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"It's like a glimpse into the future": Exploring the Role of Blood Glucose Prediction Technologies for Type 1 Diabetes Self-Management

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ABSTRACT

Self-management of type 1 diabetes (T1D) involves multiple factors, frequent anticipation of changes in blood glucose, and complex decision-making. ML-based blood glucose predictions (BGP) may be valuable in supporting T1D management. However, it may be difficult for people with T1D to integrate BGP into their decision-making due to prediction uncertainty and interpretation. In this study, we investigate the lived experience of people with T1D focusing on their needs and expectations in using apps that provide BGP. We designed MOON-T1D, an app that shows simulated BGP and conducted a five-day study using the Experience Sampling Method coupled with semi-structured interviews with 15 individuals with T1D who used MOON-T1D. A reflexive thematic analysis of our data revealed implications for the design and use of BGP, including the complex role of emotions and trust surrounding predictions, and ways in which BGP may ease or complicate T1D management.

CCS CONCEPTS

• **Human-centered computing** → **Human computer interaction (HCI)**; **User studies**.

KEYWORDS

Health, Type 1 Diabetes, Artificial Intelligence, Qualitative Study, Mobile Health

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1 INTRODUCTION

Type 1 diabetes (T1D) accounts for approximately 5% of diabetes cases, affecting nearly 9 million people worldwide [116]. It is a chronic autoimmune disease in which beta cells, insulin-producing cells in the pancreas, are destroyed by the body's immune system [39]. As insulin is a vital hormone that transfers glucose from the blood to the body's cells, individuals with T1D have a lifelong dependence on exogenous insulin supplementation [116]. The goal of *T1D self-management* is to keep blood glucose (BG) values within a pre-defined target range through the use of insulin. Failure to do so leads to out-of-range BG, known as hyperglycemia (higher than target BG) or hypoglycemia (lower than target BG). Out-of-range BG can result in severe symptoms including loss of consciousness [32], diabetes-induced coma, and in rare cases death [78]. Long-term health complications include end-stage renal disease, cardiovascular disease, and necrosis in lower extremities leading to amputation [115]. T1D self-management is complex and burdensome [38], as BG is affected by a multitude of interdependent factors, such as carbohydrate intake, insulin, physical activity, and stress. Effective management of T1D is therefore crucial but assessing immediate and long-term health outcomes is challenging, and many individuals fail to stay within clinical BG guidelines [79].

Anticipating undesirable health states and taking steps to avoid them are integral parts of chronic disease self-management. Automatically generated blood glucose predictions (BGP) could provide information about future BG levels, and therefore serve as a powerful tool in T1D management. Through recent advances in analysis of health data [117], the prediction of BG through machine learning (ML) offers new opportunities to reduce the burden of T1D management [3, 106, 118]. Advances in self-monitoring technologies enable individuals to benefit from the abundant personal health data now available [100]. Additionally, ML can facilitate the personalized and predictive analysis of large quantities of data [16, 38, 56, 80, 117]. BGP for T1D management has shown to be beneficial in reducing nocturnal hypoglycemia through insulin pump suspension [25] and compensating for time delays that occur with modern continuous glucose monitoring (CGM) systems [99].

Although the accuracy of ML models for generating BGP is key to their value for T1D self-management, it is also important to understand how people engage with and respond to BGP such that they can be integrated into technologies in a way that is beneficial to people. The design of BGP technologies is often done without the involvement of end users [57], and there has been little exploration of how BGP affects the lived experience of individuals with T1D. To better understand the role that BGP might play in the lived experience, we conducted a study in which we aim to understand:

- How individuals integrate BGP into their awareness and understanding of the condition

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- How BGP may affect T1D self-management practices, and
- How individuals with T1D want to engage with BGP

Our research focuses on human-centered aspects of BGP with an eye towards informing the design of future T1D support technologies that provide BGP. A crucial first step towards this goal is exploring how people comprehend and respond to BGP, and how they might integrate BGP into decisions surrounding self-management. Additionally, we consider the impact that BGP can have on people's self-perception and emotions surrounding T1D, and how BGP could be integrated into technologies in a way that is sensitive and appropriate to individual needs and practices.

To gain insight into the lived experience of engaging with BGP, we created a mobile application, MOON-T1D, for T1D management that integrated BGP based on simulated BG data and provided it to 15 individuals with T1D for a five-day period. We conducted semi-structured interviews before and after the deployment to understand their existing self-management practices and expectations regarding BGP, and their experiences with BGP. During the deployment we also conducted Experience Sampling Method (ESM) surveys to collect their in-situ responses to receiving BGP and reflections on how it would affect their practices. We analyzed the data using reflexive thematic analysis and derived important implications regarding the value of BGP in T1D self-management. The key findings of our study point to situations in which BGP could support self-management decision-making, considerations for how to engender trust, agency, and understanding in regard to BGP, the potential positive and negative emotional impacts of showing BGP, and how people would like to interact with technologies that provide BGP. Reflecting on these findings, we also introduce several considerations for the design of decision support systems involving BGP.

In this paper, we contribute an in-depth study on the lived experience of individuals with T1D using a BGP simulation, focusing on their needs, expectations, and changes to existing practices. Second, we present a novel application that integrates nutrition and insulin tracking, BG, and BGP. Third, we present four key themes involving 1) perceived constraints of T1D self-management and how BGP may address them, 2) the importance and impact of trust in BGP, 3) BGP and emotions involved in self-management, and 4) desired engagement with BGPs. Finally, we offer a discussion that presents several cross-theme design considerations for future applications that integrate BGP to support T1D self-management.

2 BACKGROUND AND RELATED WORK

2.1 T1D Self-management and Self-tracking

Self-management and self-management education are important aspects of living with diabetes. In T1D, self-management revolves around the use of insulin in combination with other practices to keep BG levels within a predefined target range. Factors that increase BG include food consumption, stress, and pain, and factors that reduce BG include insulin injections, physical activity, and alcohol consumption. Failing to keep BG within range can have serious long and short-term consequences such as eye, nerve, or kidney damage, cardiovascular problems [35], and cognitive impairment [19, 92, 93].

People with T1D rely on various technologies to track these factors and their subsequent impact on BG. Of the factors that raise BG, carbohydrate intake has the most significant impact, particularly concerning postprandial BG [43]. Weighing meal ingredients before cooking is the most accurate method of determining a meal's carbohydrate content [41]. However, as weighing food is time-intensive and not always convenient, people often simply estimate the carbohydrate content of a meal instead. This practice is error-prone, and studies have shown that individuals with T1D have a mean error of about 20% when estimating carbohydrates. Although nutrition tracking applications that rely on food databases or image-based carbohydrate estimations can be useful, they are also subject to significant inaccuracy [69] and may contribute to disordered eating [44].

Physical activity has been linked to decreased risk of cardiovascular disease, reduced need for insulin, and increased psychological well-being in people with T1D [29]. Despite these benefits, individuals with T1D engage less frequently in physical activity. This is often due to fear of exercise-related hypoglycemia and the difficulty of managing BG before, during, and after exercise [21].

BG levels can be measured using a portable glucometer or a continuous glucose monitor (CGM) device. Glucometer use requires blood extraction, usually via a finger prick. It provides accurate measurements of BG concentration at the time of measurement. CGM systems require the patient to wear an intradermal disposable sensor that measures glucose concentration in the interstitial fluid [12]. Measurements derived from interstitial fluid typically reflect BG levels from 6 and 10 minutes prior [10]. CGM measurements are taken automatically and usually transmitted to a smartphone at intervals of one to five minutes or as requested by the patient. CGM use has been shown to have a positive effect on HbA1c (a biomarker for long-term glycemic control) and reduce hypoglycemic events [13, 67]. Some CGMs provide trend arrows that reflect the rate of glucose change. Although these arrows can help people anticipate future BG, they differ from BGP in that they are a snapshot of the current trend rather than a prediction of the future. Moreover, unlike BGP, the BG rate-of-change shown by CGM trend arrows does not factor in influences such as insulin, food intake, and physical activity [2]. Nonetheless, Lawton et al. [63] found that using trend arrows enabled predictive short-term planning and preventative actions for self-management.

Individuals with T1D can administer insulin either through injections or through a continuous subcutaneous insulin infusion called "insulin pump therapy". The body's normal insulin secretion involves continuous low-level basal insulin secretion which stabilizes fasting BG levels, and postprandial (post-meal) bolus insulin secretion for carbohydrates in meals. Pump therapy offers automatic low-level basal secretion, while individuals who do not use pumps rely on multiple daily injections. With either approach individuals must still manually administer bolus insulin in conjunction with meals. More recently, insulin pump therapy has been combined with CGM systems to achieve more automated administration of basal insulin [12], an approach known as a hybrid closed-loop system (also referred to as "artificial pancreas"). With these systems, bolus insulin administration cannot be automated due to insulin's slow onset and long-lasting effect. Hybrid closed-loop systems have been shown to reduce hyperglycemia, hypoglycemia, and HbA1C concentrations [110].

Increased time-in-range achieved with hybrid closed-loop systems stems mostly from their effectiveness at night [22, 109].

Overnight management is important as individuals have reduced ability to respond to out-of-range values during sleep. It differs from daytime management as some factors with a high impact on BG levels such as food intake or physical activity are less relevant at night.

Despite their benefits, hybrid closed-loop systems remain uncommon as they are expensive and cumbersome, requiring frequent adjustments based on individual lifestyle factors [22]. With the increased commercial availability of hybrid closed-loop systems, they may gain wider adoption particularly in countries where commercial systems are accessible and affordable.

In response to the slow pace and high cost of commercial innovations in T1D care, motivated and tech-savvy members of the diabetes community have established the #WeAreNotWaiting movement. This has led to various platforms and projects including the do-it-yourself (DIY) remote monitoring system NightScout [64], replacement of CGM transmitter batteries [81], and DIY artificial pancreas [65]. Among the most commonly used DIY artificial pancreas systems are Open APS [34], AndroidAPS [6], and Loop [68] which served as an inspiration for our app design. While DIY systems setup is time-consuming, non-trivial, and requires technical knowledge, the #WeAreNotWaiting movement emphasizes the urgency of innovation in diabetes management and the motivation of the T1D community.

