

# Pictures Worth a Thousand Words: Reflections on Visualizing Personal Blood Glucose Forecasts for Individuals with Type 2 Diabetes

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## ABSTRACT

Type 2 Diabetes Mellitus (T2DM) is a common chronic condition that requires management of one's lifestyle, including nutrition. Critically, patients often lack a clear understanding of how everyday meals impact their blood glucose. New predictive analytics approaches can provide personalized mealtime blood glucose forecasts. While communicating forecasts can be challenging, effective strategies for doing so remain little explored. In this study, we conducted focus groups with 13 participants to identify approaches to visualizing personalized blood glucose forecasts that can promote diabetes self-management and understand key styles and visual features that resonate with individuals with diabetes. Focus groups demonstrated that individuals rely on simple heuristics and tend to take a reactive approach to their health and nutrition management. Further, the study highlighted the need for simple and explicit, yet information-rich design. Effective visualizations were found to utilize common metaphors alongside words, numbers, and colors to convey a sense of authority and encourage action and learning.

## Author Keywords

Health and wellness; diabetes; visualization; personal informatics; health communication

## ACM Classification Keywords

H.5.2. Information interfaces and presentation (e.g., HCI): User interfaces.

## INTRODUCTION

The ability to anticipate health outcomes is an essential component of informed clinical decision-making, treatment selection, and chronic disease management [1]. Increasingly, clinical decision support tools have been developed and integrated into health care settings to help clinicians identify patterns and anticipate different treatment outcomes [45]. However, many chronic conditions require self-management in addition to medical treatment. With

self-management, the task of foreseeing health outcomes falls to patients themselves, as they must anticipate the effects of daily behaviors on their health. For example, in diseases such as diabetes, the ability to anticipate the impact of meals or exercises can help to optimize glycemic control, and consequently, delay the onset of related complications [38,43]. However, anticipating immediate health effects is often challenging. As past studies demonstrate, even experienced patients and diabetes educators have considerable difficulty identifying patterns in self-monitoring data (e.g. images of meals and pre-post meal blood glucose levels) and using these data to predict the impact of future meals [28]. This difficulty is not altogether unexpected, for while the role of macronutrients in influencing blood glucose changes has been explored, the physiological mechanisms and individual factors that regulate blood glucose make anticipating outcomes especially challenging.

The increasing volume of self-monitoring data has paved the way for novel personal informatics solutions to resolve such self-management challenges. In response, a variety of tools have emerged to help users glean personal health insights from captured data [13,34]. However, the majority of these interventions focus on helping users track, set goals, and reflect on a variety of behaviors such as exercise, sleep, and nutrition [6,15,40]. While capturing these lifestyle measures is important, these solutions may be limited, as individuals often experience considerable difficulty translating past intentions into future actions [28]. Recent computational work modeling blood glucose regulation suggests advanced computational techniques can use self-monitoring data to generate reliable personalized forecasts of future blood glucose levels [2]. While thus far the vast majority of glucose models have been explored in the context of closed-loop systems and in order to drive insulin supply, these models offer another informatics approach to inform human judgment and nutritional decision-making.

However, in order for such models to be effectively utilized for health management they must be understood by non-expert users. The communication of forecasts to lay users has been well studied in a few contexts, ranging from weather to medicine. While specific communication considerations may vary between disciplines, broadly, past

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studies have demonstrated that users often find forecasts of future events challenging to understand and interpret.

One area in which forecasting has been particularly well explored and widely adopted is weather communication. This body of literature has demonstrated that individuals are able to broadly understand forecasts as guidelines for daily conditions and can interpret them, often with visual aids such as icons and graphs [25,29,30, 41]. However, users experience difficulty with understanding uncertainty in forecasts and reliably using that information to make decisions [24,25,29,37]. Additionally findings from these studies note a disconnect between the information presented by weather forecasts and that needed by lay users to make decisions, in particular highlighting the importance of using visualizations to clearly communicate uncertainty to close this gap [20,39].

From a health perspective, previous work on personalized forecasts has primarily focused on risk communication [3, 14,18,33]. As shared clinical decision-making becomes an increasingly central to chronic disease management the need to clearly communicate risk has become more evident. Studies of medical communication also point to the power of effective visualizations as they enable patients to quickly ascertain information. Specifically, studies on communicating prescription dosage information and associated risks have demonstrated that incorporating visualizations helps patients to better comprehend information [26]. Furthermore, visual representations of health information help patients clarify their mental models of disease, internalize health risks and consequences and influence nutrition decisions [16,17,19].

While both weather and medical communication research have generated considerable insights, personalized forecasting for chronic disease self-management presents a somewhat different set of requirements and constraints. Unlike weather forecasting, individuals with diabetes have the agency to intervene and alter outcomes. In contrast to health risk communication, which tends to focus on major, potentially life-changing decisions, diabetes self-management largely consists of managing several small daily choices. These differences call for further research, and a need to better understand how individuals interpret personalized forecasts and incorporate them into their daily decisions and choices.

