughout the paper), and five members of an economically disadvantaged community characterized by low education and limited prior experience with mobile apps (termed novice adopters throughout the paper). Participants were asked to use GlucOracle for 2-5 weeks and were interviewed about their experience with the tool at the end of the study. Due to the exploratory nature of this study, we were most interested in users' perceptions of the app, patterns of engagement, impressions of receiving personalized forecasts and feedback on the accuracy of nutritional assessments, and experiences using the tool for daily decision-support.

Findings showed that both user groups understood forecasts and found these personalized predictions to be intuitive. Moreover, users found forecasts helpful in decision-making and used them to make immediate changes in potential meals, plan future meals, and plan other activities in conjunction with meals for glycemic management. Counter to our expectations, the enthusiasm towards the app was considerably higher among novice adopters who found the process of recording meals and nutrition to be insightful in itself. Conversely, our experienced adopters found recording meals and entering nutrition information to be too burdensome, given that forecasts mostly confirmed what they had previously learned about their diabetes through self-experimentation. Here, we draw on these results to examine differences between designing tools for intensive learning and for daily decision support in health, for analyzing engagement with technologies for health, and for the design of future tools that incorporate personalized forecasts to help individuals manage chronic conditions, such as type 2 diabetes.

2 RELATED WORK

Previous work exploring the impact of predictions on individuals' behaviors has occurred in several different domains. Past work in decision-making has noted that individuals incorporate forecasted information differently when reasoning with single one-off decisions (such as the choice to undergo major treatment) than they do when reasoning with repeated decisions [2]. Because the self-management of chronic diseases like diabetes involves making multiple small choices over an extended period of time, we were particularly interested in understanding how individuals repeatedly reason with forecasts in the context of daily decision-making.

Predictions in Modern Life

Perhaps one of the better known applications of forecasting in daily life is forecasting of weather. Broadly, work in this domain has shown that users across multiple backgrounds are able to interpret forecasts and rely on them to assess daily conditions [20, 34]. This work has also suggested that individuals often struggle with understanding the uncertainty associated with forecasts (e.g., understanding the chance of rain) and using forecasts to definitively guide behaviors (e.g., whether or not to take an umbrella) [20, 35]. However, it is important to note that general weather forecasting differs from the forecasting in self-management contexts, as in chronic disease management individuals do have the agency to alter outcomes, instead of just relying on predictions to react to anticipated events.

In addition to weather, forecasting tools for navigating traffic and commutes have been used to guide daily behaviors. Traffic navigation tools often help individuals identify the most efficient routes for travel coupled with real-time traffic flow feedback [3]. While controlling traffic is also beyond the users control, individuals can still make instantaneous choices that can impact their arrival times. Studies note that such navigation tools are often most useful for users who lack long-term experience in a particular place, and are navigating novel roads [3]. Interestingly, while providing knowledgeable users with traffic flow information can increase the short term flexibility in choosing new routes, over the long term users tend to seek out solutions that they know are reliable based on both predictions and their own experiences [3]. While predictions in traffic are similar to predictions in health in that they involve routine daily choices, these dynamics are also somewhat less personal and, unlike in health, do not have an aggregate long term impact upon individuals' wellbeing and quality of life.

Predictions in Health

Within the realm of health, predictions have often been used in the context of communicating risks of possible negative health consequences of different behaviors to users [14, 17]. However, these predictions are typically meant to help users make big changes in their lives, rather than inform routine daily choices, such as meal selection.

Personal informatics tools that help users track daily behaviors and indicators of health allow users to reflect upon their collected data, build better mental models of disease, and assess trajectories towards desired outcomes [18, 19, 27, 32, 33, 35]. Within the context of diabetes, past work has shown the utility of data collected with a continuous glucose monitor (CGM) in contributing to robust mental models for individuals' glucose dynamics [13, 31]. Furthermore reflection upon past outcomes can give rise to an understanding of how to anticipate the impact of behaviors on blood glucose (BG) dynamics. For example, Gibson et al. has shown that anticipating the impact of exercise on BG can lead individuals to adopt more robust exercise routines [18, 19]. However, while these tools are important in helping users monitor progress they do not focus on in-the-moment decision support and helping users navigate anticipated outcomes.

There exist several examples of previous solutions that specifically investigated personalized predictions in health. In diabetes, several initiatives focused on predicting changes in BG levels (e.g., artificial pancreas projects [5] and the NightScout project [24]). However these solutions offer forecasts divorced from planned activities, such as meals. While these tools help users carefully track ongoing dynamics, they are not built to help users anticipate the impact of daily activities on these dynamics. Within the HCI community, Hollis et al. incorporated prediction of changes in mental health along with different activities that affect mood [21]. In our own previous work, we explored ways to visualize personalized BG forecasts to diverse populations and found general enthusiasm for such tools among potential users using a set of design mockups [12]. In this study, we build upon this exploratory research and deploy an early version of GlucOracle into the field to assess the feasibility of using personalized forecasts as a decision support for daily nutritional choices in diabetes.

3 GLUCORACLE DEVELOPMENT AND STUDY DESIGN

Personalized Forecasts

The main focus of GlucOracle was on providing in-the-moment meal-time decision support using personalized forecasts to predict changes in BG levels in response to meals. To achieve that, GlucOracle asks users to log their meals by providing: a photograph of the meal, a brief text description, and BG levels before and 2 hours after eating the meal. GlucOracle uses these data to train a personalized computational model of BG regulation. Once the model is trained, for all newly captured meals, GlucOracle displays a forecasted range of future BG levels between the lowest and highest points of a continuous stream of predicted BG levels within 3 hours after the meal. The users can then decide whether to continue with the planned meal, or whether to change it, for example by adding or removing foods, recording a new meal, and reviewing corresponding changes in the forecasted BG (Figure 1). Because the computational model uses macronutrient amounts as inputs, and to ensure timely delivery of forecasts, GlucOracle uses individuals' own estimates of nutrition in meals to generate forecasts. However, it uses nutritional assessments by Registered Dietitians (RDs) to train the computational model.