2.2 AI in Healthcare: Predictions and T1D

Predictions such as BGP have become increasingly important in healthcare. Predictive applications have addressed various healthcare issues such as mood [56], physical functioning in multiple sclerosis [7], exacerbation episodes in chronic obstructive pulmonary disease [98], and COVID-19 hospital admissions [14]. In recent years, the use of ML to support T1D self-management has gained prominence in research [3, 106, 118]. Diabetes-specific applications of ML include food classification and recommendation [102], classification and association of specific behaviors with health outcomes, association of GPS location with BG variability [40, 84], decision support [42, 112], bolus recommendation [97], hypo- and hyperglycemia prediction [36], and BGP [91, 119].

T1D and T2D can differ substantially regarding cause (autoimmune vs. resistance), typical onset (childhood vs. adulthood), insulin dependence (always vs. sometimes and may be addressable by diet, physical activity, etc.), as well as preventability [111]. As a result, cohorts and self-management practices can differ substantially between T1D and T2D patients. Compared to T1D, there has been considerably more investigation of how technology can support people with type 2 diabetes (T2D) in the HCI research community. Of particular note, Desai et al. [38] investigated personalized mealtime predictions for individuals with T2D. Their work found that forecasts were useful for immediate meal decisions and meal planning. ML-based methods to support the prediction of BG trajectories can also benefit individuals with T1D. Battelino et al. [11], for example, reported that using predictions of low BG to initiate insulin secretion in continuous subcutaneous insulin infusion systems can significantly decrease the occurrence of hypoglycemia in patients with T1D. Additionally, using BGPs may compensate for the inaccuracies and time delays associated with CGMs, particularly during periods of rapid BG fluctuation [99].

Current system designs for T1D self-management often require users to interpret their own health data rather than explicitly providing actionable insights or recommendations [60]. Individuals must consider their situational context [82], such as running a marathon, and time-based changes in the condition [61] to draw insights from their data. However, adapting to the changing personal needs and abilities of users is often unsuccessful [94]. Recommendations based on BGP may relieve some of this user burden. However, Stawarz et al. [103] found that people with T1D rejected the idea of ML-based decision support for everyday situations, as individuals had greater trust in their own experience. Moreover, most commercially available apps for glucose monitoring do not yet provide BGPs. The few that do require users to manually log meals and other management related data consistently for a prolonged period of time before providing users with any prediction at all. It therefore remains unclear how predictions should support T1D management, how users will integrate predictions into their daily management, and what benefits they could provide.

2.3 T1D Sensemaking and Personal Informatics

As the amount of personal data available for T1D self-management increases, interpretation and decision-making based on this data become increasingly complex [74]. The term "personal informatics" refers to the research field that focuses on the analysis and creation of technologies using personal data [66]. The question of how AI may or should influence the field of personal informatics, particularly in chronic disease management remains an open one in the HCI research community [70]. Personal informatics systems usually encourage self-reflection and awareness, but how and whether ML can support self-reflection remain open questions [70].

Self-management is highly specific to the lives of affected individuals [17, 28, 52–54]. As more than 95% of self-management in T1D is done by the patients themselves [52], patients deal with their condition by learning to make sense of their own experiences. The importance of sensemaking is reflected in the fact that the American Diabetes Association included it as one of the 7-stages for diabetes self-management [4]. Hill-Briggs and Gemmell [55] showed an association between sensemaking and better HbA1c levels, and Schumann et al. [96] suggested that decision-making could be facilitated by problem-solving interventions to support sensemaking. People rely on experiential learning to interpret health outcomes in chronic conditions by drawing links to past actions [71, 75, 89]. It is therefore important to understand whether individuals with T1D interpret BGPs as possible health outcomes and can connect them to past actions, thus making them useful in T1D self-management. Mamykina et al. [76] introduced sensemaking as a theoretical framework to describe experiential learning and understanding in chronic disease management. They differentiate between two modes of diabetes self-management: habitual and sensemaking. In the habitual mode, pre-existing mental models can be used to incorporate new experiences, making them more implicit and passive. The sensemaking mode requires individuals to engage analytically with new experiences in a more explicit and active fashion. Both modes can be broken down into three activities: 1) Perceiving new information that may lead to gaps in understanding, 2) Drawing inferences based on existing knowledge and reflection on experiences, and 3) Action based on a selection of the most plausible explanation [76]. In a study of context-enhanced visualizations, Raj et al. [88] found that counterintuitive insights impeded trust in data, and large amounts of data may result in an inability to identify trends and draw insights from the data [88]. As the inclusion of BGPs in T1D self-management tools contributes to both the amount of data provided and the effort necessary to interpret it, it is important to understand how individuals with T1D experience and understand them.

3 METHOD

To understand the perspectives and experiences surrounding BGP, we deployed a prototype that integrated simulated BGP to individuals with T1D, and conducted a study using semi-structured interviews and experience sampling.

3.1 Participants

A total of fifteen people participated in the study. Participants were required to have been diagnosed with T1D at least one year prior to the study, be primarily responsible for their T1D management, use an Android or iOS Smartphone, have internet connectivity, and be proficient in English or German. We recruited people by distributing flyers to 17 local endocrinology practices, a medical newsletter, a center for endocrinology, and through Prolific, an online recruitment platform. We received approval from our institution's ethics board and obtained informed consent digitally from participants. As an incentive, participants received $150, with a portion allocated to cover Prolific fees.

There were five (33.3%) male, ten (66.7%) female, and no (0%) non-binary participants. The mean age was 37.9 years (±12.7), and the average time since diagnosis was 16.4 years (±13.4). Two (13.3%) participants used a glucometer, and 13 (86.7%) a CGM for BG monitoring. Eight (53.3%) participants were on multiple-dose injection insulin therapy, and seven (46.7%) were on insulin pumps of whom four (26.7%) were using a hybrid closed-loop system.

3.2 Study Procedure and Data Collection

To understand the lived experience of individuals with T1D, we conducted a study with three phases. Before beginning the study, we conducted a pilot study to test MOON-T1D's functionalities and the flow of the interview protocol.

The first phase consisted of a semi-structured interview (~30 min, online or in person based on participants' preferences) to understand participants' current T1D self-management practices and their potential influence on BGPs (see Appendix A.2). Before starting the first interview, participants signed the consent form and completed a short online demographic questionnaire (see Appendix A.1), with the option of opting out. This data can be found in Table 1. After the first interview, we introduced participants to MOON-T1D and its features. During this process, we informed participants repeatedly that MOON-T1D showed simulated data and that the BGPs they would see were based on this simulated data, and not on their actual BG. We guided participants' through the installation process and provided an instructional document detailing the functionalities of MOON-T1D.

The second phase of the study started the day after the initial interview and consisted of an Experience Sampling Method [113] study (5 days) using MOON-T1D. The goal of the second phase was to understand the situational importance of BGPs in participants' everyday lives and environments. Participants were asked to record aspects of their food intake, insulin injections, and exercise via the app at various points throughout the day. To capture situational context, participants received individually scheduled and unannounced prompts to complete a short questionnaire (~5 min) in MOON-T1D (see Appendix A.3). Although people with T1D typically view their BG levels many times throughout the day, we opted for 2-3 prompts per day such that there would be multiple sample points but the burden of completing questionnaires would be kept to a manageable level in line with recommendations by Van Berkel et al. [113]. The questionnaire was designed to capture preferences regarding BGP and uncertainty. It also included questions about the participant's current situation (e.g., "What is your current mood?" "What are you doing right now?") and current willingness to provide input for the predictions (e.g., recording food intake.) Questions about the participants' situations were intended to prime their thinking about how they would hypothetically respond to seeing BGP in real-life contexts. Excerpts of the questionnaire are shown in Figure 1 (also see Appendix A.3).

The third phase of the study was a semi-structured interview (~45 min), in person or online based on participant's preference), conducted the day after the completion of the second phase. The interview questions were designed to gather participants' perceptions and experiences with MOON-T1D and the simulated BGPs it provided, for example: "What was your experience using MOON-T1D over the past few days?", "Did seeing the predictions change your perception of your blood glucose in any way?", "Are there things you do to anticipate your BG?" (also see Appendix A.4).

3.3 Simulated Data

In designing our study, we considered the tradeoffs of using actual CGM data versus simulated data on which to base the BGP. We opted to use simulated data; our main consideration in this decision was the safety and privacy of our participants.

First, BG is sensitive personal health data which we felt we should not collect from participants at this early stage of research. As our study was intended to be a qualitative first exploration of people's general response to seeing BGP to understand whether it is a valuable direction to pursue in T1D management, we opted to remain conservative in our data collection, starting with simulated BGP, and saving studies with real medical data for future, more targeted investigations. Second, we also felt it would be safest in this early stage for participants to reflect on what they would hypothetically do in response to BGP, rather than actually integrating real predictions into their self-management. As we did not know how people might interpret the predictions they received, or whether the information they provided to the app was sufficient and accurate enough to yield accurate BGP, we did not feel it would be safe to provide predictions to participants and have them base their self-management decisions and actions on them. By doing so, participants might run the risk of negative health consequences stemming from actions they might not have otherwise taken in their T1D self-management.

Table 1: Demographic Information of the Study Participants

ID	Age	Gender	Nationality	Years Lived with T1D	CGM or Glucometer	Pump or Pen (Insulin)
1	?	Female	Switzerland	9	CGM	Pump (Hybrid Closed-Loop)
2	53	Male	Switzerland	27	CGM	Pen
3	67	Male	Switzerland	52	CGM	Pump (Hybrid Closed-Loop)
4	39	Female	United Kingdom	31	CGM	Pen
5	34	Female	United Kingdom	?	CGM	Pen
6	33	Male	Germany	9	CGM	Pump
7	44	Female	United Kingdom	11	Glucometer	Pen
8	53	Female	United States	15	CGM	Pump (Hybrid Closed-Loop)
9	23	Male	United Kingdom	2.5	CGM	Pen
10	41	Female	United Kingdom	25	CGM	Pen
11	29	Female	United States	2	CGM	Pen
12	29	Female	United Kingdom	19	CGM	Pump
13	23	Female	Germany	18	CGM	Pump (Hybrid Closed-Loop)
14	22	Male	Poland	8.5	CGM	Pump
15	41	Female	United States	1	Glucometer	Pen

The drawback of this approach is that the predictions based on simulated data may not reflect the participant's actual situation (e.g., receiving a low BGP while the participant is experiencing high BG). Unrealistic or illogical predictions may emphasize the simulated nature of the experience for participants, potentially causing them to feel less invested in the study than they would if they were engaging with their real health data.