The challenge of communicating personalized forecasts is further exacerbated by the need to communicate them to individuals with lower levels of literacy and numeracy, disproportionately affected by chronic conditions such as diabetes [7,35]. Past research defined literacy as the ability to understand, interpret, and engage with health information [31], and numeracy as the ability to specifically interpret and communicate quantitative health information [21]. Past studies have shown that the effectiveness of different visualizations differs with patient numeracy. High numeracy individuals tend to prefer number and graph based

visualizations, while low numeracy patients found information presented through icons and pictographs to be the most understandable [3,18, 22,33].

Moreover, behavior and cognition science highlights two distinct ways of interpreting presented information: verbatim versus gist information [18,24]. According to this theory, verbatim information consists of explicit numerical and situational data provided. By contrast, gist information conveys the broader implications of the data, communicating the general takeaway. Past studies have found that when it comes to clinical decision-making, low numeracy patients best understand visualizations that communicate gist information [22].

In this paper we report the results of a study that explored different approaches to communicating personalized blood glucose forecasts to individuals recruited from medically underserved communities. Specifically we aimed to identify the key visual elements that resonate with populations typically characterized by low numeracy and the factors that contribute to constructing effective visualizations that help individuals internalize the predicted impact of their meals and inform their nutritional decision-making

In order to address these questions, we conducted 4 focus groups with 13 individuals with type 2 diabetes recruited from a predominantly immigrant community with a high prevalence of chronic disease (including diabetes), high levels of unemployment and low levels of education. These individuals reviewed several different visual representations of post-meal blood glucose forecasts, ranging from simple numerical presentations, to graphs and visualizations that utilized common metaphors. We asked the participants to reflect on visualizations in an open discussion.

The study demonstrated that individuals rely on simple heuristics for nutrition management and tend to take a reactive approach to their health and nutrition. Further, our results highlight the need for simple and explicit, yet information rich design. Effective visualizations were found to utilize common metaphors alongside words, numbers, and colors to convey sense of authority and were perceived to encourage action and learning.

## **RELATED WORK**

From the literature on communicating forecasts, risk, and health information for low numeracy users, four key dimensions of ongoing work have emerged. Solutions varied in design style, displays of uncertainty, context provided, and if temporal dynamics were communicated.

### **Design Style: Graphs and Metaphors**

Past studies in health and weather have used a variety of different styles to communicate information to users, particularly those from low numeracy backgrounds. Commonly used techniques such as graphs have been found effective in communicating numeric information [25,42]. For other types of information, recent research in health communication pointed the value of metaphors, which relate

a concept to another similarly functioning model, and infographics, which use visualizations to illustrate a concept [4, 9, 10, 23, 27]. These two techniques have been found to be highly effective in communicating information to users and fostering sustained engagement with tools for users from all backgrounds.

Past studies, specifically within the context of health, have successfully used metaphors to encourage tracking and foster behavior change. UbiFit utilized a virtual garden to help patients set and reach exercise goals and track activity [10]. In another context, Playful Bottle used the metaphor of watering a tree to help users increase their water intake [9]. Broadly, these studies found that utilizing metaphors made information easy to discern and heightened individual's awareness of specific modifiable behaviors.

### **Temporal Dynamics: Internalizing Glucose Curves**

Commonly blood glucose values have been displayed as a graph connecting individual readings or with CGM data, which shows blood glucose variation throughout the day. Studies from weather forecasting suggest that seeing the anticipated range of temperature variation in weather forecasts increases user trust and the likelihood returning to a particular forecast display [25]. Beyond weather, work in health demonstrates that patients find displays of how their health varies over time to be informative, and even motivational. In one study where past logged blood glucose values were displayed as a curve, participants were found to have an enhanced understanding of how lifestyle factors (stress, physical activity) affected blood glucose values [17]. Furthermore, work with CGM displays have found that viewing instantaneous glucose levels is highly motivational as it enables individuals to directly associate behaviors with glucose changes [32].

Other diabetes studies have focused on displaying glucose curves associated with physical activity in mobile applications and in laboratory interventions [19, 32]. Broadly, these studies validate the utility of curves in helping individuals understand data. One study demonstrated that viewing glucose curves not only allowed reflection on past choices, but enabled patients to understand their glucose dynamics well enough to accurately predict how exercise behaviors would alter their glucose levels [19]. Powerfully, these findings suggest that displaying glucose curves in the context of behaviors that may moderate blood glucose levels can help patients generate a mental model of glucose dynamics and accurately anticipate the impact of daily behaviors.

### **Visualizing and Comprehending Uncertainty**

A key concern when displaying glucose information to individuals is the amount of the model's uncertainty and their understanding of what that uncertainty means. While lay individuals often struggle to interpret the meaning of uncertainty, they are often able to grasp the gist of this concept and use it to inform decision-making [24, 29, 39]

Studies have demonstrated that depictions of uncertainty differ for single points, versus data trends summarized as trend lines. Weather studies indicate that individuals prefer displays of uncertainty ranges to purely deterministic displays [37]. For data displayed as lines, one study tested a variety of ways to display uncertainty ranges (dashed lines, solid lines gradients). Results indicated that individuals had an optimistic bias towards displays of uncertainty as dashed lines versus gradient displays, anticipating reduced risk. Furthermore results suggest differences with numeracy, as low numeracy individuals had a higher optimistic bias than high literacy individuals [42].