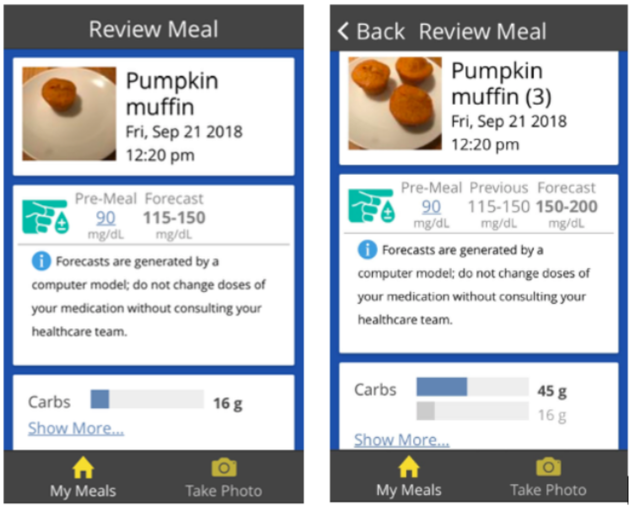

Figure 1: Personalized BG forecasts: on the left, the user photographs one pumpkin muffin and views the forecast; on the right, the user increases the amount of pumpkin muffins and views comparison between the two forecasts.

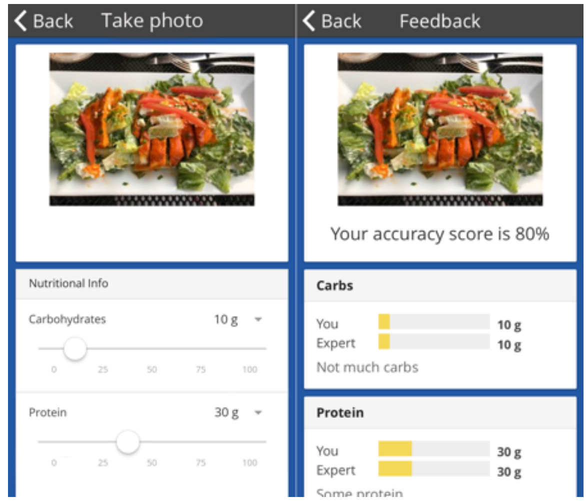

Figure 2: Screenshots of GlucOracle Interface: on the left, a set of sliders to enter macronutrient and caloric estimates; on the right, a comparison between user and expert's macronutrient assessments.

Prediction Model in GlucOracle

GlucOracle's personalized prediction uses a statistical framework (data assimilation) to generate personalized, nutrition-driven, real-time forecasts of blood glucose [1]. We use a prediction-correction scheme, an unscented Kalman filter (UKF) to incorporate self-monitoring data into mechanistic models of physiologic glucose-insulin regulation [37]. The filter allows the machine to update and forecast, in real-time, an individual's constantly evolving endocrine state (e.g., glucose and insulin levels, as well as insulin sensitivity and nutrition absorption rates) based on each new data point. Albers et al. showed that the UKF's prediction errors grow quite large initially (as part of its exploratory learning phase), but converge to an error rate comparable to that of diabetes experts after roughly 50 glucose measurements [1]. To accommodate this, GlucOracle does not provide forecasts until the error-prone training phase is completed.

Nutritional Assessment Feedback

GlucOracle relies on users' own nutritional assessment to generate in-the-moment forecasts; yet achieving high accuracy in such assessments can be challenging [27]. Previous research established the feasibility of using correctness feedback with explanations to promote nutritional learning [6, 30]. Building on this work, GlucOracle helps individuals increase accuracy of their nutritional assessments by providing them with correctness feedback and explanations. For each meal captured by a user, an expert Registered Dietitian (RD) reviews the meal and provides their own assessment. This expert assessment is then displayed to the user next to their own, with discrepancies highlighted and the overall correctness score. GlucOracle includes a web-based workflow for a team of RDs who can each provide assessment of meals; to ensure consistency, all RDs follow a standardized protocol using a USDA nutritional database.

Notably, because of several challenges that emerged during the study, this set of features was disconnected and one cohort of users did not receive RD feedback. We further explain on what led to these choices and implications on findings in the results section of the paper.

4 EVALUATION OF PERSONAL HEALTH ORACLE

Participants

To evaluate feasibility and usefulness of personalized blood glucose forecasting in diabetes self-management, we conducted a pilot study with two cohorts of users with different backgrounds. The first cohort (n=5) were members of an online health community focused on diabetes self-management. Based on our previous research with this community, we expected these users to be knowledgeable about diabetes self-management and nutrition, technologically savvy, and have prior experience with self-management technologies [28]; thus, we termed this cohort ***experienced adopters*** of health technologies (Participants 1–5).

Our second cohort (n=5) was recruited among residents of a predominantly Latino, economically disadvantaged community with low level of education, high level of unemployment, and high prevalence of diabetes [25]. We expected these individuals to be less knowledgeable about nutrition and diabetes self-management and less experienced with self-management technologies. We termed these participants ***novice adopters*** (Participants 6–10). These participants were predominantly Spanish-speaking and used a Spanish version of the app. We included these two populations to identify potential barriers to technology engagement for individuals from populations with low literacy and low motivation to engage with technologies for health. Members of the online diabetes community were recruited through advertisement on the community website, and through personal communication with moderators. Individuals from our local community were recruited among participants of a different study that also involved using a smartphone app for diabetes self-management.

Study Design

Participants in both cohorts received 1 hour training on using GlucOracle delivered over Skype (experienced adopters) or in-person (novice adopters) and were asked to use the app for 2-5 weeks. The experienced adopters used the app without receiving predictions during the training phase (which included the first 50 BG records and lasted on average 1 week). The novice adopters took part in a study that involved keeping track of their meals and BG levels with a different smartphone app that used different features to promote self-management (goal-setting and feedback on goal achievement from expert dietitians). Consequently, these participants already had sufficient data to generate personalized predictions from the first day of the forecasting study. This prior exposure to self-tracking, however, may have introduced bias in individuals' experiences, noted in the limitations section.