However, as previously described in Section 2.1, the T1D population has a strong intrinsic motivation for finding solutions for self-management, and the problem is of great personal urgency. Given the problems importance for study participants, we believe that they were highly engaged and invested in the study, despite the fact that they were seeing simulated data. The high rate of survey return (99%) and the general enthusiasm for the idea of BGP, described in Section 5, is evidence of their engagement.

To simulate BG data, we determined a set of requirements that we thought would yield a realistic experience for the participants:

(1) **Granularity**: BG values should be generated every 5 minutes to reflect CGM measurement frequency.
(2) **Non-Extremes**: Extreme (low/high) BG values that reflect highly dangerous situations should be avoided. The target range is between 4.0 mmol/L and 10.0 mmol/L.
(3) **Value-Change Control**: BG level change must be natural, without extreme jumps, usually less than ± 1.0 mmol/L every 5-minute interval.
(4) **Insulin-Responsiveness**: BG values should respond to participants' actual insulin entries, considering individuals' insulin sensitivity.
(5) **Carbohydrate-Responsiveness**: BG values should respond to participants' actual carbohydrate entries, consider individuals' BG change for every gram of carbohydrates, and account for different meal absorption rates.

Our BG-simulation approach responds to carbohydrate entries by leveraging Loop's algorithm [68], calculating a linear carbohydrate effect. Also, to calculate the active insulin after a bolus is delivered we utilize an exponential decay curve, similar to Loop [68]. Please refer to Appendix B for more details.

3.4 Blood Glucose Prediction

In selecting the ML model used to generate BGP based on the simulated BG data, we identified requirements to ensure the model's quality and appropriateness for our app:

(1) **Model Compatibility**: The prediction model should have been trained on a large, accurate, and complete real-world data set of CGM data, insulin, and carbohydrate entries of individuals with T1D.
(2) **Prediction Horizon**: The prediction horizon must be at least one hour, with predicted intermediate values for every 10 minutes.
(3) **Instant Response**: Participants' actual insulin and carbohydrate entries should instantly affect the simulated BGP, with a prediction speed of less than 1 second to guarantee uninterrupted user flow.

The simulated BGP we used for this work is based on the model by Freiburghaus et al. [50]. The ML model matches all requirements, including CGM data, basal/bolus insulin, as well as meal/carbohydrate values. Freiburghaus et al. [50] trained the model on the OhioT1DM dataset, with 134'790 training examples from 12 individuals with T1D [77]. This dataset includes eight weeks of CGM entries collected every 5 minutes, bolus and basal insulin doses as delivered by their pumps, and self-reported meal entries[77]. Missing BG values were mitigated by a simple linear interpolation scheme.

3.5 Data Analysis

To analyze our survey and questionnaire data, we conducted a six-phase reflexive thematic analysis [20]. Being type 1 diabetic helped the first author relate to participants and supported our understanding of their experiences. However, due to subjectivity potentially resulting in some participants' statements resonating more with the

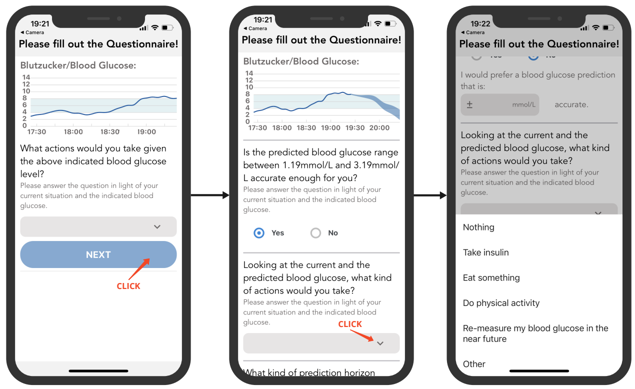


Figure 1: An extract of the ESM questionnaire (see Appendix A.3). On the left is a visualization of the past two hours of simulated BG values with a single select question on what actions they would take. In the middle is the same visualization but with a prediction one hour into the future, asking the same question about action. Additionally, there is a single select radio button question on prediction accuracy. On the right, options for what actions participants could take are shown.

first author, continuous self-challenging and reflecting on subjectivity with the other authors of this paper was an essential part of our analysis. The transcripts were coded and iteratively refined by the authors using a systematic inductive coding approach. Sub-themes relevant to BGPs were selected during the process. During theme and sub-theme development we focused on whether participants engaged in sensemaking and focused on the three essential activities 1) perception, 2) inference, and 3) action [76]. For the perception activity we focused on gaps in understanding resulting from BGP, and in particular gaps related to hypoglycemic and hyperglycemic BGPs. For the inference activity, we focused on participants' reactions to low and high simulated BGPs and what efforts they associated with including BGP in their self-management. For the action activity, we focused on how participants thought they would change their actions based on BGPs. This approach resulted in the four themes presented in our findings.

4 PROTOTYPE

To give participants exposure to BGP in a contextualized way that reflected potential real-world use of predictions, we created a T1D self-management app that incorporated BGP simulation. This section provides an overview of design choices and functionalities of the MOON-T1D prototype.

4.1 Design Process

The design targets for MOON-T1D were mainly based on a review of related literature and the analysis of existing apps for T1D management. Along these lines, we followed the principle of having an encompassing view of four main factors that influence decision-making, as desired by participants in a related study [37]. After the analysis of design targets, we conducted an iterative design process, including feedback rounds with visualization experts. Some of the refinement of MOON-T1D was also inspired by a professional visualization workshop on Dashboard Design Patterns [8].

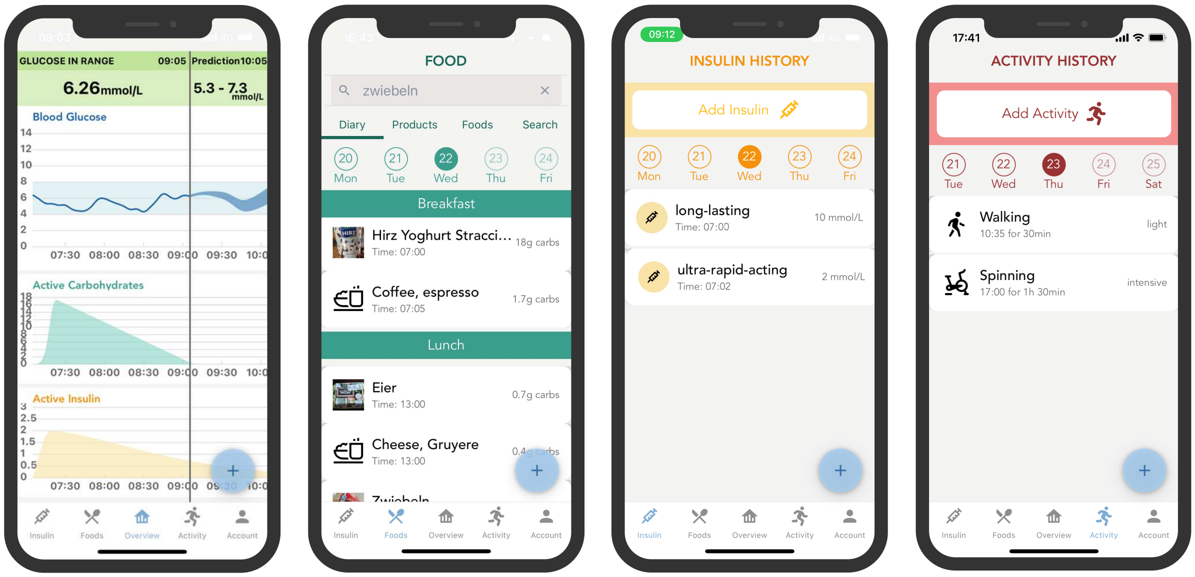
4.2 Components

As a general design principle, MOON-T1D always shows the *BG level* factor in blue, *active carbohydrates* (food) in green, *active insulin* in yellow, and the *activity history* in red. The four main components of MOON-T1D are presented in Figure 2. The *Overview* is centered around BG values, augmented and aligned with active carbohydrates and active insulin information. The three remaining components are *Meal Diary*, *Insulin History*, and *Activity History*, each of which allows for the entering and analysis of data. In these components, the addition of event data by users automatically triggers the re-calculation of associated factors, and updates the overview.

Overview. The Overview in Figure 2 (A) provides views for BG and two other factors (food, insulin) that influence decision-making. Because of the strong temporal dependencies between these factors, time is always mapped to an absolute x-axis and aligned with all factors in a juxtaposed way: the BG (upper part), active carbohydrates (center), and active insulin (lower part). In addition, all views feature a vertical gray line which corresponds to the current point in time. The display of previous values is common in current CGMs and helps users understand factors that influence the current state and its trajectory. The display of future values (i.e., predictions) can help users understand how their actions could affect their future state, potentially facilitating the prevention of hypoglycemia or hyperglycemia. Finally, users can switch between the mmol/L and mg/dL units to allow users to use the units that they are accustomed to for management.

In line with most CGMs, we show the current BG (6.26 mmol/L in the figure) and the predicted BG levels (5.3-7.3 mmol/L) as textual elements. Below, MOON-T1D shows a light blue band that represents the default BG target range (4.0 mmol/L-10.0 mmol/L) [5]. On the left of the current point in time, a blue line chart displays the simulated BG values (see Section 3.3). On the right, a blue area chart shows BGP [107] predicted by the ML model (see Section 3.4). Below, a green area chart represents the amount of active carbohydrates (in grams) remaining to be absorbed by the body. The yellow area chart represents how much active insulin remains to be absorbed by the body.

Meal Diary. The food/meal component of MOON-T1D, shown in Figure 2 (B), offers a meal diary to facilitate the assessment of active carbohydrates. We deliberately did not show any caloric values associated with the foods to avoid exacerbating or contributing to disordered eating behaviors associated with nutrition tracking [44]. MOON-T1D also allows users to add new meal entries to the diary using a search functionality for existing foods based on two food databases: Open Food Facts [83] and FoodData Central [1]. As an alternative approach, users can add a self-defined meal by specifying name, nutritional values, serving size, number of servings, time of consumption, and an estimate of how long it will take for the body to absorb the carbohydrates.