However, perhaps the most significant finding of past studies is that is that displays of uncertainty enable individuals to have greater trust in the data presented, and as such, uncertainty displays make participants more willing to continue using such displays to collect data [25].

These different types of visual presentations of temporal trends in blood glucose levels, temporal trends with uncertainty, and visual metaphors to communicate complex data served as an inspiration for visual representations of post-meal blood glucose forecasts. Below we describe the study conducted to assess feasibility of these representations in communicating predictions for post-meal blood glucose levels for individuals with diabetes.

## **METHODS**

### **Participants**

Participants were individuals with type 2 and gestational diabetes recruited from the Washington Heights/Inwood Informatics Infrastructure for Comparative Effectiveness Research (WICER) participant database. This participant database includes records of over 6,000 residents in the Washington Heights (WaHI) community. WaHI is a densely populated urban area (close to 280,000 people) with a high minority (predominantly Dominican) population.

A large proportion of the community residents are Hispanic (71%) and nearly 90% of the residents belong to a racial/ethnic minority group. African Americans represent 14% of the population. Less than 50% are proficient in English and 27% lived below the federal poverty level in 2007. A large percentage (44%) of community residents did not graduate from high school, and the unemployment rate is over 12% [3].

For this study we focused specifically on evaluating designs among individuals with type 2 and Gestational diabetes. Individuals with type 1 diabetes were excluded from this study as type 1 typically requires insulin management, which we did not address in this study. However, insights generated here may be applicable to all diabetes self-management and to communicating information in chronic disease self-management more broadly.

### **Visualization Materials**

Members of the research team developed 16 unique visual representations of forecasted post-meal BG. Our approach

to developing these visualizations was inspired by prior work in visualizing health information, and, specifically by past visualization work with the WICER population [3]. These designs differed across 4 key dimensions: (1) style, (2) context presented, (3) display of normative ranges, and (4) temporal dynamics and (5) uncertainty. Visualizations were shown in pairs that differed on one experimental dimension (e.g. similar style, context, normative range, and temporal dynamics, but with or without information regarding uncertainty).

Due to the diverse styles with which this information could be presented, we sought to understand whether particular styles resonated more closely with users. Consistently with past research on visualizing health information, we relied on three different styles of visualizations: (1) numbers, (2) metaphors/infographics, and (3) graphs. “Number” style visualizations reported blood glucose levels by displaying the number and with simple number-line representations. In contrast, “metaphor/infographic” styles often used common references or abstractions to convey blood glucose impact. For example, they may use the weather metaphor to communicate blood glucose levels (with higher BG levels corresponding to hotter weather forecast) “Graph” style visuals utilized curves to demonstrate blood glucose values in temporal context (over time).

Further, we wondered how user preference for designs might differ with the amount of information presented. To this end, our visualizations differed in the information presented to help users contextualize their blood glucose forecasts. Discrete visualizations communicated only the forecasted blood glucose for 2 hours post meal, while continuous visualizations placed the forecasted blood glucose reading in the spectrum of possible blood glucose levels that indicate good or poor glycemic control (these ranges include 80-130mg/dL for fasting levels and 80-180mg/dL for post-meal levels) [12].

In order to understand if contextualizing glycemic impact within normative ranges was more helpful to individuals seeking to gain insight from this information, we used colors and words to code the glycemic impact of a meal. We used a combination of colors and words to accommodate for individuals with color blindness or other difficulties perceiving color. The color red and the word “danger” indicated dangerous values (considerably higher or lower than the recommended ranges); the color yellow was paired with the word “moderate” for values just outside the healthy range, and the color green paired with the word “healthy”. The colors (red-yellow-green) were chosen to be consistent with recent trends in nutrition education that use traffic lights to characterize the healthiness of meals.

Next we sought to understand if participants thought about and resonated with visualizations that depicted the temporal nature of blood glucose and how it varied over time. Several curves were developed to show this data, and to understand

if this dynamic helped users add to their mental model of diabetes.

Finally we sought to understand how users interpreted uncertainty within the graphs, and if they preferred visualizations that indicated the uncertainty of the model. This uncertainty was captured by displaying a number range rather than a single number, highlighting a range of possible values, and using multiple lines on glucose curves to indicated the full spectrum of possible values.

### **Study Design**

A series of focus groups were conducted in both English and Spanish with participants ( $N=13$ ) who had a history of diabetes and were recruited from the WICER population. Our focus groups ranged in size from  $N=2$  to  $N=6$ .

While we did not assess participant literacy and numeracy, all participants were recruited from a larger sample that has been previously identified to exhibit low scores on literacy and numeracy measures [3]. Perhaps due to the size of the sample, English focus groups did not include any Latino participants.

The focus groups included two parts: First, participants engaged in a discussion about their diabetes self-management and nutrition decision-making practices. Second, they were asked to review 13 visual representations of blood glucose forecasts in the context of a smartphone app (for added realism) in pairs that differed by a single test feature (context, normative indicators, style, temporal indicators). For each design pair participants were asked about their perceived interpretation of the design, to reflect on the blood glucose information communicated, and to indicate a preference between the presented styles. All focus groups were audio recorded and transcribed verbatim for analysis. A Spanish-speaking moderator moderated Spanish-speaking focus groups; the transcripts of these groups were translated into English for analysis.