For all 10 participants, we tracked their usage of the app and interviewed them about their subjective experiences upon completion of the study. Interviews with Spanish-speaking participants were conducted by a Spanish-speaking moderator. The Institutional Review Board of the Columbia University Medical Center approved the study.

As this study focused on the feasibility of such a tool and users experiences interacting with it, we did not examine the impact of the app on learning about nutrition or individuals' behaviors and BG levels after receiving forecasts. Similarly, we do not report on the accuracy of the forecasts; we plan to provide a detailed analysis of forecasts' accuracy and sources of errors in our future publications.

5 DATA ANALYSIS

We analyzed participants' usage logs for frequency of use for different features overall and over time.

The qualitative interviews were transcribed verbatim; interviews conducted in Spanish were translated into English for analysis. We used inductive thematic analysis to analyze transcripts for emerging themes [9]. Two authors independently coded two interview transcripts, one from each user group; their coding schemes were then compared in-person and all discrepancies in codes reconciled through discussion. The remaining interviews were coded independently by the last author using the merged coding scheme. Further, we examined similarities and differences in occurrence of codes between the two user groups and used member checks to confirm the validity of our findings.

6 RESULTS

GlucOracle Usage Patterns

Overall, the participants showed varying degrees of engagement with GlucOracle in the course of the study. Users recorded 0 to 5 meals on different days with average daily median of 1.25. Experienced adopters (P1-P5) on average logged a median of 1.4 meals/day, while novice adopters on average logged a median of 1.1 meals/day. Usage over time suggests that the median number of meals logged per week for both groups declined steadily, though there were individual differences. Interestingly, while in the first week of the intervention the experienced adopters logged substantially more meals than the novice adopter (a median of 15 and 8 meals/week respectively), by the fourth week of the intervention of the study both groups were logging similar numbers of meals (a median of 7 and 6 meals/week respectively) [see supplemental material]. Most participants (7 out of 10) changed at least one meal during the study. Six participants actively used notes to capture comments about consumed meals or captured BG levels.

Overall life experiences and diabetes management

We report on participants' overall experiences with diabetes and nutrition as they provide important background for understanding their engagement with GlucOracle.

Experienced Adopters

As we expected, experienced adopters (Participants 1-5) were already actively engaged in their self-management and self-monitoring; 4 out of 5 had experience with different self-monitoring technologies, including continuous glucose monitor (CGM) and all had experience with diabetes self-management apps. Most of these participants had spent considerable time refining their self-management strategies using their self-monitoring data and through experimentation:

I mean, I'm all about the data. (P5)

Table 1: Participant Demographics

	Experienced Adopters	Novice Adopters
N	5	5
Sex	80 % Female	100 % Female
Ethnicity	100 % White	100 % Hispanic
Age	54 +/- 5 yrs	55 +/- 7 yrs
Length of Diagnosis	15 + yrs	3 – 20 yrs
Experience with Health Apps	100%	0%

For me it's easy because I experiment with myself and I pay attention to what I eat. (P2)

Further, these individuals reported feeling relatively successful in maintaining control of their diabetes and were not too concerned about fluctuations in their BG.

I'm not terribly concerned about the blood glucose…(P3).

These individuals also reported feeling quite knowledgeable in regards to diabetes self-management and nutrition, and considered their knowledge to be above average for a person with diabetes:

I am pretty knowledgeable about [nutrition]. Certainly about carbohydrates. In terms of the other, the other macronutrients, maybe not as much but you know, so many years of following different eating styles, so I'm fairly knowledgeable. That may not be typical. (P2)

Further, they had well-established practices regarding monitoring nutrition in their meals:

And I have a single serving thing that I use sometimes like I always measure exactly how much rice. How many carbohydrates. (P1)

However, even for these participants estimating nutrition in their meals and anticipating impact of meals on their BG levels remained a challenge. In regards to nutrition in meals, participants most comfortably estimated carbohydrates – the main driver BG changes — but were less confident estimating other macronutrients, particularly fiber. When it came to anticipating the impact of meals on BG levels, all participants lacked confidence and discussed multiple complexities of BG management. Part of this was due to the multiple factors that impact BG:

And I think that I – I'm sure that if you could drive yourself by micromanaging every molecule you put in your mouth and it still never get it right…It's still – still very difficult. You know because blood glucose is not just what you're putting in your mouth, but it's also activity and it could be a lot of biochemistry going on (P5).

Others referred to bodies as having "a mind of its own":

And then – then of course the body has its own mind and you think it's going to do one thing and it does something else totally different. (P2)

As a result, even these individuals often settled on relatively simple techniques for managing their nutrition. One such strategy was something they referred to as "eating to your meter". Instead of trying to estimate nutrition in every meal, they checked BG before and after common meals to assess their glycemic impact; if the impact was deemed acceptable, these meals were added to individuals' mental library of "safe meals" that can be relied on:

Guess it's sort of backing up one step, my approach to dealing with diabetes and eating is to figure out what are safe meals for me to eat, or sort of – and do variations on those that I know will work for me, rather than doing an estimation of each meal that I eat (P5)

Novice Adopters

In contrast to the experienced adopters, novice adopters (P6–P10) had limited structured experience or education with diabetes self-management and nutrition, and with any technologies for managing their disease:

Honestly, I never had the support with my food education. [This study] was the first thing that helped me. I liked it a lot (P7).

Perhaps, not surprisingly, these individuals reported relatively poor glycemic control and were accustomed to high blood glucose levels:

It is very rare that my blood level is low. Before I woke up with low sugar, like 60, 70, 80 until I reached 44 or 50. But after they changed my insulin, instead of going down, it goes up. Although I do not eat, it goes up. Then I sometimes stop eating. Then I inject myself in the night and I sleep with a 300 BG and I wake up with the highest sugar. (P8)

These individuals also remarked on struggling with other health challenges, including weight management, which often presented barriers to diabetes self-management:

My life has been like that always. I have to have something. An operation, that now I have this, that I have arthritis, that I can no longer walk. (P8)

These individuals typically did not have any established self-management practices. Most of them reported on poor eating habits and lack of exercise:

I had a lot of mess with the food. I ate what appeared and what was in the fridge. Or sometimes worse, I would go in and buy coconut things and sweet things, something to kill the anxiety.(P10)

Most perceived a need to change their diets, but lacked both the knowledge and resources to carry out these changes:

The money, because you have to change the food. Sometimes you have to eat what there is. They do not give me coupons, what helps people and what they give you does not help you.(P8)

Personalized Forecasts as Decision Support

The main focus of GlucOracle is on providing personalized BG forecasts as meal-time decision support. However, in order to receive forecasts, individuals need to continuously track their meals and BG levels, and provide estimates of nutritional composition of their meals. Below we report on individuals' experiences with data collection, nutrition estimation, as well as with receiving the actual forecasts.