(A) (B) (C) (D)

Figure 2: The design of our prototype MOON-T1D used during the ESM study - A) Screen showing the Overview component. Simulated present and future BG in textual form at the top (e.g., present: 6.25 mmol/L, predicted: 5.3-7.3 mmol/L), below a BG line chart including a BGP area chart. In the middle an area chart of active carbohydrates and at the bottom an area chart of active carbohydrates B) Screen showing the Meal Diary component. Search bar to search for meals in the food database on top. Just below, a calendar where users can select which day to view. Below the calendar, a list of meal entries separated by meal type, including meal name, time of consumption, and number of carbohydrates consumed. C) Screen showing the Insulin History component. On top, a button for adding new insulin injections, followed by a calendar where users can select a day to view. Just below, a history of insulin injections, including insulin type, injection time, and units. D) Screen showing the Activity History component. On top, a button to add new activities, followed by a calendar enabling users to select which day they would like to view. below the calendar a history of activities performed, including information on activity type, duration, start time, and intensity.

Insulin History. Using the insulin history in Figure 2 (C) users have a record of their daily insulin injections with details on insulin type, number of units, and time of injection. When recording a new injection users can also specify the administration location.

Activity History. The activity history component in Figure 2 (D) allows users to view activities from the past two days. The activity history includes type, start time, duration, and intensity of the activity. Users provide this information when adding a new activity in MOON-T1D using the control at the top.

It is important to note that although MOON-T1D was designed with careful consideration of its features, content, and interaction, the primary purpose of our study was not to evaluate the app or its design. Rather, the app was intended primarily as a vehicle for the naturalistic delivery of simulated BGP via a T1D support tool such that we could gain insights on the potential role and impact of BGP in T1D self-management.

5 FINDINGS

Participants' responses to the simulated BGPs were overwhelmingly positive, and our study revealed myriad ways in which they wanted to make use of the predictions, and how they thought having BGP would affect various aspects of their T1D management. Based on the analysis of our ESM and interview data, we report on how participants wanted to integrate BGP into their actions, why they thought predictions would be particularly useful in these situations, and in what aspects of management they felt BGP would have the biggest impact. We subsequently discuss the four main themes we derived through reflexive thematic analysis [20] which point to critical considerations regarding the use of BGP for T1D management.

Participants filled out the ESM questionnaire 181 times in total (completion rate of 99%), an average of 12 times per person over the five days. Concerning the perceived usefulness of the simulated BGP, 178 responses were positive (98.3%), and only three were negative (1.7%). Two of the latter were due to the participants not seeing the BGP visualization, and one because of a mismatch between the simulated value and the participant's actual BG. Participants were enthusiastic about the idea of receiving BGP and integrating the information into their understanding and self-management, with P7 describing it as being "like a glimpse into the future" (P7).

Participants felt that BGP would influence their self-management in several ways: 1) guiding action "I can see it's level but light activity may mean I need to eat soon" (P5), 2) informing adjustments to one's behavior "it tells me that whatever I ate should be adjusted next time my [BG] gets too low to prevent spiking" (P11), 3) supporting better understanding of BG "it helps me to understand patterns in the rise and fall of glucose levels." (P11), 4) feeling reassured: "it allows me to keep gardening without any worries" (P7), and 5) avoiding undesirable situations (e.g., hypoglycemia): "I know even though I'm going low it will pick up." (P10).

During the interviews, participants highlighted specific situations in which they thought that taking action based on predictions could be particularly beneficial for self-management. The situation mentioned most frequently was when engaging in physical activity:

> "Yes, before physical activity would be great, since well my problem with physical activity is that I have to always eat a lot beforehand just to get through that activity at all." (P6)

Using predictions for planning was important to many participants:

> "I can plan better since I just know where it [BG] will go in the next few hours." (P13)

Similar to findings discussed in Stawarz et al. [103], participants thought BGP was especially useful in non-routine situations.

> "If you are home later than you normally would be, if you miss a meal, I think it [BGP] would be really useful for that." (P7)

This is in contrast to routine activity in which participants rely primarily on their own knowledge about their BG. Finally, participants thought that if their BG was in an ambiguous state predictions could help inform difficult decisions:

> "If [BG] goes up, then I ask myself, is it going up now because blood sugar has to go up after I eat, or did I inject incorrectly [too little]? For things like that, I would be very interested in a prediction." (P1)

5.1 Theme 1: Facilitating Everyday Activity and Management Choices

Participants expressed how T1D impacts every aspect of their lives, be it dealing with out-of-range BG values in public or adjusting diet and lifestyle to improve disease management, as has also been found previously [76]. Participants felt constrained in everyday life choices by T1D management and thought BGP could address or alleviate these constraints in certain situations.

Using BGP for Situations with Constraints to Management Practices. Participants expressed a desire for BGP in situations in which they are unable to view data needed for self-management decision-making. One prominent scenario in which participants felt BGP would be helpful was regarding sleep:

> "So I would always like to know in the evening before I go to sleep how [BG] will be when I get up in the morning." (P2)

> "If I had a prediction at 8:00 PM till midnight that told me, ohh by 11:30 you may be dropping. I would know ohh okay, maybe I need a snack before bed to kind of stop that happening."(P4)

Many participants mentioned fearing nocturnal hypoglycemia, as prolonged nocturnal hypoglycemia can result in seizures and, in rare cases, death [24].

Participants explained that BGP would be desirable for decision-making in situations in which they need to remove their insulin pump:

> "I anticipate my glucose level, especially before training [...] because I need to know if [BG] will go lower [...] Because yeah when I'm playing football, I need to disconnect my pump because I can damage the pump." (P14)

Similarly, participants wanted BGP in contexts in which they refrained from using their self-management devices for social reasons:

> "If I was like going into a meeting at work, for example, and [my BG was predicted to drop] I would probably have something sweet just to avoid the risk of having a hypo in the meeting." (P9)

Others refrained from using their devices to avoid making others uncomfortable:

> "It's hard as a teacher [...] I don't like to [measure BG] in front of my class because my students get a little freaked out about it." (P15)

O'Kane et al. [82] found previously that most individuals with T1D have at some point hidden their medical devices during social situations [82], pointing to the potential value of having access to predictions ahead of such situations.

Informing and Supporting Decisions. Participants thought that BGP could inform and support decision-making in everyday situations, particularly for preventing and accounting for out-of-range BG values. In taking action to avoid out-of-range BG values, some went as far as not going out due to the potential of out-of-range BG. Participants' thus felt that BGPs would empower them to engage in social activities without worrying about their BG levels:

> "It was just a worry and a fear, and you know I was always panicky because I didn't know if could go out with my friends and what would happen. [BGP] will show you that you can go out because you can see what your prediction of your [BG] is going to be – so it takes away a lot of stress." (P10)

Participants also believed that BGP would help them make choices about what and when to eat, particularly when BG was on the lower or higher side:

> "I think that's actually pretty cool [BGP] because you make a more precise decision about what you eat. And I think that especially when you're in the border regions of blood sugar, you make a more conscious decision to eat or drink." (P6)

Similarly, P9 believed that he would adjust his portion size if what he was planning to eat would send his BG out-of-range:

> "And if I knew beforehand that if I have two handfuls of sweets, it was going to send me to 21 [mmol/L] or

> something like that, then I'd probably just stop at the one handful." (P9)

Participants expressed how BGPs could also be reassuring when their BG was out of range, for example by indicating when it was expected to return to target range. P1 believed that when she was hyperglycemic, BGP could help prevent her from taking additional insulin prematurely, thus potentially avoiding hypoglycemia:

> "So I sometimes had very high values [...] then of course I would ask myself whether the blood sugar goes down in the next hour or in the next 4 hours. [...] But there I would have liked to know [BGP] whether it [BG] was already decreasing or if I should be patient because the insulin would start working in 1.5 hours, causing my blood sugar to drop completely [hypoglycemia] if I acted too rashly." (P1)

5.2 Theme 2: Trust and Control

Participants discussed how BGP may engender trust while still allowing them to feel in control of their condition. However, they also expressed thoughts about situations in which they might not trust BGP or how it could contribute to feelings of not being in control. P8 pointed out that predictions that contradict individual knowledge might lead them to disregard the prediction in self-management:

> "[On the topic of why she stopped using BGP] Like now I'm looking at the Loop app [which shows BGP]. It's telling me I'm going to be dropping to 2.7 [hypoglycemia] like I don't believe that's true. I haven't taken any insulin. I'm not doing anything." (P8)

However, many participants also expressed that they would trust BGP:

> "I wouldn't even think about whether that [BGP] would be trustworthy and I would rely on it 100%." (P2)

It should be noted that such a high level of trust may not always be desirable. For example, one participant stated:

> "A lot of the time I'll just take something [to eat] out with me when I walk in case of lower BG, but if I relied on this thing [BGP app] and I trusted the prediction and I knew that I wasn't going to have a hypo it would save me carrying a backpack around." (P9)

Such a decision goes against the medical recommendation that people with T1D have food or sugar tablets with them at all times in case of unexpected hypoglycemia.

Informing the Technology Engenders Trust. In situations in which participants doubted the correctness of the prediction, some mentioned that they would have liked to provide the system with more information to see if the BGP would align more closely with their BG expectations. P9 for example wanted to enter more detailed exercise information to improve the BGP simulation shown in our app:

> "I feel like I couldn't get the BGP [to be] accurate. Just because sometimes it would be a relaxed walk for 45 minutes, then other times would be like a bit more intense. But because there are only three categories [low, medium and intense exercise], like, it was hard to say [that to the app]." (P9)

Similarly, P1 mentioned that she would want to provide more details about her actions to receive more accurate predictions:

> "One thing I would add would be the possibility to give the app more information about times when you eat something but you do not inject any insulin, or if you do sports but do not turn off the pump, so the prediction would be better." (P1)

Participants also wanted to understand the quality of the predictions they received to help calibrate their trust in the predictions in general, and so they would know if they were providing sufficient input to generate good predictions:

> "[I would like if] I could actually see, [...] if I'm inputting everything correctly, see how close [accurately] the readings can predict." (P4)

Some participants also expressed a desire to improve the accuracy of the predictions by calibrating the predictions with their real BG:

> "Especially if there was the option to calibrate [BGP] with what ends up happening [with BG] so that way it can get an even better sense of accuracy [of BGPs]." (P11)

The notion of calibration in T1D management comes from CGM sensors that rely on users entering glucometer data to transform the sensor's signal to the patient's BG [31]. Patient-calibrated CGM devices give the patient a sense of control over the accuracy of the CGM they use [47]. Similarly, allowing individuals with T1D to calibrate BGP by using their glucometer data as feedback could help increase the accuracy of future predictions and engender trust.