### **Data Analysis**

Translated transcripts were analyzed through an iterative coding process typical for thematic qualitative data analysis [11,36]. Coders met weekly to discuss, review, and synchronize new codes. First, researchers read the transcripts to familiarize themselves with the content (though all researchers were present at the focus groups, not all spoke Spanish and thus were unfamiliar with the content of those discussions). Next, researchers conducted collaborative open coding sessions to assign meaning to excerpts from the transcripts. Together the researchers coded one transcript to develop an initial coding scheme. After that, the first author continued coding independently, and all authors continued to review emerging coding results during weekly meetings. All disagreements among researchers were resolved in personal communications. Finally, the researchers thematically grouped insights to identify high-level themes. These themes are presented in the results section.



**Figure 1. Screenshots of visualizations presented. From left to right visualizations are: (a) gradient number line, (b) segmented number line, (c) speed dial, (d) the traffic light, (e) cartoon, (f) single line glucose curve, and (g) multiple line glucose curve.**

Dimension Assessed	Strong Design Elements	Weak Design Elements
<p><b>(1) Style:</b> Forecasted information can be rendered in a variety of ways including: numbers, metaphors, and graphs. Of these styles we wondered what might be most engaging for users and resonate with their perceptions of forecasted blood glucose. Findings point to the power of action-oriented visual metaphors and graphs in conveying this information.</p>	<p><b>Action-Oriented Metaphors:</b> Metaphors grounded in reality that directed a specific action such as “too much” (e.g. Traffic Light, Speed Dial) and induced personal emotions.</p> <p><b>Simple Graphs:</b> Graphs that tracked the temporal nature of blood glucose and emphasized the normative ranges of values enabled easy reflection.</p>	<p><b>Unrelated Metaphors:</b> Metaphors that were not related to blood glucose and did not feel serious disengaged users (e.g. cartoons)</p> <p><b>Numbers Only:</b> Styles that only used numbers provided few ways to engage with the design.</p>
<p><b>(2) Context Presented:</b> We focused on understanding the importance of showing forecasts in the context of all possible BG ranges. Findings suggest that words (e.g., high, low) and color (e.g. green, red) provide valuable clues on how to frame forecasts, such that seeing the full spectrum of values can be confusing.</p>	<p><b>Words and Color:</b> Colors and words provided specific context on how healthy a meal was, suggesting these clues were sufficient to interpret forecasted readings without the need of the full range of values.</p>	<p><b>Full Spectrum of Values:</b> Participants rarely used the relative position on the full spectrum of values to contextualize findings, instead relying on colors and words to provide context.</p>
<p><b>(3) Display of Normative Ranges:</b> We sought to investigate the degree to which visual elements that indicate the normative range of blood glucose levels and anticipated glycemic impact of meals resonates with users. Emphasizing normative ranges appears useful in helping users categorize forecasts and quickly glean gist information.</p>	<p><b>Color Coding:</b> Separation of numbers by color to code for meal impact. (e.g. Segmented Number Line, Speed Dial).</p> <p><b>Words:</b> Using words to indicate meal impact in an associated color. (e.g. traffic light, medical visualization).</p>	<p><b>Black Numbers:</b> Using black numbers with no other indicator of meal impact (words, color) is unhelpful in letting users gather information at a glance.</p>
<p><b>(4) Temporal Dynamics:</b> We wondered how participants would react to representations of their blood glucose dynamics over time. While graphs offered opportunities to reflect on general trends, individuals struggled to understand complex curves.</p>	<p><b>Display of Curve:</b> Curves enabled reflection on specific changes and provided rich information desired by participants.</p>	<p><b>Probability:</b> Participants were confused about how to synthesize complex data (e.g. gradient curve) and understand the representation high and low points each curve.</p>
<p><b>(5) Uncertainty:</b> Finally, we sought to observe how users treated representations of uncertainty displayed in forecasts. Findings suggest that users were easily able to interpret uncertainty when presented as number ranges but struggled with visual presentations of uncertainty as multiple possible trajectories (multiple curves).</p>	<p><b>Segmentation:</b> Breakdown of numbers into discrete buckets enabled a clear categorization, and minimized graphic confusion with uncertainty (e.g. Segmented Number Line).</p> <p><b>Number Ranges:</b> Seeing numbers was a representation of uncertainty participants accepted.</p>	<p><b>Blending of Buckets:</b> Participants were confused to see numbers occupy a in-between region on a spectrum (e.g. gradient).</p> <p><b>Many Lines:</b> Including several lines to show the range of possible values confuses and disengages users (e.g. multiple lines).</p>

**Table 1. Breakdown of successful and weak elements related to each of the five design dimensions assessed.**

## RESULTS

### Participant Demographics

A total of 13 participants took part in 5 focus groups; 2 focus groups were conducted in English (with N=2 participants) and 3 focus groups were conducted in Spanish with N=9 participants). All study participants were women; their mean age was 51 and ranged from 20 to 61. Participant's education level ranged from eighth grade or less to completion of a bachelors degree.

Findings generally aligned along two separate themes: participants' general attitudes towards their health and nutrition, and their attitudes towards visualizations of personal forecasts. We discuss both of these themes and their related sub-themes below.