Tracking personal data

Most participants found the ***photo-diary approach*** to tracking nutrition to be a relatively easy way of capturing meals. However, several commented on the awkwardness of taking pictures of one's meals while eating out or in social settings. Most participants also appreciated the opportunity to keep both nutritional records and BG records in the same app, something they referred to as an ***"all-encompassing app"***. The practice of frequently checking BG levels, and particularly scheduling checks ***before and after meals***, while common for experienced adopters, was new for the novice adopters group. While experienced adopters had prior experience with this method of tracking and often used it to refine their self-management approaches, novice adopters had limited experience doing so before joining the study. As a result, all five individuals in the novice adopters group made multiple comments about "before and after" as one of the most useful strategies learned during the study.

However, the perceptions were mixed in regards to the need to assess macronutrients in the meals. Surprisingly, novice adopters were not burdened by the need to track nutrition and found this feature to be informative, raising their awareness of the nutritional content of their meals:

I learned a lot. I learned to read calories, fats, proteins, if it contained fiber or if it didn't. All of that I liked. (P9).

On the other hand, experienced adopters found this feature to be exceedingly burdensome:

The variety of foods and all these macronutrients and it felt a little overwhelming at times because it was just so much – from variety – you know I try not to memorize the chart, you just sort of learn the characteristics just go with that because – and I'm not very good at just roughly memorizing things I need to have a reason (P2).

Further, all experienced adopters expressed frustration with features for meal capture, and found them to be overly simplistic and inconsistent with their typical eating behaviors. For example, they described meals with multiple courses stretched overtime, or a possibility of choosing multiple servings of different dishes, leftovers, optional desserts, and many others. The simple approaches to using one photograph to capture the entire meal was perceived as inconsistent with these more***flexible and complex eating behaviors***. Notably, these perceptions were only typical for the experienced adopters group.

Learning to estimate nutrition

Overall, experienced adopters had mixed reactions to receiving feedback on nutritional assessment from RDs. Further, they had high expectations for accuracy from RDs, and were often put off by what they perceived as errors in RD assessments:

Okay, the feedback from the dietitian was strange. I tried to put clarifying notes –several times I've entered things and indicated that the nutrition information I was putting down was what was on the package, and the responses I would get were so all below, I would tend to go scratching my head and going, how did they get 1000 calories in a four-ounce nut bar? (P1)

Further, because participant's meals were estimated by different RDs on the team, participants noted discrepancies between estimates from different RDs. Perhaps more importantly, all of these participants were somewhat put off by what they perceived as judgmental feedback from the RDs, for example when comments on high fat in meals were perceived as implying poor nutritional choices:

And there was also a real difference in terms of the style of the information, some of them felt very kind of factual and others felt more judgmental, which is sort of be – yeah, I'm trying to think, just the way it was phrased, you know, this meal carries –has a lot of fat in it and you know as opposed to, there is this amount of fat in this ingredient and this amount of fat in this ingredient, it was sort of – it felt like there was a little bit of judgment there about what was being eaten. (P5)

However, even despite these negative perceptions, 4 out of 5 participants felt that their understanding of nutrition increased after using the app.

So it was a learning experience and I felt like I got better at it. You know I don't have a – I don't know – there needs to be a score on how well I did overall and whether I did – you know started out poorly and then I refined my estimation list. (P2)

These four participants cited written feedback from RDs as being critical to their learning:

And you know it says – and not just your fibers – if was wrong if I said you 30 carbs and it came out as 40 or something like that it was to me – the number itself would have made me go ah – but it was a really good break down – show where all the carbs are coming from. And so it helped me learn that I mean this is a lot of information to take in all at once.(P3)

RD burden and removal of feedback features

Despite the generally positive perceptions regarding the impact of RD feedback on individuals' nutritional learning, we had to disconnect this set of features from the app. This was primarily because of the high burden on RDs. We recruited 6 RDs to work as paid consultants providing nutritional assessments; all six had full-time jobs and provided feedback in their spare time. After the first week of the study, with each participant recording 3-8 meals per day (including snacks), the pipeline of meals requiring assessment grew to over 200 meals, which led to considerable delays. Follow-up discussions with RDs showed that meals with many ingredients required 30-40 minutes to generate both assessment and feedback. Consequently, we removed RD feedback for our second population. In this second part of the study, RDs were still asked to provide nutritional assessments that were used to train the forecasting model, but no longer provided explanations.

Experiences with Personalized Forecasts

Overall, the participants in both groups quickly understood the concept of personalized predictions and what they indicated, and found many creative ways to incorporate these predictions in their decision making. Yet, there were also a number of important differences in their perceptions of the forecasts. Below we discuss our findings in several different categories, including 1) the experience receiving forecasts, 2) interpretations of forecasts' meaning; 3) different approaches to incorporating forecasts into daily decisions, and 4) the perceived impact of forecasts on individuals' self-management.

Experience receiving forecasts

Generally, experienced adopters perceived forecasts as fun and engaging, and as a bit of a novelty. For some, receiving forecasts felt like a fun game:

So I liked that part of it, I liked the predictions; its like a game almost so that made it fun. In that in itself I think is a motivator to use the app in getting the prediction. (P2)

Most participants in this group perceived forecasts as relatively accurate, which led to a growing trust to predictions:

It would make me, if I trusted the–and I thought it was pretty good, again, they were really right, so it was pretty much on, and you know, it did a pretty good job (P1).