Uncertainty Engenders Trust. When discussing how predictions were displayed, participants mentioned that they preferred visualizations that communicated a degree of uncertainty as they thought they would be less likely to be outright incorrect than visualizations that expressed BGP as a single value:

> "People might think [single value predictions are] inaccurate - more so than they really are and then people might judge [BGP] as not useful." (P11)
> "[single value predictions] look a little bit more definite [...] I don't know with a prediction if that's as good because it's not like 100% accurate." (P15)

On a similar note, when asked whether they would prefer to see a trend over time or a single point in time prediction, participants expressed a preference for trends:

> "I would probably focus too much on [a single point] and then if [my BG] was outside that [uncertainty] range then I'd kind of get frustrated. [If that happens] I probably see myself not needing to use it [BGP]." (P5)

5.3 Theme 3: Interplay of Emotions

Participants highlighted the importance of emotions in self-management and discussed how BGP could foster both negative and positive emotions. They also described and how these emotions could affect their self-management practices.

Addressing Negative Emotions. Participants frequently described experiencing negative emotions such as guilt, fear, and self-consciousness, and how BGP could foster or alleviate these emotions. P12 mentioned that she felt self-reproachful about eating choices that resulted in high BG:

> "And then it did send me too high, I was at 13 [mmol/L], and then I'm annoyed about the fact that I've eaten the raisins and didn't inject." (P12)

After using the simulated BGP in MOON-T1D, P12 mentioned the potential for BGP to help her deal with self-blame:

> "You know, so you've had something that's sweet and it instantly made your BG go high. But then you see that the projection is showing you that it's going to come back down to a normal range. I think that would make me less likely to be like ohh well, I'm just, you know, shit at this." (P12)

Some participants described how previous negative self-management experiences resulted in fear of future instances of these experiences, which in turn affected their self-management. For example, P9 described fearing hypoglycemia to the extent that he sometimes avoided taking insulin even when in hyperglycemia:

> "If my blood sugars are like say 14 or 15 [mmol/L], so generally quite high, [...], I'm not as keen to inject just because it increases my chance to hypos." (P9)

In some cases, fear of out-of-range BG values led participants' to avoid taking any insulin at all:

> "One time I just dropped all the way to like 3.3 [mmol/L], which is really low for me. So, um, it was pretty scary and it kind of made me wary of using my [insulin-] pens." (P11)

These examples mirror previous findings about the negative impact that fear of hypoglycemia can have on BG levels [18] and quality of life [87].

BGP could be highly valuable in addressing these fears. For example, after using the simulated BGP in MOON-T1D P11 described how predictions could reduce fear by allowing her to safely explore the potential outcomes of hypothetical actions:

> "[...] or add [insulin to the app] before I take it just to see where the prediction ends up at. So that way I can adjust it accordingly before I take those actions. I'd rather not learn from a mistake or learn after the fact that I shouldn't have done something." (P11)

Participants also mentioned ways in which BGP might be valuable for relieving negative emotions related to out-of-range BG values in general. P7, for example, thought that seeing BGP could help relieve stress after actions with potential negative effects on BG:

> "I think with the predictions that allow you just to think, OK, it's not a complete disaster. My level's gonna stay at this until I can get something to eat. So it would calm me down a little bit." (P7)

Although BGP has great potential for supporting T1D self-management, it should be noted that out-of-range predictions in particular may result in negative emotions and risky decisions. P1 described that out-of-range BGPs provided by MOON-T1D led her to feel stressed, even though she was aware that the predictions were based on simulated data:

> "Even though it wasn't my own BG level when it showed a not good value, that was stressful for me." (P1)

Careful consideration of how and when to convey information about out-of-range BG is necessary to minimize negative effects.

T1D Fatigue. Participants described fatigue-like states in which they knew what to do regarding self-management but could not execute these actions because of lack of energy or mental capacity, a phenomenon known as "diabetes fatigue" [51, 59]. P12 for example stated how she felt overwhelmed by having to take her menstrual cycle into account in self-management:

> "The amount [of insulin] that I'm being sort of given per hour massively varies especially because of the impact of my menstrual cycle as well. I know that I need to have different basal rates for different times of the month. But to be honest, I just don't have the mental capacity or time to figure that out at the minute." (P12)

After using MOON-T1D, P12 thought that BGP helped her engage with self-management more without feeling overwhelmed:

> "I think it [BGP] definitely helped me engage a bit more with my diabetes. As I said previously, I have been quite burnt out with it all and a bit lost. So you know engaging with it [BGP] kind of allowed me to bring that conscious attention to what I was doing, which I think was helpful." (P12)

Similarly, P10 described diabetes management as a constant battle:

> "I have dawn phenomena. So as soon as my feet hit the floor, my blood sugars rise. I'm then having fast-acting insulin, just to combat that rise. But by the time it comes to breakfast, I'm high, and my blood sugars continue to rise. And so then I'm battling all day trying to get my bloods in range. So it's a very trying time at the moment." (P10)

The dawn phenomenon affects approximately 54% of individuals with T1D and is an increased need for insulin in the morning that often leads to hyperglycemia [27]. After using MOON-T1D P10 thought that BGP could help her with the effects of the dawn phenomenon and reduce her stress:

> "I've got two toddlers and I can wake up in a hypo, and then if I over-treat that hypo I end up sleepy and tired and not fully with it. So for me to be able to see that yes so far now I'm going into a hypo but then I know in an hour it's telling me my bloods are going to reach 14 [mmol/L] just by waking up that will help me preempt that [hyperglycemia] and hopefully bring myself into a nice steady range." (P10)

While BGPs have the potential to reduce stress and negative emotions, it is important to consider whether BGP may also increase the cognitive load on individuals or exacerbate fatigue by providing more information to consider for decision-making.

Reassurance in Self-management. Participants brought up the potential for BGP to reassure them of their management practices and provide them with positive feedback. P10 mentioned that BGPs would serve this purpose:

> "It just gives you massive like reassurance in what you're doing with your body and your diabetes management and so for me, that was a big eye-opener." (P10)

The fact that people found value in seeing within-range predictions is particularly interesting as most studies focus primarily on the value of BGP in the context of hypo or hyperglycemia avoidance [33, 36]. Participants also felt that BGP could serve as a backup to their own understanding of their BG:

> "I think that is just about—when you have [T1D] for years, then you develop a gut feeling [of where your BG is]. But of course, it would be better to have something [BGP] that assures you what's what. So you won't make a mistake with this, and you can plan better." (P13)

5.4 Theme 4: Engagement and Support

Participants discussed how they would like to interact with and be supported by an app that shows BGPs. Some participants, for example, stated that seeing the BGP simulations would motivate them to pay more attention to diabetes management overall:

> "[BGP] was useful for me and a pleasant way to pay more attention to my diabetes." (P1)

Sometimes paying more attention to their diabetes management was situation-dependent, such as before physical activity:

> "I think it would definitely help me to probably care a little more. Maybe give a little more attention, especially before activity." (P8)

Proactive and Reactive Management Approaches. Our analysis revealed two distinct approaches to T1D self-management a proactive approach and a reactive approach. These different perspectives also affected how participants wanted to interact with BGP. The proactive approach is characterized by active checking of BG or BGP without any specific trigger for the interaction.

> "Yes, so I actively go to the app and look for information." (P1)
> "And what I do maybe once every hour is just scan and see where I am [BG-wise] in which direction it [BGP] goes compared to how I feel." (P2)

In contrast, a reactive approach entails participants engaging with their devices based on some prompt or signal. Some participants generally did not look at their BG unless the pump indicated an out-of-range BG:

> "Mostly it looks like me just going about my day-to-day business and checking my CGM information if I get a notification on my phone to tell me that I'm high or low, then I do whatever I need to do to treat that situation. Otherwise, that's it. I don't do a whole lot of stuff." (P8)

> "I mean I must really say that I only really look at it [BG] if it [pump] signals me." (P13)

In their current self-management practices participants varied in the extent to which they relied on proactive versus reactive management, with some relying mainly on one or the other. Reacting after the fact, for example to a signal indicating high BG, may be too late to prevent negative effects. BGP notifications could therefore be beneficial, particularly for people who rely primarily on reactive self-management by alerting the individual and triggering action early enough to prevent a dangerous state. One drawback of the reactive approach to self-management is that it may result in individuals having a less comprehensive picture of their condition. BGP's potential to support a good understanding of BG even if used in a reactive management approach was also discussed by our participants:

> "I think it would make me more self-aware and able to take into account what's going to happen rather than just wait for it to happen and then try to deal with it." (P11)

BGP Reminders, Notifications, and Suggestions. Our participants reflected on the potential benefits and drawbacks of BGP notifications, reminders, and suggestions in regard to self-management. Being reminded to interact with our app and view the simulated BGP by the ESM questionnaire was perceived as beneficial as it increased participants' engagement in their self-management:

> "I automatically became more intensively involved with it [diabetes]." (P2)

Some participants even wished for similar daily prompts to record their values and look at BGPs. P11 stated that receiving reminders to complete the ESM questionnaire led to her being more consistent about logging information and expressed a desire for similar reminders in the future:

> "I learned that I really don't pay enough attention to my blood sugar unless somebody is prompting me with surveys 3 times a day. So at least make a notification once in a while to remind me to keep up with logging everything." (P11)

CGMs already provide alarms to notify patients about out-of-range BG values; participants thought having similar alarms for out-of-range BGP would allow them to take preventative actions:

> "Especially if I had like a notification feature to say, hey, look, your glucose in the next three hours is going to be trending low or trending high." (P8)

Similarly, Reddy et al. [90] showed that CGMs that alerted users of out-of-range BG values led to a reduction in hypoglycemia and raised hypoglycemia awareness when compared to systems that did not [90]. BGPs also have the potential to help individuals with T1D take preemptive actions to avoid out-of-range BG values. Active notifications from technologies have been shown to be beneficial for supporting self-management. For example, Bentley and Tollmar [15] showed how prompts lead to increased logging activities by users.

However, participants also mentioned some negative effects of active notifications. In the context of BGP, participants reflected upon how certain an out-of-range prediction would need to be for them to appreciate notification and not be overwhelmed by it:

> "I wouldn't want it so often that it would be like, it would make me start ignoring it because I'd be sick of it." (P8)

Similarly, some participants mentioned disabling the aforementioned CGM notifications to sleep:

> "It beeped throughout the night and then I could not sleep." (P1)

Others cited the general frequency of out-of-range notifications or incorrect low BG notifications as reasons why they disabled them.