### Attitudes towards diabetes self-management

#### *Simplifying Glycemic Control*

Overall, focus groups revealed that most participants were aware of the need for self-management and took initial steps towards adopting healthy behaviors. However, the majority of them took a highly simplistic black-and-white approach to self-management, shying away from more precise data-oriented strategies in favor of more intuitive ones.

For example, discussions about acceptable blood glucose levels showed that participants tended to conceptualize their blood glucose in broad ranges, and used these ranges to characterize values as healthy or not healthy. While some participants, particularly those on insulin therapy, reported keeping track of their blood glucose levels on a daily basis, most monitored their blood glucose levels infrequently. Instead, many participants relied on how they felt physically and emotionally to indicate fluctuations in blood glucose levels. Most participants noted that their blood glucose fluctuations were often accompanied by physical symptoms including blurry vision, sweating, drowsiness, difficulty speaking, and heavy legs.

*"For example, yesterday [...] it went down, I know it went down [...] my hands were shaking, my vision was blurry, and like I [didn't] have that much stability." – FG 13, Spanish P*

In many cases it appeared that the onset of these physical symptoms rather than habitual self-management routines that cued individuals to take concrete steps towards managing blood glucose levels.

#### *Simplifying Nutrition Management*

For the vast majority of the participants, nutritional choices were primarily driven by taste, price, and convenience. While participants noted that eating healthfully was important, for many, these health concerns were trumped by distaste for traditionally healthy foods.

*"[...]Don't substitute my taste for you money, if I want this, give me this[...]Like tofu, it looks like a bar of Ivory soap sitting in water, I cannot eat that." – FG 4, English*

In regards to nutrition management, participants tended to employ simple and easily implementable strategies; for example by avoiding foods they knew to have high impact on blood glucose levels. In fact, avoidance of carbohydrates was reported as the most common strategy for maintaining glycemic control. Common foods included in this category were rice, starches, sweets and pastries.

Others, instead of avoiding foods altogether, used similarly simplistic strategies for regulating portion sizes: for example by only eating half of their allocated portion of carbohydrate-rich foods or by serving their meals on smaller plates.

*"I don't take big plates. The biggest error people [make] is eat in big plates. I never eat in a plate like that I get a small one." – FG 10, Spanish*

Interestingly, participants reported often using visual approximations to help them determine healthy portion sizes at a glance. Many used strategies such as dividing their plate into fractions for different nutritional components, similar to meal planning tools such as My Food Plate by the United States Department of Agriculture [39]

*"My doctor says that half of my plate has to be greens and a quarter has to be grains and on the other side has to be the protein, so that's the way that I manage it now" – FG 7, English*

Other techniques included using body parts as a reference for serving sizes, or spoons such as ice cream scoops to control serving sizes.

*"Yes I eat pasta but I don't eat rice, but only a little. A little, whatever fits on the palm of my hand" – FG 12, Spanish*

However, such simple subtraction-based strategies used to avoid carbohydrate-rich foods were hard to sustain. Many participants reported experiencing cravings for comfort foods and familiar tastes. For participants with Dominican backgrounds, rice and beans, while rich in carbohydrates, represented a cultural staple and a foundational part of their diets.

*"It was hard! You know that as a people, that you are accustomed to eat your rice your beans and to suddenly stop to eating" – FG 8, Spanish*

#### *Desire for Direct Feedback and Guidance*

While many acknowledged that nutrition was foundational to diabetes management, some felt that overthinking nutrition was boring and drained joy of meal planning and cooking.

*"Boring because it's things that basically I knew [...] I know too what's good and what's not good and [...] I have sugar and it's too much [...] But you know a nutritionist, is not going to tell you to eat what you like" – FG 4, English*

Instead of the more comprehensive nutritional education, many preferred simple in-the-moment nutritional guidance

in the form of concrete recommendations for changing their meals that would be easy to implement.

*“You know what will be helpful, if [has] feedback... somebody [to] say, you know what, you need to have more fruit, so it’s not a debate, [it] will help me to keep myself in a track” – FG 7, English*

In addition to recommendations from experts, participants sought peer feedback in online and in-person communities often looking to these communities for support, as well as nutritional and health guidance. Many noted that staying accountable to others and having them vet decisions increased their own awareness of their habits. Furthermore, many desired continued feedback on nutritional choices from nutrition experts and peers, finding the process educational.

*“I have the people of the community feedback because I may believe that I’m doing the right choice, but somebody will, I don’t see that has enough of lean protein” – FG 7, English*

#### **Attitudes towards Personal Forecasts**

As many acknowledged challenges in anticipating the impact of different foods and few engaged in advanced planning or trying to anticipate the impact of different meals on their blood glucose, we introduced our blood glucose forecasting tool. Overall, the participants were intrigued by the idea of personal blood glucose forecasts and felt such a tool would be useful in their daily life. However, some raised concerns that viewing personalized forecasts at mealtimes were not actionable. These individuals often viewed their meals as something that, once prepared, could no longer be changed. Others simply did not want to waste prepared meals due solely to nutritional concerns.