At the same time, for most participants in this group, the forecasts were neither surprising, nor particularly informative. All five participants in this group had relatively well-controlled BG that rarely deviated from the recommended ranges. Moreover, their diets primarily included meals they found to have minimal impact on their BG through experimentation. As a result, many of the participants felt that the forecasts provided more of a confirmation of what they knew already, rather than led to any new discoveries:

I think generally it was sort of a confirmation of what I thought already that may have been affected somewhat by just where my blood sugar was to start with. Yeah. (P5)

In contrast, for novice adopters, the entire idea of considering glycemic impact of meals before consuming these meals was new and exciting. These participants had full awareness of the negative impact of high blood glucose excursions on their health. Seeing high numbers in the forecasts inspired them to more seriously consider consequences of their nutritional choices:

...of course, because imagine, I use to eat like crazy. And with the forecast you think, "I don't want them to cut off my legs" or "I don't want to go blind" or "I don't want to get dialysis". That would at least help me control myself. (P7)

Similarly, forecasts within BG ranges typically considered safe were perceived as reassuring and motivating:

I liked it a lot because, for example, it would sometimes predict that my blood glucose would go high and I had to bring it down. It would also tell me when I was doing wonderful. I am taking care of my sugar. (P7)

Interpreting forecasts

When asked to explain the meaning of the range included in forecasts, the experienced adopters generated a variety of explanations, yet few of them remembered the actual meaning of the range explained to them during the training. The most common explanation for the range was that it was indicative of uncertainty inherent in the computational model. Since most of these participants had experience with CGM curves, all of them wished that the app showed them the actual continuous BG predictions as curves:

I would definitely be interested in seeing the curves...If it's going to be a moderate raise over a long period versus a short spike that doesn't last very long,...that might change the way I felt about what was happening. (P5)

Somewhat in contrast to this, novice adopters did not construct particular explanations for the range and simply focused on whether both numbers in the forecasted range were within the recommended "safe" zone.

Using forecasts for making decisions

Overall, all participants appreciated the opportunity to consider outcomes of their planned meals before these meals were consumed, rather than facing consequences of their decisions:

[In diabetes] that's a lot of fore planning, but you know so you can sort of – a lot of it in diabetes is all about oh I shouldn't have done that. (P2)

The participants in both groups described relatively similar strategies for incorporating forecasts into their decision-making. Some participants described using forecasts to ***choose between meal options***; this was particularly common for pre-packaged meals available for purchase. For others, a most common way of using forecasts was to ***change the planned meal***; this included both changing the amount of food on the plate, or adding and remove different parts of the meal:

Well, when I eat a meal that I know is going to raise my sugar, I try to eat less. A little less of that food. (P6)

However, for many study participants in both groups, receiving forecasts after the meal was already prepared and served and could be photographed was too late; these individuals proceeded to eating their planned meal, but used the forecasts to ***adjust similar meals in the future***:

By the time I can photograph a meal, I'm pretty much committed at that point. And probably what I would be looking at is if my blood sugar spikes more than I wanted to with that meal, then the next time I make that meal, I would cut down the carbohydrates or add more protein or eat a smaller serving or something like that. (P5)

Yet others found different ways to compensate for the anticipated rise in the BG levels without changing their planned meal, for example by taking a walk or eating smaller meals later in the day:

Or ... walk around the neighborhood after I eat because I don't want to maintain the high blood glucose you know so – I can take action one or two ways. (P2)

Perceived usefulness and impact of forecasts

Even though participants in both groups found numerous ways to incorporate forecasts into their decision-making, they varied somewhat in their assessment of GlucOracle's usefulness as a tool for nutritional decision support. Experienced adopters generally saw forecasts provided only at meal-time as limited in their ability to have an impact on self-management that would justify the burden of continuous self-tracking. They made many recommendations for making forecasts more useful. For example, one common suggestion was to introduce forecasts at the time of meal planning, when they had more opportunities to change ingredients and proportions:

So I guess actually, maybe one thing for me would be, if it were possible to put in my recipe and estimate based on that, that would be something I'd be more likely to do upfront. But by the time it's – by the time it's a meal, I'm likely just to eat what's in front of me and use the information for later. (P5)

Similarly, they made multiple recommendations for making the tracking part of the app less burdensome and more flexible. For example, a common suggestion was to further simplify meal capture by creating personal libraries of common meals or selecting meals from nutritional databases. Further, they wished for an ability to edit captured meals, add second helpings, and capture left-overs.

Overall, these participants saw GlucOracle as a tool most useful for short periods of intensive learning and experimentation that could be repeated if needed, or for exploring impact of new unfamiliar nutritional options, rather than a tool for everyday decision-making:

So I think, I would tend to look at it not as something that I would use all the time, but as something that I would use religiously for a week or two every few months to just get a sense of where I am… And yeah for unusual meals or for dining out, I think it would be a really good thing, we don't tend to dine out very much these days … (P5)

In contrast, novice adopters talked about forecasts as an eye-opening experience that had significant impact on their self-esteem and anxiety associated with eating:

Satisfied. I feel more, how do I say… Before I had a low self-esteem. But now, I am in better shape, I am satisfied. Thanks to the program [GlucOracle]. (P7)

It has helped me a little bit more to control that anxiety of eating. (P6)

These participants felt that using the app considerably increased their knowledge of nutrition and their understanding of how different foods impact their BG levels, which for many translated into concrete changes to their diets and perceived improvements in their BG levels:

Yes, for example, Latinos would always eat green plantains … And in the forecast I noticed that it [plantains] really didn't raise it by much. The sugars rise more with rice, carbohydrates and candy/sweets. Everything that contains sugar like white rise, white things like cassava, and all of that raises [blood glucose]. I noticed that banana, whole wheat, and plantains did not raise my blood glucose by much. (P9)

7 DISCUSSION

This study examined the feasibility of using personalized blood glucose (BG) forecasts to help individuals with type 2 diabetes select nutritional choices by exploring the potential impact of meals on BG levels. To this end, we developed a smartphone app, GlucOracle that incorporated a novel computational model to generate personalized predictions of BG fluctuations. GlucOracle used forecasts to help individuals consider different meal options and select a meal that satisfied their nutritional preferences and self-management priorities. We explored the feasibility of this tool with 2 different populations: individuals recruited from an online diabetes community, knowledgeable in nutrition and diabetes and committed to self-management, and individuals from an economically disadvantaged community characterized by limited enthusiasm for health technologies and limited knowledge of nutrition and diabetes self-management. Overall, the study found much support for the idea of using personalized forecasts to support nutritional decisions.