Participants also expressed a desire for concrete suggestions based on BGP and their current situation, rather than only showing the prediction:

> "It could say "oh you had less than six hours of sleep last night. Your insulin resistance might be up today" or I'm gonna go for a walk at 3 pm and it'll [app] say "Okay make sure that when you eat lunch at one do a little bit less insulin." I think I would find that useful for managing my diet and nutrition and exercise and diabetes overall." (P5)

While clear guidance in the form of suggestions may be desirable, good recommendations are dependent on the user consistently entering relevant information which requires effort. Our participants also mentioned the burden of logging and how outside of the study setting they would be less consistent:

> "The only problem with that [BGP] and the other apps I use is that I'm very inconsistent, like way more than I was with this [app] about logging the insulin I take and the food I eat." (P11)

Additionally, the individuality of the condition would require suggestions to be highly personalized, accounting for physical and emotional differences. For example, psychological factors such as fear of hypoglycemia might affect how a suggestion is perceived and what actions the individual takes in response.

Awareness and Contextualization. Participants try to contextualize BGP in their current situations and this act of contextualization raises their awareness about self-management practices. They expressed how seeing the simulated BGP and contextualizing the predicted value with factors such as insulin or carbohydrates helped them understand how those factors affected their BG levels in general:

> "I think it [BGP] makes you more aware of what you're eating, what you're drinking and how it can affect your [BG] levels." (P7)

They also felt that seeing predictions might help to improve their awareness of the impact of nutrition on their BG, and how much insulin to take in response:

> "Maybe to what extent the BG can change through the food - so I found it a bit easier to see; ah I might need a little more [insulin] or maybe a little less [insulin], simply because I had this prediction." (P13)

While heightened awareness of the factors that affect BG was desired by some participants, others believed that they may not need to rely as much on their understanding of the effects of food and insulin as BGP would be sufficient:

> "I sometimes have like a poor idea of how foods are going to affect me because I'm just not a nutritionist, but if I had a way to see a prediction of what they would do to me, I could determine whether I want to be in that state of health." (P11)

6 DISCUSSION

As BGP introduces new information to individuals with T1D, many aspects of our themes fit well with the sensemaking framework presented by Mamykina et al. [76]. Predictions of out-of-range values may yield gaps in understanding, especially if they are unexpected. In our findings, participants discussed how constructing explanations for out-of-range BGP could cause feelings of self-blame and self-consciousness. Participants thought that even simulated BGP helped them understand the effects of food and insulin on their BG levels, thus supporting the inference activity. However, it is important to note that if individuals rely on BGP to support decisions, this may reduce important self-reflection in the inference stage, as has been discussed previously by Mamykina et al. [70]. Finally, participants often discussed how BGP could help them take informed actions, such as eating less to avoid hyperglycemia.

6.1 Shifting Perception from Past- to Future-Focused Management

Participants mentioned that viewing the simulated BGP in the app instigated a shift towards a more future-oriented approach to self-management. Every participant expressed an intention to incorporate BGP into their decision-making process. However, we observed varying levels of emphasis placed on BGP when participants were making decisions. Some participants mentioned the value of incorporating past, present, and predicted future BG values into decision-making. Others, however, were primarily future-focused (i.e., expecting to rely mainly on BGP and their notifications). The use of BGP may cause a shift from a past- and present-focused management perspective to a more future-focused one.

The three different temporalities can provide users with different insights. Viewing past BG values enables patients to consider BG changes when making decisions, leading to more informed choices about background insulin dosing and mealtime control [63]. Seeing past and future BG provides users with information about what might influence their BG and thus BGP, engendering trust through increased understanding. Viewing current BG helps people assess their current state and immediate actions needed, e.g. correcting an out-of-range BG.

Although a future-focused perspective on BG management may be desirable for hypo- and hyperglycemia avoidance, it may introduce some drawbacks. Being overly fixated on one's predicted BG could result in unjustified negative emotions about T1D management. Some participants, for example, expressed feeling stressed about the simulation of a hypoglycemic BGP.

When designing technologies that provide BGP, it is important to consider individual differences in the perception of and degree of focus on predicted BG. People with a more future-oriented perspective may be more proactive about planning and thinking ahead, but might also miss crucial past information that could be relevant for decision-making. People who are less future-oriented in their management may profit less from BGPs, but may have a better grasp on basing management decisions on past and present BG. This spectrum of temporal focus could be addressed through design by personalizing how implicitly or explicitly the BGP is communicated. For example, a more implicit BGP notification might state, "Your BG is rising and could become too high in the next hour", while a more explicit notification might state, "Your BG is predicted to be between 11.0 - 13.0 mmol/L in one hour".

6.2 Personalizing the Delivery of BGP Design

In analyzing our findings, it became clear that people's T1D management practices and their responses to simulated BGP were idiosyncratic and varied greatly between participants. Our participants described individual preferences pertaining to interaction, engagement, and visualization for predictions. Our study also showed highly individual preferences of interaction, e.g., the frequency of reminders depending on whether people took a more reactive or proactive management approach. Participants' desire to inform BGP with their experiential knowledge highlights the importance of accounting for the very personal nature of T1D self-management exemplified by the comment from P1:

> "So whenever I go to the doctor, he also tells me that I am the expert when it comes to my diabetes. I mean, compared to the doctor, because you have it every day." (P1)

Other preferences that varied among participants pertained to the desired degree of control, degree of prediction uncertainty shown, and impact of emotions on information perception. These variations suggest that future technologies that incorporate BGP should be personalizable to address individual needs and preferences.

Several other studies investigating applications for T1D self-management have also highlighted the importance of personalization. Storni [104] for example, assessed designs of self-care technologies and found that personalization for diabetes management would be desirable to address conflicting practices and perspectives [104]. Chen [28] investigated the use of health information systems for diabetes management. They found that patients with diabetes had unique approaches to management, and suggested that system design should address individual differences [28], not currently applied in research on BGP [57]. Mamykina et al. [72, 73] investigated the use of MAHI to foster positive self-image in patients with diabetes, which was bound to their individual needs. Situational differences in diabetes self-management were discussed by O'Kane et al. [82]. They found that there were individual differences in technology use and concealment of its use in certain situations [82].

Personalization in the context of BGP has mostly focused on adapting algorithms to account for individual physiological differences [114]. However, most BGP approaches do not account for the range of factors affecting glycemic control [114], nor do they consider how BGP should be presented, based on the individual user. Our findings show that these two aspects of BGP are important areas for personalization. However, we believe that personalization of technologies for chronic disease management should be based not only on user preferences but on clinical guidelines to protect their safety, e.g., to prevent personalization of information display in a way that might exacerbate an eating disorder.

6.3 Mindful BGP Design

Analyzing the four themes, the need for the mindful design of BGP interactions, feedback, notifications, and information delivery was apparent. BGP design can have a positive or negative impact on participants' self-management practices, often driven by emotion. Participants frequently mentioned receiving feedback that felt negative, such as simulated out-of-range BGP or BGP notifications, and how the way in which the feedback was presented influenced their emotional state and self-management agency. In the context of new T1D technologies, specifically hybrid closed-loop systems, there has been an interest in evaluating their psychological effects including impact on quality of life, diabetes distress, and fear of hypoglycemia [45, 48, 49]

Emotions related to new information like BGP impact every stage of the sensemaking process. Participants discussed how additional cognitive load or lack of trust may lead to the dismissal of new information such as BGP, thus stopping the sensemaking process at the perception stage or considerably changing the progression through subsequent stages. BGP-associated emotions may affect what internal representations are activated, which in turn may affect the selection of the most plausible action, potentially in a negative fashion. Our participants for example discussed how hypoglycemic BGP may surface their fear of hypoglycemia.

T1D management places a high burden on individuals with T1D, with continuous confrontation with negative and positive feedback on BG control, e.g., conveyed via notifications [85]. While feedback is essential for T1D self-management, frequent negative feedback can be especially frustrating. BGP provides individuals with additional feedback about future BG values. Our participants discussed positive feedback, e.g. a within-range prediction, being reassuring, while negative feedback, e.g. an out-of-range prediction, causing emotional distress. Conveying negative feedback while keeping users engaged, has also been discussed by Katz et al. [60]. This may be particularly true for BGP, as the outcome has a variable degree of uncertainty associated. For example, should designers notify individuals with T1D about future hypoglycemia with 10% certainty or only if the prediction is 95% certain? Our participants emphasized that they did not desire notifications about out-of-range BGP that were not very certain, as it would cause them unnecessary stress and in some cases surface their fear of hypoglycemia. The need to find this balance between drawing participants' attention to negative information and not causing unnecessary stress was also highlighted by Katz et al. [60] and may be highly individual.

The influence of emotional response to negative feedback on T1D management is exemplified by diabetes distress and diabetes-related fatigue, or diabetes-fatigue syndrome. The term "diabetes distress" refers to the emotional burden, stressors, and frustration associated with managing diabetes [101, 108]. Diabetes distress has an estimated prevalence of $20 - 40\%$ in individuals with T1D [46, 105] is associated with elevated HbA1c levels [95], and has a significant impact on diabetes outcomes [86, 105]. Engaging in the sensemaking necessary for T1D management requires substantial effort, which may lead to diabetes burnout [86]. Our participants discussed the cognitive load of T1D self-management and how BGP could relieve or exacerbate that load. Our participants also discussed fatigue-like states and how BGP helped them engage and pay attention to their self-management without feeling overwhelmed.

To avoid inducing or exacerbating diabetes distress and diabetes fatigue, it is important to consider the additional cognitive load BGP could create, and how to design to minimize it. Understanding which aspects of BGP may alleviate diabetes distress and fatigue may also suggest future beneficial design directions.

6.4 Finding a Balance Between Human and Machine Control

The self-management approach we explore in this research combines ML-based simulated BGP with individuals' personal experience and knowledge. This raises questions about how control should be distributed between human and technology. For individuals with many years of experience managing the condition, trusting ML-based approaches over their own experience may be difficult. Participants found it difficult to trust predictions that did not align with their experiential knowledge, leading to them to want more control over the prediction.

In the sensemaking framework [76], BGP adds a new stream of information that individuals must reconcile with their existing experience to comprehend and trust. However, while Mamykina et al. [76] discuss trying to make sense of factual information such as an elevated BG measurement, it is important to recognize that BGPs, by nature, are predictions rather than facts. This means that trust plays an important role in sensemaking in the context of BGP. When there is a significant discrepancy between an individual's understanding and the prediction, the individual can either trust the BGP and try to understand what is lacking in their knowledge, or decide that the prediction is incorrect and not to be trusted. This can result in missed opportunities to understand T1D better or engage in preventative actions.