*“But if you cook something, you’re not growing to throw it in the garbage” – FG 4, English*

#### **Attitudes towards Forecast Visualizations**

Overall participants gravitated towards a few select designs, chiefly: the traffic light representation, the face visualization, a medical visualization, the discretized number line and a simple blood glucose curve. Visuals such as a simple number range, the number line with gradients, cartoons, and curves with uncertainty were the least preferred. Below we describe common themes that emerged from the focus group discussions.

#### **Visualizations are effective communication tools**

In conversing with participants we found that some actively incorporate visual techniques as a regular part of daily life management and to track goals. In particular, participants described creating a board of goals or keeping a notebook to set goals and monitor progress. Furthermore, conversations with participants pointed to the usefulness of information visualizations as an engaging way of communicating health information, for presenting information in this manner

makes the most salient information easier to identify, internalize and translate into action.

*“It’s more visual and you can really identify and maybe like go reading information, you’re going to lose track and say okay whatever” – FG 7, English*

Along this vein, participants had more emotionally driven responses to infographic and metaphor visualizations, often personifying them and perceiving them as alerts prompting greater awareness and as a call to action.

*“You imagine that is burning the pork skin. Because it has an ugly face, it is burning [...] Something that is burning, that is not good, that is not healthy” – FG 11, Spanish (referencing Face Visualization)*

However these emotional responses did not necessarily relate to preference of the design for displaying forecasted blood glucose information.

#### **Preference for Simple and Explicit Designs**

Discussions with participants overwhelmingly demonstrated the importance of simple and unambiguous visualizations. Overall, participants were most interested in extracting the ‘gist’ of their blood glucose information, and were less concerned with details such as more precise or more detailed indications. Moreover, they sought this information to be presented as explicitly as possible without the need for further interpretation, preferring designs that included explicit categorizations of blood glucose impacts through colors and words, rather than those that required interpretation of forecasted ranges.

For example, participants easily internalized use of colors (green, yellow, red) to indicate glycemic impact of different meals. The color red, in particular, triggered a universal and unequivocal association with danger and was interpreted as a warning sign.

*“[...] if it’s in the red zone, I know it’s out [...] Smack right in your face. If you’re overdoing it” – FG 4, English*

Beyond color, participants preferred designs that included words to clearly indicate the anticipated impact of meals (“healthy”, “moderate”, and “dangerous”) largely because they helped make the crucial takeaways more explicit. Many participants incorporated these words into their own description of the impact of corresponding meals.

*“The blood? Dangerous. It says that at 210 they have to be monitoring themselves.” — FG 12, Spanish (referencing Medical Visualization)*

Furthermore, the designs that included these elements were perceived to be educational. By calling attention to the implications and teaching individuals the impact if it was not already known, words helped to contextualize forecasts within existing frames of reference about self-management and the implications of meals on blood glucose.

*“Because this one teaches you what is healthy, what is not healthy, and that is dangerous, meanwhile [a design without words] doesn’t show any of that” – FG 11, Spanish*

While participants desired simple and clear visualizations, they did not want to sacrifice the richness of information presented, even if they struggled to understand it. This was particularly the case with information about blood glucose dynamics. While many participants struggled to understand visualizations of blood glucose curves intended to show predicted fluctuations it was still important to them that this information was presented.

*“[...] if my sugar has been up and down and I [want to be] aware of all those up and downs, just for me to have a better sense of how can I manage” – FG 7, English*

#### **Incorporating Action**

Another important characteristic that emerged from the focus group discussions was action orientation. The participants clearly preferred visualizations that communicated the need for action. The traffic light metaphor (Figure 1d) in particular was perceived as easy to interpret and as a good fit for indicating the impact of different meals because it also implied a certain action: stop for dangerous meals; go for meals with low impact.

#### **Communicating Authority**

At the same time, the response to visualizations was often linked to the tone of the design. Participants tended to prefer more serious designs that appeared to convey a sense of authority and gravitated towards visualizations they perceived to be more “sensible” (for example Figure 1d). While visualizations such as cartoons (Figure 1e) were described as “cute” and elicited emotion driven responses from participants, they were also perceived as “childish” and distracting when it came to communicating blood glucose information.

*“It’s like showing the kids something before you give them a lollipop and then give him a needle. Just tell me, we’re grown, tell me if I’m in danger, don’t give me a smiley face.” – FG 4, English (referencing Cartoon, Figure 1e)*

#### **Uncertainty**

Any computationally generated prediction, whether in reference to weather or to post-meal blood glucose levels, involves a level of uncertainty. Consequently, one important question in this study was in regards to ways individuals understand and interpret uncertainty, and ways uncertainty can be represented visually. The study showed that while the participants generally understood the concept of uncertainty, when applied to the context of their health and mealtime blood glucose forecasts, they found it confusing and difficult to interpret.

Overall, we found that the participants expected some imprecision with forecasted blood glucose values, and were willing to accept predictions with a small range of error.