Across both populations, participants found the app to be relatively simple to use, and personalized predictions to be intuitive to understand. Similarly, across both populations, participants identified many different ways to incorporate forecasts into their nutritional decisions. For some, forecasts guided immediate changes to a planned meal in order to avoid a predicted rise in their BG. Others were reluctant to change already cooked and served meals; instead, these individuals used feedback from the forecasts to plan adjustments to future meals. Yet others used forecasts to guide other behaviors that would mitigate the glycemic impact of a meal without changing the meal itself, for example by increasing their physical activity that day. These findings are consistent with previous research that has highlighted the utility of personalized predictions in health [18, 19, 21]. Specifically it affirms past work showing that reflecting on personalized self-monitoring data and personalized predictions contributes to building a dynamic mental model of disease that can guide future choices [4, 13, 18, 19, 31, 35]. However, the study also identified several new areas for consideration that may inform the design of data-driven tools for health management, and, more generally, for research in technologies that use personalized prediction in health. Below we describe these considerations and corresponding implications.

From experience to expectations

When choosing populations for inclusion in our study, we expected technologically savvy members of an online diabetes community to be possible early adopters, more likely to engage with new technologies, and more willing to overlook some of its limitations. However, the study suggested that while these individuals were indeed excited about new technological solutions, they also had high expectations for both ease of use and usefulness of novel tools. These users had previous experience with self-tracking technologies and were accustomed to richer, more flexible sets of features for diet tracking that would not disrupt their eating practices. GlucOracle, designed as a proof-of-concept research prototype, fell somewhat behind their expectations.

Further, these users found the need to manually enter nutritional estimates to be cumbersome and a major barrier to using the app on a regular basis. Moreover, these individuals had a relatively well-established set of routines and practices for diabetes self-management, strong support networks, and few remaining concerns regarding their BG. These participants felt that forecasts affirmed what they already knew about their BG control. As a result, for these individuals the trade-off between the burden of use and benefit gained from using GlucOracle was not in favor of the app.

In contrast, participants recruited from the local community had limited experience with diabetes or nutrition education, few opportunities to develop diabetes self-management practices, and little support for their self-management, technological or otherwise. Perhaps for these reasons, participating in the study was an eye-opening experience for this cohort. The practice of tracking activities and BG levels and the possibility of examining glycemic impact of meals were novel experiences and participants found these practices to be valuable and informative. Interestingly, these individuals paid little attention to inconvenience of recording meals or entering macronutrient composition; in contrast, they found both of these activities to be educational in themselves. These findings are consistent with characterization of factors that influence technology adoption within the Technology Adoption Model (TAM) [11]: for experienced adopters, high perceived burden and low perceived usefulness lowered interest in adoption, whereas for novice adopters, these attitudes were reversed, which led to higher interest in adoption.

These findings have implications for the design of future solutions for health management that target diverse populations. While it is common for new technologies to target early adopters, this study further highlights that perceptions towards technology may not generalize between populations, sometimes in unexpected directions. This further reinforces the need for more focused tailoring of technologies for self-management to both experienced users and novices. In the case of self-monitoring tools, more experienced users may value richer features that integrate multiple types of self-tracking data, elegant workflows, and novel feature presentation. By contrast, novice users may be less deterred by friction when using tools, and instead more motivated by the benefits and insights they gain from using an app.

Short-term learning VS long-term decision support

A related consideration that emerged during the study was regarding differences in perceptions regarding the purpose of GlucOracle. Given their already well-established self-management practices and perceptions of high burden of self-tracking, experienced adopters saw GlucOracle as a useful tool for intensive short-term learning and experimentation, rather than for everyday decision support. All these participants described the multiple challenges they experienced when still forming their self-management routines and saw a clear need for tools that could provide support for this learning phase. Consistent with that, these participants found GlucOracle useful in helping them assess impact of new meals they have not tried before, or as a support for occasional re-learning, needed given the progressive nature of diabetes. On the other hand, many participants in the novice adopter group were lacking both established self-management practices and support structures necessary to establish such practices. Perhaps as a result, they were enthusiastic not only about GlucOracle's potential to support short-term intensive learning, but also provide longer-term ongoing support.

This finding suggests a potentially new way of considering user burden associated with self-monitoring in health. Specifically, in the context of diet tracking, user burden has often been cited as one of the critical factors preventing long-term adoption [15]. Epstein et al. found usage lapses are often due to users forgetting to track and the burden of upkeep. Further, users are often disinclined to continue if there is limited perceived impact and information gain [15]. Our study suggests that users may be more willing to endure high self-tracking burden for the purpose of learning and exploration over a short time. However, the same level of tracking intensity would be unreasonable in the context of everyday decision support. In contrast, tools for everyday decision support may choose to prioritize convenience of use and integration with daily practices that could promote continuing engagement.

This distinction may also have implications for defining and studying engagement with tools for self-management, an area of active research [4, 7, 8, 26, 33]. We suggest that expectations for optimal engagement may vary between tools for learning and tools for decision support. For example, for tools that target ongoing decision support, decline in use overtime may indicate undesirable decrease in engagement and a need for new strategies to motivate continuing use. However, for tools that focus on learning, decline in use may indicate successful achievement of learning goals and adoption of new behaviors.