At this point in the sensemaking process, participants wanted the calculation of the BGP to reflect the activation of relevant experiences. Being able to to reconcile discrepancies through the integration of personal knowledge could help to engender trust and increase the feeling of control in AI-powered solutions. Activating past experiences is an integral part of sensemaking [76]. However, relying on one's memory to find similar past situations for decision-making may be prone to errors. A previous study revealed that diabetes educators are wary of reliance on experiential knowledge as it may be grounded in incorrect beliefs and misinformation [30]. For these reasons, systems that allow individuals to include their experiential knowledge while providing them with explanations of why a current situation (e.g., BGP) may differ from their previous experiences could be beneficial. Such a system could help individuals to understand and accept predictions that diverge from their expectations that they might otherwise discount.

Finding a balance that takes advantage of both human expertise and machine capabilities is thus also dependent on engendering an appropriate degree of trust in technology. However, it is also important to keep the limitations of technology in mind when designing to engender trust; technologies may not always be correct [26] and their ability to adapt in response to drastic change or novel situations may be limited [58].

7 LIMITATIONS

In reflecting upon our research, we identified some limitations that we address here. For the safety of our participants, we did not show them predictions based on their actual BG, as described in the Methods section. However, although we feel this was the best choice given the stage of the research and the privacy and safety of the participants, we acknowledge that the use of simulated BGP may have some effect on participants' perceptions and responses to BGP, compared to if they had been seeing predictions based on their actual BG. It should be noted though that our study pool of individuals with T1D have a high degree of investment in T1D management. This may make their data more reflective of real-world practice than, for example, generic participants recruited to complete a questionnaire. To limit the burden of manually logging meals, insulin, and activity, as well as answering the ESM questionnaires, we restricted our study duration to five days. Although we feel that this provided a valuable overview of participants' situational context, observing evolving needs and expectations of BGP in long-term use was beyond the scope of this study. We do however believe that it is important to understand short-term expectations and needs, as they may either foster or present barriers to the adoption of BGP in general. Finally, our participants were mostly from western European countries due to the recruiting strategies we employed. This may have an impact on our findings as models of care and degrees of T1D knowledge, support, and resources available for self-management differ by location. The role of additional social and societal factors, such as social stigma and lack of diabetes awareness [9, 23], also varies across the world.

8 CONCLUSION AND FUTURE WORK

BGP presents new opportunities to address the challenges of T1D self-management. However, with the complexity and personal nature of T1D self-management, having a clear understanding of the needs and expectations of individuals with T1D is essential for designing appropriate technologies. To investigate the needs and expectations of BGP for individuals with T1D, we conducted an ESM study using our BGP prototype, framed by two semi-structured interviews with 15 individuals with T1D. Based on our findings, we present four themes important to individuals with T1D in the context of BGP: 1) potential of BGP to overcome constraints, 2) balancing trust in BGP with one's experiential knowledge 3) emotional reactions to BGP and their impact on self-management practices, and 4) desired engagement depending on individuals' management approach. In light of our findings, we introduce broader cross-theme considerations for future decision support systems involving BGP, focusing on designing to 1) address a perspective shift from the past/present to the future, 2) consider individual differences in chronic disease self-management, 3) integrate BGP in a way that is mindful of emotional response, and 4) foster an appropriate level of trust by balancing control between human and machine. Our findings point to challenges and opportunities for the design of technologies to support the self-management of chronic conditions. To this end, our future research entails additional studies of BGP including the careful use of real-world BG data over a longer time period and analysis of their effects on health and self-management practices, exploration of different approaches to visualizing BGP, and the design of systems for T1D support that integrate BGP into self-management in novel ways.

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A INTERVIEW PROTOCOL

A.1 Demographic Questionnaire

(1) **What is your age?**
Input Type: Text input (ignorable)
(2) **With which gender do you identify most?**
Input Type: Single choice with optional text input
Input Options: female, male, non-binary, prefer to self describe [text input], prefer not to disclose
(3) **What time do you usually eat breakfast?**
Input Type: Text input
(4) **What time do you usually eat lunch?**
Input Type: Text input
(5) **What time do you usually eat dinner?**
Input Type: Text input
(6) **How many years have you lived with type1 diabetes?**
Input Type: I have lived [text input] years with type 1 diabetes.
(7) **What is your target blood glucose range?**
Input Type: My target blood glucose range is between [text input] and [text input]mmol/L
(8) **On average, what percentage of the time is your blood glucose within your target range?**
Input Type: My blood glucose is [text input]% of the time within my target range.
(9) **What is your insulin sensitivity factor?**
Input Type: my insulin sensitivity factor is [text input]mmol/L
Reason: To adjust MOON-T1D settings.
(10) **By how many units does one gram of carbohydrates raise your blood glucose?**
Input Type: When I eat 1 gram of carbohydrates my blood glucose will raise by [text input]mmol/L
Reason: To adjust MOON-T1D settings.
(11) **How do you usually take your insulin?**
Input Type: Single choice with optional text input
Input Options: Tethered insulin pump, patch insulin pump, Insulin pen, Insulin syringe, Other (please specify)[text input]
(12) **How do you measure your blood glucose level?**
Input Type: Single choice with optional text input
Input Options: Glucose meter(finger prick), Continuous glucose monitoring (CGM), Other (please specify)[text input]

A.2 Interview 1

(1) **What motivated you to participate in this study?**
(2) **Can you describe how you manage your diabetes on a daily basis?**
(3) **How happy are you with your current diabetic control?**
(4) **How knowledgeable do you feel regarding your diabetes self-management?**
(5) **How knowledgeable do you feel regarding nutrition related to diabetes management?**
(6) **How comfortable do you feel regarding nutritional estimations of food?**
(7) **What are techniques you use to manage your nutrition intake?**
(8) **What kind of diabetes-related technologies are you currently using?**
(9) **What kind of diabetes-related apps are you currently using?**
(10) **Are you content with the technologies that you are currently using?**
(11) **How much time do you think you currently spend on average per day taking care of diabetes-related activities?**
(12) **Do you feel like you have a good idea of how your blood glucose levels change throughout the day?**
(13) **Are there things you do to anticipate your blood glucose?**
(14) **Have you heard of blood glucose prediction, or even used an app supporting blood glucose prediction?**
(15) **Do you think blood glucose prediction could be useful for you?**

A.3 ESM-study questions

(1) **How do you feel physically right now?**
Input Type: Likert scale
Input Options: Selection from very bad (1) to excellent (5)
(2) **How do you feel emotionally right now?**
Input Type: Single choice with optional text input
Input Options: relaxed, energetic, happy, stressed, tired, down, sad, other (text input)
(3) **What are you doing right now?**
Input Type: text input
(4) **What actions would you take given the above-indicated blood glucose level? [see Figure 1 (left)]**
Explanation: Please answer the question in light of your current situation and the indicated blood glucose.
Input Type: Single choice with optional text input
Input Options: nothing, inject insulin, eat something, do physical activity, re-measure my blood glucose in the near future, other (text input)
(5) **Is the blood glucose prediction shown above useful to you?**

Explanation: Please answer the question in light of your current situation and the indicated blood glucose.
Input Type: Single choice with optional text input
Input Options: yes, no (follow-up question)
Follow-up question: Please explain your answer in a few words. (text input)

(6) **Is the predicted blood glucose range between [current blood glucose - 0.5] mmol/L and [current blood glucose + 0.5] mmol/L accurate enough for you? [see Figure 1 (center)]**
Explanation: Please answer the question in light of your current situation and the indicated blood glucose.
Input Type: Single choice with optional text input
Input Options: yes, no (follow-up question)
Follow-up question: I would prefer a blood glucose prediction that is: +/- [text input] accurate.

(7) **Looking at the current and the predicted blood glucose, what kind of actions would you take? [see Figure 1 (center)]**
Explanation: Please answer the question in light of your current situation and the indicated blood glucose.
Input Type: Single choice with optional text input
Input Options: Same as for question 4.

(8) **What kind of prediction horizon would you like right now?**
Explanation: Please answer the question in light of your current situation and the indicated blood glucose.
Input Type: Single choice with optional text input
Input Options: less than 30 minutes, 30 minutes, 1 hour, 2 hours, 3 hours, 4 hours, 5 or more hours

(9) **I feel like my answers were influenced by the following:**
Input Type: Multiple choice with optional text input
Input Options: the blood glucose is stable, the blood glucose is changing fast, the blood glucose is too low, the blood glucose is too high, sports activity, carbohydrate consumption, feeling uncomfortable, nothing in particular, other (text input)

A.4 Interview 2

(1) **What was your experience using MOON-T1D over the past few days?**
(2) **Did you learn anything new while using the app?**
(3) **Were you able to navigate and use the app easily?**
(4) **Which of the functionalities of the app did you think could be the most useful to you?**
(5) **How much time do you think you spend per day interacting with the app?**
(6) **Would you keep using the app as is, if possible?**
(7) **Could you click around the app for me and point out things that you liked or disliked about the app?**
(8) **What did you think about being able to see a prediction of your blood glucose?**
(9) **Did seeing the predictions change your perception of your blood glucose in any way?**
(10) **While using the app, did you feel there were times when you would have liked to see a prediction of your blood glucose more than others?**
(11) **You mentioned you would like to see a prediction before you do [answer to previous questions] - how far into the future would the prediction ideally be?**
(12) **When answering the ESM-study questionnaire, you entered that you wanted to have a prediction horizon [of, between]. Can you explain to me why you wanted [this particular, different] prediction horizon(s)?**

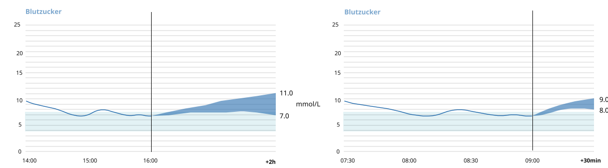

Figure 3: Participant preference for predictive glucose uncertainty visualizations. During the second interview, participants were presented with two options for predictive glucose uncertainty visualizations. Option A (left) displayed a prediction horizon of 2 hours with a range of 7.0-11.0 mmol/L meaning an accuracy of +/- 2 mmol/L. Option B (right) displayed a prediction horizon of 30 minutes with a tighter range of 8.0-9.0 mmol/L and thus a greater accuracy of +/- 0.5 mmol/L.