*“Nothing is exact with diabetes, so if you’re still in the range, you’re still good [...] If you’re supposed to be at 125 and it’s 130 or 127, you’re still good” – FG 4, English*

However, when reacting to visualizations, the participants overwhelmingly demonstrated a preference towards exactness over ranges; many found visualizations of uncertainty to be confusing and overwhelming to interpret. This was almost universally the case for all such visualizations, including gradient (Figure 1a) and blood glucose curves with multiple lines (Figure 1g). Participants strongly disliked visualizations of uncertainty on blood glucose curves, finding having multiple lines more difficult to interpret. Furthermore, participants preferred seeing their blood glucose values such that they could be discretely classified in ranges, as opposed to representations of them as continuous values.

*“This has too many colors put in together. Either it’s not good or it’s kind of good, you know, between green it has the yellow and then the yellow mix with red, this right here is direct, it’s green, it’s yellow, it’s red. It’s not yellow going into red.” – FG 4, English (referencing Gradient and Discrete Number-line, Figures 1a and 1b)*

#### **Extraneous and Unintended Interpretations**

Throughout the study, the participants showed clear preference for simple and explicit, yet information-rich visualizations and their dislike for more complex depictions of uncertainty. This strive for literal and direct presentations sometimes had unexpected consequences when participants attempted to extract meaning from design elements that were not intended to carry any.

For example, our designs used the colors red, yellow, and green to denote significant normative ranges from blood glucose, other colors such as blue were intended as neutral, not carrying any particular information. However, many participants were confused by this color and attempted to interpret it as well.

*“Since before eating...and the color blue is moderate [...it’s] confusing – the blue hand because here we saw the streetlight, although the streetlight is green it’s healthy but the blue can be confusing” – FG 13, Spanish*

In other cases, such unintended interpretations were due to differences in personal experiences between participants. For example, participants with different life experiences frequently interpreted the speed dial visualization (Figure 1c) and blood glucose curve visualization (Figures 1f-1g) differently. The speed dial was often interpreted as a scale, wheel, barometer, or even a rainbow. Blood glucose curves on the other hand were sometimes interpreted as bridges. However, these alternate interpretations had little bearing on participant’s ability to correctly interpret the information presented. Sometimes, these extraneous associations further contributed to participants’ engagement by reminding them of personal experiences.



*“When you go to the streets, when you see the traffic light green, you can continue, green means good. Everything that is green has hope.” – FG 5, Spanish (referencing Traffic Light, Figure 1d)*

At other times, associations with negative personal experiences sometimes led to disengagement from visualizations; for example, blood glucose curves reminded of the participants of math, her least favorite subject:

*“When it start getting too technical and looking like algebra, I start running” – FG 4, English (referencing Multiple Lines, Figure 1g)*

## **DISCUSSION**

Results from this study highlighted several broad themes in both how patients perceive health information, and in the characteristics of what makes this information more usable. As the ability to generate personalized forecasts expands, there is a need to ensure that individuals can understand and use this information. Our study set out to explore trends in designs that resonated with individuals recruited from populations typically characterized by low health literacy and understand intersections in how these individuals thought about nutrition and self-management and potential design solutions. The study showed that many participants take a reactive approach towards self-management, responding to undesired blood glucose changes, rather than proactively preventing them. This reactive approach may be due to the difficulty of accurately anticipating changes in one’s blood glucose levels due to different activities. This finding highlights the need for novel solutions that can help individuals with this challenging task and can use computational modeling and self-monitoring data to generate accurate personalized insights. The study also identified a number of trends in individuals’ reactions to different visualizations that help to guide future work.

### **Tell me, don’t show me**

Broadly we had anticipated that users would resonate most closely with metaphor-based visualizations and would find these solutions to be the most engaging and best able to capture complex data in a simple way. However, while overall participants resonated most closely with highly graphic visualization styles, their preferences for particular styles were more nuanced.

Based on past studies we expected that participants would gravitate towards metaphor based designs to communicate health information due to ease of understanding [9, 10]. However, this was not the case as the participants often sought more literal and directive designs, which gave them feedback they could act upon (stop or go) rather than simply convey a feeling or emotion. For example, in our study, the cartoon and abstract designs that incorporated human facial features were designed to convey feelings and emotions that could match the positive and negative reactions to blood glucose forecasts exhibited by the participants. However, the participants often gave preference to the more

straightforward, and more action-oriented traffic light or speed dial. Research on the influence of infographics has demonstrated that these information types make information relevant and thus make it easy to convey information [23].

Beyond images however, many of our participants responded positively to the inclusion of simple text that accompanied visualizations. In particular, participants used this text to contextualize the gist of the design, and appreciated the convenience and explicitness of a single word summary. Similar results have been found regarding the inclusion of text in cartoons for nutrition education, and have noted the importance of short, simple and direct text to provide a gist of the main takeaways [44].

These insights suggest that directive abstractions and simple text are important design elements for conveying gist information to participants. While much research on presenting gist information has focused on patient numeracy, gist elements may be particularly useful in the context of forecasting by simplifying in-the-moment decision-making.

### **The Rich-Simple Paradox**

What became apparent throughout our analysis was that participants often sought simplified but rich solutions to understanding their health. This desire was reflected in both individuals’ self-management strategies and the visual styles that resonated most closely with them. In daily life, they appeared to seek solutions that were both easy to implement and comprehensive (for example a portioned plate). In terms of design the most effective solutions were those that a balanced ease of interpretation with thoroughness.