Making forecasts useful

Finally, the study highlighted new opportunities to make personalized forecasts in diabetes self-management more useful and impactful for supporting nutritional choices. First, participants sought to incorporate predictions not only for immediate decision-making at the time of a meal, but also during meal planning, cooking, and grocery shopping. For them, receiving forecasts for already cooked meals provided little opportunity for action. This is consistent with previous research that highlighted distinction between everyday action and purposeful planning [29]. Second, those who had experience with CGM wished for more information in forecasts, specifically for temporal patterns of changes in BG after meals. This is consistent with previous research that explored different ways to visualize forecasts and highlighted the need for more informative yet easy to understand presentations of forecasts [8, 12]. Finally, participants wished for more guidance in identifying strategies to address undesirable forecasts, similar to other calls for introducing more direct recommendations in decision support tools in health [4, 6]. Each of these opportunities, opens new questions and requires further research into using predictive models in health

8 LIMITATIONS

This study had several limitations. First, the small sample size (N=10), while not uncommon for feasibility studies, limits generalizability of this work to broader populations. Further, novice adopters' previous experience with a different research prototype may have impacted their perceptions of engaging with GlucOracle. Further studies of the tool with broader populations can help to address these limitations.

9 CONCLUSIONS

We examined the feasibility of personalized meal-time BG forecasts to facilitate nutritional decision-making for individuals with type 2 diabetes. In this study, we focused on the experience of two different populations. We found that technologically savvy individuals with well-managed BG found tracking meals and analyzing nutrition to be burdensome, and forecasts to be unsurprising and rarely prompting action. Conversely, individuals with limited health technology experience and knowledge of diabetes self-management found predictions to be insightful and encourage concrete changes in diet and BG management. This work underscores the potential of personal forecasting for health decision support solutions, and provides insights for how to tailor tools, facilitate engagement, and reduce friction to support diverse cohorts of users.

ACKNOWLEDGMENTS

This work was funded in part by grants from the National Institute of Diabetes and Digestive and Kidney Diseases (NIDDK) R01DK090372 and R56DK113189; and the National Library of Medicine (NLM) R01 LM012734-01. Many thanks to the participants, translators, and members of the ARCH Lab who made this work possible.

REFERENCES

[1] David J Albers, Matthew Levine, Bruce Gluckman, Henry Ginsberg, George Hripcsak, and Lena Mamykina. 2017. Personalized glucose forecasting for type 2 diabetes using data assimilation. *PLoS computational biology* 13, 4 (2017), e1005232.

[2] Greg Barron and Ido Erev. 2003. Small feedback-based decisions and their limited correspondence to description-based decisions. *Journal of Behavioral Decision Making* 16, 3 (2003), 215–233.

[3] Eran Ben-Elia, Ido Erev, and Yoram Shiftan. 2008. The combined effect of information and experience on drivers' route-choice behavior. *Transportation* 35, 2 (2008), 165–177.

[4] Frank Bentley, Konrad Tollmar, Peter Stephenson, Laura Levy, Brian Jones, Scott Robertson, Ed Price, Richard Catrambone, and Jeff Wilson. 2013. Health Mashups: Presenting statistical patterns between wellbeing data and context in natural language to promote behavior change. *ACM Transactions on Computer-Human Interaction (TOCHI)* 20, 5 (2013), 30.

[5] Marc Breton, Anne Farret, Daniela Bruttomesso, Stacey Anderson, Lalo Magni, Stephen Patek, Chiara Dalla Man, Jerome Place, Susan Demartini, Simone Del Favero, et al. 2012. Fully integrated artificial pancreas in type 1 diabetes: modular closed-loop glucose control maintains near normoglycemia. *Diabetes* (2012), DB_111445.

[6] Marissa Burgermaster, Krzysztof Z Gajos, Patricia Davidson, and Lena Mamykina. 2017. The role of explanations in casual observational learning about nutrition. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*. ACM, 4097–4145.

[7] Meng-Chieh Chiu, Shih-Ping Chang, Yu-Chen Chang, Hao-Hua Chu, Cheryl Chia-Hui Chen, Fei-Hsiu Hsiao, and Ju-Chun Ko. 2009. Playful bottle: a mobile social persuasion system to motivate healthy water intake. In *Proceedings of the 11th international conference on Ubiquitous computing*. ACM, 185–194.

[8] Sunny Consolvo, David W McDonald, Tammy Toscos, Mike Y Chen, Jon Froehlich, Beverly Harrison, Predrag Klasnja, Anthony LaMarca, Louis LeGrand, Ryan Libby, et al. 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.

[9] Juliet Corbin, Anselm Strauss, et al. 2008. Basics of qualitative research: Techniques and procedures for developing grounded theory. (2008).

[10] S Daenen, A Sola-Gazagnes, J M'Bemba, C Dorange-Breillard, F Defer, F Elgrably, E Larger, and G Slama. 2010. Peak-time determination of post-meal glucose excursions in insulin-treated diabetic patients. *Diabetes & metabolism* 36, 2 (2010), 165–169.

[11] Fred D Davis. 1989. Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS quarterly* (1989), 319–340.

[12] Pooja M Desai, Matthew E Levine, David J Albers, and Lena Mamykina. 2018. Pictures Worth a Thousand Words: Reflections on Visualizing Personal Blood Glucose Forecasts for Individuals with Type 2 Diabetes. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*. ACM, 538.

[13] Sandrine Ding and Michael Schumacher. 2016. Sensor monitoring of physical activity to improve glucose management in diabetic patients: a review. *Sensors* 16, 4 (2016), 589.

[14] James G Dolan and Stephen Iadarola. 2008. Risk communication formats for low probability events: an exploratory study of patient preferences. *BMC Medical Informatics and Decision Making* 8, 1 (2008), 14.

[15] Daniel A Epstein, An Ping, James Fogarty, and Sean A Munson. 2015. A lived informatics model of personal informatics. In *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing*. ACM, 731–742.

[16] Centers for Disease Control, Prevention, et al. 2017. National diabetes statistics report, 2017. *Atlanta, GA: Centers for Disease Control and Prevention* (2017).

[17] Rocio Garcia-Retamero, Yasmina Okan, and Edward T Cokely. 2012. Using visual aids to improve communication of risks about health: a review. *The Scientific World Journal* 2012 (2012).

[18] Bryan Gibson, Robin L Marcus, Nancy Staggers, Jason Jones, Matthew Samore, and Charlene Weir. 2012. Efficacy of a computerized simulation in promoting walking in individuals with diabetes. *Journal of medical Internet research* 14, 3 (2012).