(13) **When filling out the ESM-study questionnaire, you said that an accuracy of +/-[their answer] mmol/L would be accurate enough for you - can you explain why?**
(14) **With blood glucose predictions, it is generally the case that the further into the future we try to predict, the greater the error we can expect. [Handing participants Figure 3] Therefore, on the left you can see a prediction horizon of 2 hours with a prediction between 7.0 mmol/L and 11.0 mmol/L, meaning +/- 2 mmol/L. On the right you can see a prediction horizon of 30 minutes into the future with a prediction between 8.0 mmol/L and 9.0 mmol/L, meaning +/- 0.5 mmol/L. Which of these 2 predictions would you prefer and makes more sense regarding your daily management?**
(15) **Until now, you have always received a prediction based on what you have entered. But now there is another way I could make blood glucose predictions for you, it is called "what if" predictions. I'll explain it to you best with an example. For example, "If I eat 2 [croissants] now, what would my blood glucose be versus if I eat one [croissant]?" If you had the option to have "what if" predictions - would you prefer them?**
(16) **Did you like the design of the prediction?**

B ALGORITHMS

This Appendix describes the algorithms that we used to create the BG and BGP simulation. First, we describe how we modeled the absorption of carbohydrates and insulin by the body. It's necessary to understand this description to understand the following algorithm on how we simulated BG values for our participants. All implementations are based on the algorithms by the DIY artificial pancreas algorithms of Loop [68].

B.1 Modelling Carbohydrate Absorption

While carbohydrates raise BG levels, the speed and degree to which they get absorbed by users is highly variable. Since carbohydrate absorption is variable and user-dependent, we allow users to input how long they think it will take for the carbohydrates to be absorbed. Users can select between fast, medium, and slow absorption. The time for fast (60min), medium (120min), and slow absorption (360min) in keeping with Loop [68]. Taking a more conservative approach, we extended the absorption time entered by users by 50% following the suggestions from Loop [68]. Thus, the minimum absorption rate (MAR) is calculated using the following formula:

$$MAR = \frac{CHO}{1.5 \times d} \tag{1}$$

where d is the absorption time in hours entered by the user and CHO is the number of carbohydrates in grams, also entered by the users.

B.2 Modelling Insulin Absorption

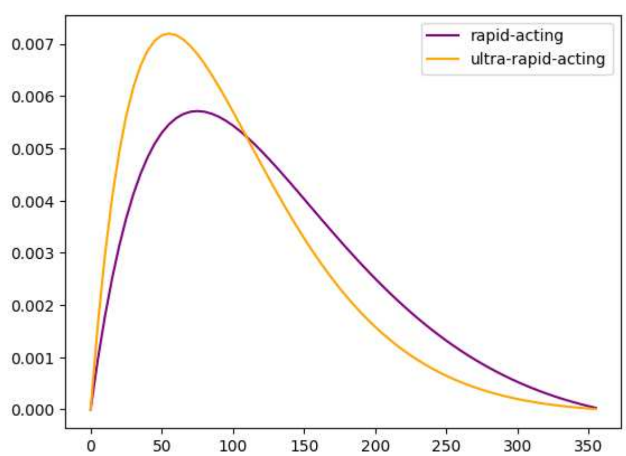

Figure 4: Exponential insulin activity curve (Ia_t) for ultra-rapid-acting insulin (orange) with a peak active time of 55 minutes, and rapid-acting insulin (violet) with a peak active time of 75 minutes, both have an action duration of 360 minutes

We used the algorithm of Loop [68] to model the amount of active insulin left in the body. Active insulin is modeled as an exponential insulin curve with two user-adjustable inputs: 1) the insulin peak time (PT) and 2) the duration of insulin action (DIA). The default value for PT is 55 minutes for ultra-rapid-acting insulin (e.g. Fiasp) and 75 minutes for rapid-acting insulin (e.g. Novorapid), in line with [68]. The default value for DIA is 6 hours. The exponential insulin activity curve Ia_t (Figure 4) uses the following algorithm:

$$Ia_t = \frac{S}{\tau^2} \cdot td \cdot \left(\frac{1 - td}{DIA} \cdot e^{\frac{-td}{\tau}}\right) \tag{2}$$

PT is the insulin peak time in minutes after giving the dose (55 minutes for Fiasp).
DIA is the total action duration of insulin activity in minutes (360 minutes for both Fiasp and Novorapid).
$\tau = \frac{PT \cdot (1 - \frac{PT}{DIA})}{(1 - \frac{2 \cdot PT}{DIA})}$; the time constant of exponential decay in minutes.
$a = \frac{2 \cdot \tau}{DIA}$; the rise time factor in minutes.
$S = (1 - a + (1 + a) \cdot e^{\frac{-DIA}{\tau}})^{-1}$; the auxiliary scale factor.
$td = t - t_0$; the number of minutes passed since insulin injection.

Following from the insulin activity curve, the percentage of insulin remaining in the body at time t (also called the Insulin On Board; IOB) can be derived as follows:

$$IOB_t = 1 - S \cdot (1 - a) \cdot \left(\left(\frac{td^2}{\tau \cdot DIA \cdot (1 - a)} - \frac{td}{\tau} - 1\right) \cdot e^{\frac{-td}{\tau}} + 1\right) \tag{3}$$

Multiplying the IOB at time t with the insulin injected at time t_0 results in the units of insulin remaining in the body.

B.3 Blood Glucose Simulation

To generate random but reasonable blood glucose values taking into account carbohydrate consumption and insulin delivery the algorithm needs to adapt to four different states; 1) only the current blood glucose data is considered 2) the user consumed carbohydrates 3) the user injected insulin and 4) the user injected insulin and consumed carbohydrates. A description of key requirements can be found in Section 3.3.

State 1 - Default. To create the default BG simulation algorithm, we decided to use a normal distribution. The semi-random BG level was constructed as follows: Addressing the requirement that the BG value change from time t to time t+1 must be reasonable, we created a truncated normal distribution with the current blood glucose as the mean (μ) of the distribution and a standard deviation of $\sigma = 0.5$ as well as a lower and upper bound of the current value +/- 1.0 mmol/L. We chose a value of +/- 1 mmol/L based on comparing the highest rate of change used for visualizations by different CGM manufacturers, which was between 0.1 and 0.2 mmol/L per minute [62]. As we are generating a new BG value every 5 minutes, we decided to use +/- 1 mmol/L. For example, if the previous blood glucose value was $BG_{t-1} = 7.0$ mmol/L then the next blood glucose value will lie between $BG_t \subseteq [6.0, 8.0]$ mmol/L. The distribution of likelihood for the next value to be between [6.0, 8.0] mmol/L is depicted in Figure 5. To address too high values, we implemented an overall upper threshold of 25.0 mmol/L. If a value is generated that is above 25.0 mmol/L then the upper bound of the distribution is set to be equal to the mean (μ), only allowing for smaller values to be generated. Additionally, if the current value was above 25 mmol/L we set the lower bound of that distribution to be $25.0 - 3 = 22$ mmol/L. The same concept is applied to address too low blood glucose values. If a generated blood glucose value falls below 2.0 mmol/L the lower bound is set to be equal to the mean (μ) of the distribution.

State 2 – Carbohydrate Consumption. The second state the algorithm can be in is if the user consumed carbohydrates without injecting insulin, only raising BG levels. To account for the effect

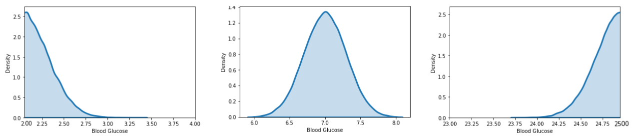

Figure 5: Probability of the next blood glucose value. The x-axis depicts the blood glucose value, while the y-axis depicts the probability for each value to be sampled. In the middle, there is the truncated normal probability with a mean μ of 7.0 mmol/L, standard deviation σ of 0.5 mmol/L, a lower bound of $7 - 1 = 6$ mmol/L, and an upper bound of $7 + 1 = 8$ mmol/L. On the left is the case depicted that the previous blood glucose value was below 2.0 mmol/L. While σ stays the same (0.5 mmol/L), the lower bound and μ are set to the same value (2 mmol/L) while the upper bound is set a bit higher, namely to 4.0 mmol/L. On the right is the probability of the next blood glucose value if the previous blood glucose value was above 25.0 mmol/L. The upper bound of the distribution is set to equal its mean (25 mmol/L) while the lower bound is decreased to 23.0 mmol/L.

carbohydrate consumption has on the BG level, the mean (μ_{t+1}) used for generating the normal distribution to determine the BG value at time t+1 is adapted according to the following formula:

$$\mu_{t+1} = BG_t + (\sum_{i=1}^{n}(COB_{(t+1)i} - COB_{(t)i}) \cdot CBGR) \tag{4}$$

where $COB(t)$ are the carbohydrates on board at time t (see Appendix B.1) and $CBGR$ (Carbohydrate Blood Glucose Raise), represents how much the blood glucose is raised by one gram of carbohydrates consumed. This value is individually different and was asked during the demographic questionnaire in Appendix A.1. Additionally, we increase the upper bound of our truncated normal distribution by 0.25 mmol/L to allow for a more rapid blood glucose raise.

State 3 – Insulin Injection. The third state the algorithm can be in is if the user injected insulin without consuming carbohydrates, only lowering the Bg levels. The following formula is used to account for the decrease in blood glucose:

$$\mu_{t+1} = BG_t - (\sum_{i=1}^{n}(IA_{(t+1)i} - IA_{(t)i}) \cdot ISF) \tag{5}$$

where $IA(t)$ represents the remaining insulin in the body at time t (see Section B.2) and ISF is the insulin sensitivity factor that represents how much the BG falls after injecting one unit of insulin. ISF was individually different for each participant and was determined in the demographic questionnaire (see Appendix A.1) Also, the lower bound of the truncated normal distribution is decreased by 0.25 mmol/L, to allow for a faster fall of BG levels.

State 4 – Insulin and Carbohydrates. To address if there is insulin and carbohydrates actively absorbed in the body, we chose to combine the above two approaches leading to a proportional increase or decrease of the BG depending on the effect of the amount of carbohydrates and amount of insulin being absorbed.

$$\begin{aligned}\mu_{t+1} =& BG_t + (\sum_{i=1}^{n}(COB_{(t+1)i} - COB_{(t)i}) \cdot CBGR) \\ &- (\sum_{i=1}^{n}(IA_{(t+1)i} - IA_{(t)i}) \cdot ISF)\end{aligned} \tag{6}$$

The lower and upper bounds are both raised by 0.25 mmol/L to account for the increased uncertainty usually associated with carbohydrate consumption and insulin administration.