Past studies with the WICER cohort have noted similar findings: in particular, a preference for simple design but a strong desire for complete information [4,5]. In one participatory design study with 102 participants from this cohort, participants liked the traffic light design for visualizing blood pressure levels but preferred other designs that included rich information [4]. However in our study participants did not explicitly vocalize such concerns; on the contrary, the traffic light was one of the more universally liked visualizations. This may be due to the different contexts in which these designs were framed. High blood pressure levels typically do not require immediate action, leading to a mismatch with the traffic light metaphor. In contrast, viewing BG forecasts does require a quick decision regarding a planned meal. Perhaps in this context of an immediate decision the action-oriented nature of the traffic light presented a good fit.

Successful designs used simple models such as a traffic light, medical infographics, and speed dial to give rich context and overall kept complex topics such as uncertainty relatively elementary. This composition may be a reflection of what participants deemed to be most important in the immediate decision-making contexts we design this tool for. In striking this balance, designs enabled individuals to reflect deeply on outcomes and quickly make decisions.

These findings highlight the potential for well-crafted designs to be not just interesting but educational for users.

### **Uncertain about Uncertainty**

One of the key finding that emerged from our study was the extent to which individuals struggle to understand the meaning and utility of uncertainty when presented visually. While overall participants had a cursory understanding of uncertainty and could grasp its significance, visual representations of uncertainty with multiple or fuzzy blood glucose curves added little to how patients thought about blood glucose and caused confusion by triggering other interpretations or memories which influenced interpretation (e.g., bridges, or algebra).

Past work has shown that how uncertainty is visualized around a trend line can influence individual's perception of risk and understanding of information presented. Generally, this work found solid lines and gradients around a trend line to most effectively demarcate regions of uncertainty [42]. Of the blood glucose curves shown in our study, participants preferred representations with the fewest indicators of uncertainty (a single line with no uncertainty) and most disliked the design that visualized the granularity of the statistical model (multiple lines representing different statistical possibilities). Beyond graphical representations, participants struggled most with uncertainty displayed on a number line where instead of discrete normative ranges values could fall along a continuous gradient ranging from dangerously low to dangerously high (Figure 1a). Instead of helping participants contemplate the complex dynamics of blood glucose, these visualizations of uncertainty often seemed to cloud the information presented and participants struggled to extract even the gist of the information shown.

While past research has noted that interpreting uncertainty is often difficult for individuals with low numeracy, these studies have also demonstrated that visualizations including uncertainty information were more trusted by users even if not completely understood [25]. Conversely, we found no indication that users' trust of forecasts varied based on visual depictions of uncertainty. Instead uncertainty displayed in graphs often appeared to disengage users and elicit discomfort.

However, it is important to note that past literature on uncertainty and decision-making in medical domain and in weather forecasting has focused on high-risk situations (a dangerous surgery or a catastrophic weather event). In such scenarios, understanding and accounting for uncertainty is of high importance. In contrast, diabetes self-management consists of numerous small, relatively low risk decisions, which have an important cumulative impact over time. In this context, understanding and incorporating uncertainty may be less important. This suggests the need to balance the cognitive burden of understanding uncertainty with its impact on decision-making in health and nutrition management.

### **Future Directions and Opportunities**

Our findings highlight opportunities for future work in several areas, and outline critically relevant considerations for the development of future solutions. Forecasting for daily health management is still a new idea, and our understanding of how individuals perceive the usefulness of and engage with personal forecasts, particularly in the context of long-term self-management remains limited.

Importantly we found that words play a critical role in helping individuals understand the gist of their forecast, and learn from visualizations to contextualize findings in larger narratives. This finding suggests that future work on communicating personalized forecasts in health could utilize a combination of these two approaches; words with numbers, combined with visual representation of context (normative information, temporal trajectory, and uncertainty) could lead to visualizations that are both rich in information and easy to understand [6, 34].

This work highlights the deeply personal nature of health, and influence of culture on disease self-management. Thus far little work has examined health communication in a culturally diverse populations. Past work has identified gaps in understanding of how cultural differences shape user preferences towards interface design and content delivery [8]. While our work begins to address these gaps with regards to diabetes management, it also emphasizes a need to better understand how culture influences aspects health communication and management to further empower inclusive and effective health practices for all patients.

More broadly, this work is a first step in considering how designs can be used to aid behavior change in routine self-management practices, as these daily considerations are over the long term essential for preventing the onset of complications. With the growth of forecasting technologies, it is essential to help individuals adopt a more proactive, rather than reactive mindset, and equip them with tools that can help them anticipate health impact of different activities, rather than simply react to changes in their health. This work demonstrates how design can help drive this shift and enable patients to better translate information to action. However, it is important to note study limitations, such as the small sample size and qualitative nature of investigations, rather than comprehensive quantitative assessments of visualization and forecast comprehension.

### **CONCLUSION**

In this study we examined the perceptions and attitudes of individuals with type 2 diabetes recruited from low literacy populations towards visual representations of personalized blood glucose forecasts. The findings emphasize the importance of actionable, direct, simple, and information rich visualizations. These findings highlight the need for future work investigating the most effective ways of communicating health information and uncertainty in low-risk contexts where individuals have the agency to make decisions.

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