[19] Bryan Gibson, Leah Yingling, Alisa Bednarchuk, Ashwini Janamatti, Ingrid Oakley-Girvan, and Nancy Allen. 2018. An Interactive Simulation to Change Outcome Expectancies and Intentions in Adults With Type 2 Diabetes: Within-Subjects Experiment. *JMIR Diabetes* 3, 1 (2018), e2.

[20] Gerd Gigerenzer, Ralph Hertwig, Eva Van Den Broek, Barbara Fasolo, and Konstantinos V Katsikopoulos. 2005. "A 30% chance of rain tomorrow": How does the public understand probabilistic weather forecasts? *Risk Analysis: An International Journal* 25, 3 (2005), 623–629.

[21] Victoria Hollis, Artie Konrad, Aaron Springer, Matthew Antoun, Christopher Antoun, Rob Martin, and Steve Whittaker. 2017. What does all this data mean for my future mood? Actionable Analytics and Targeted Reflection for Emotional Well-Being. *Human–Computer Interaction* 32, 5-6 (2017), 208–267.

[22] Elisabeth T Kersten-van Dijk, Joyce HDM Westerink, Femke Beute, and Wijnand A IJsselsteijn. 2017. Personal informatics, self-insight, and behavior change: A critical review of current literature. *Human–Computer Interaction* 32, 5-6 (2017), 268–296.

[23] Jennifer King, Vaishali Patel, Eric W Jamoom, and Michael F Furukawa. 2014. Clinical benefits of electronic health record use: national findings. *Health services research* 49, 1pt2 (2014), 392–404.

[24] Joyce M Lee, Mark W Newman, Achamyeleh Gebremariam, Preciosa Choi, Dana Lewis, Weston Nordgren, John Costik, James Wedding, Benjamin West, Nancy Benovich Gilby, et al. 2017. Real-world use and self-reported health outcomes of a patient-designed do-it-yourself mobile technology system for diabetes: lessons for mobile health. *Diabetes technology & therapeutics* 19, 4 (2017), 209–219.

[25] Young Ji Lee, Bernadette Boden-Albala, Elaine Larson, Adam Wilcox, and Suzanne Bakken. 2014. Online health information seeking behaviors of Hispanics in New York City: a community-based cross-sectional study. *Journal of medical Internet research* 16, 7 (2014).

[26] Lena Mamykina, Elizabeth M Heitkemper, Arlene M Smaldone, Rita Kukafka, Heather Cole-Lewis, Patricia G Davidson, Elizabeth D Mynatt, Jonathan N Tobin, Andrea Cassells, Carrie Goodman, et al. 2016. Structured scaffolding for reflection and problem solving in diabetes self-management: qualitative study of mobile diabetes detective. *Journal of the American Medical Informatics Association* 23, 1 (2016), 129–136.

[27] Lena Mamykina, Matthew E Levine, Patricia G Davidson, Arlene M Smaldone, Noemie Elhadad, and David J Albers. 2016. Data-driven health management: reasoning about personally generated data in diabetes with information technologies. *Journal of the American Medical Informatics Association* 23, 3 (2016), 526–531.

[28] Lena Mamykina, Drashko Nakikj, and Noemie Elhadad. 2015. Collective sensemaking in online health forums. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*. ACM, 3217–3226.

[29] Lena Mamykina, Arlene M Smaldone, and Suzanne R Bakken. 2015. Adopting the sensemaking perspective for chronic disease self-management. *Journal of biomedical informatics* 56 (2015), 406–417.

[30] Lena Mamykina, Thomas N Smyth, Jill P Dimond, and Krzysztof Z Gajos. 2016. Learning from the crowd: Observational learning in crowdsourcing communities. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*. ACM, 2635–2644.

[31] Davy Preuveneers and Yolande Berbers. 2008. Mobile phones assisting with health self-care: a diabetes case study. In *Proceedings of the 10th international conference on Human computer interaction with mobile devices and services*. ACM, 177–186.

[32] Mashfiqui Rabbi, Min Hane Aung, Mi Zhang, and Tanzeem Choudhury. 2015. MyBehavior: automatic personalized health feedback from user behaviors and preferences using smartphones. In *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing*. ACM, 707–718.

[33] Amon Rapp and Federica Cena. 2016. Personal informatics for everyday life: How users without prior self-tracking experience engage with personal data. *International Journal of Human-Computer Studies* 94 (2016), 1–17.

[34] Anders D Sivle, Stein Dankert Kolstø, Pål J Kirkeby Hansen, and Jørn Kristiansen. 2014. How do laypeople evaluate the degree of certainty in a weather report? A case study of the use of the web service yr. no. *Weather, Climate, and Society* 6, 3 (2014), 399–412.

[35] Brian K Smith, Jeana Frost, Meltem Albayrak, and Rajneesh Sudhakar. 2007. Integrating glucometers and digital photography as experience capture tools to enhance patient understanding and communication of diabetes self-management practices. *Personal and Ubiquitous Computing* 11, 4 (2007), 273–286.

[36] Jaakko Tuomilehto, Jaana Lindström, Johan G Eriksson, Timo T Valle, Helena Hämäläinen, Pirjo Ilanne-Parikka, Sirkka Keinänen-Kiukaanniemi, Mauri Laakso, Anne Louheranta, Merja Rastas, et al. 2001. Prevention of type 2 diabetes mellitus by changes in lifestyle among subjects with impaired glucose tolerance. *New England Journal of Medicine* 344, 18 (2001), 1343–1350.

[37] Eric A Wan and Rudolph Van Der Merwe. 2000. The unscented Kalman filter for nonlinear estimation. In *Adaptive Systems for Signal Processing, Communications, and Control Symposium 2000. AS-SPCC. The IEEE 2000*. Ieee, 153–158.

[38] Lisa Whitehead and Philippa Seaton. 2016. The effectiveness of self-management mobile phone and tablet apps in long-term condition management: a systematic review. *Journal of medical Internet research* 18, 5 (2016).