Towards Precision Behavioral Medicine with IoT: Iterative Design and Optimization of a Self-Management Tool for Type 1 Diabetes

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***Abstract*—*Internet of Things* (IoT) technologies are revolutionizing healthcare, providing many so-called "smart health" opportunities, ranging from remote monitoring of health statistics to self-management of chronic conditions. This paper describes an IoT-based approach to the management intervention of type 1 diabetes (T1D), which is a major chronic disease with significant economic and social impact worldwide. Specifically, we focus on the structure, functionality, and development process of MyDay, which is an IoT-based, multi-faceted self-management problem solving tool for pediatric T1D patients. By leveraging IoT technologies, MyDay can connect with various devices to integrate traditionally paper-documented physiological data (*e.g.*, blood glucose values) in real-time with psychosocial and contextual data, such as mood, stress, and social activities. By integrating relevant—but heterogeneous—data sources, MyDay can create personalized feedback for self-awareness of factors associated with diabetes self-management patterns and promote data sharing and problem solving.**

Iterative user-centered design cycles were used throughout the development of MyDay to document and/or troubleshoot feasibility and technical stability, optimize feedback for effective health communication through data visualization, identify barriers to app use, optimize assessment, and evaluate capability of the app as a problem solving tool. Each iterative design round identified technical and design issues that were addressed in subsequent rounds by incorporating user input and expertise. An in-vivo case study and one-month pilot study of the system indicated high feasibility and use of our IoT-based MyDay tool.

***Index Terms*—Type 1 diabetes; ecological momentary assessment; user-centered; iterative design; feedback; data visualization; mHealth; IoT in healthcare**

I. Introduction

Emerging trends in IoT-based healthcare. *Internet of Things* (IoT) technologies are enabling interworking between computing devices embedded in everyday objects (such as smartphones, wearables, and sensors) with themselves and humans over the Internet to achieve useful objectives, such as improving traffic control, monitoring food safety, and evaluating allergic reactions to new medications [1], [2]. IoT technologies are increasingly applied in domains like smart cities, supply chains, and healthcare [2] to enable better decision making and to enhance safety and productivity. For example, IoT is driving the evolution of healthcare, providing many smart health opportunities from remote health statistics monitoring to chronic condition self-management [1], [3].

As personal mobile and wearable devices, as well as smart sensors (such as motion sensors for activity tracking and implantable biosensors for chronic disease monitoring [4]) become ubiquitous and adopted in healthcare, data related to an individual's health status (such as heart rate, step counts, eating patterns, and psychosocial behavior) is more accessible than ever in the form of IoT-based apps [3]. When these apps are integrated with cloud computing services, they can amass heterogeneous data for analyses and communicate insights gleaned from the analytic results back to end users, such as patients and healthcare professionals. As a result, IoT-based healthcare apps provide insight into treatment options specific to an individual or a cohort with similar traits, leading to lower cost of care and improved chronic disease self-management.

Our focus → IoT-based type 1 diabetes self-management. Type 1 diabetes (T1D) is a chronic disease with worldwide impact, *e.g.*, annual costs associated with T1D are over $14 billion [5]. In the US, T1D affects over 1.25 million people, including ~200,000 children and adolescents younger than age 20 [6]. By 2050, T1D diagnoses are projected to triple, with ~600,000 youth cases [7].

Patients with T1D must perform many self-management tasks several times a day to avoid or delay complications. Despite extensive (and costly) healthcare efforts, less than one-third of T1D patients achieve target blood glucose control levels, which are essential in reducing the risk of diabetes complications, such as hyperglycemia and kidney disease [8]. As a consequence, T1D patients incur an estimated loss of life-expectancy of up to 13 years [9].

Driven by the advent of IoT in healthcare, researchers have explored various applications of smart devices in T1D management intervention, such as subcutaneous sensors for continuous glucose monitoring [10], [11], mobile devices for self-management gamification and education [12], [13], wearables for physical activity tracking [14], [15], and Bluetooth devices for cheaper data transmission [16], [17]. Existing research, however, mainly focuses on monitoring physiological characteristics (such as blood glucose and HbA1c values) that are directly associated with T1D. In contrast, little research focuses on non-physiological traits, such as psychosocial behavior and contextual factors, that may also be relevant in identifying T1D self-management phenotypes.

Our prior work on T1D [18]–[20] suggests the importance of studying non-physiological traits, especially in a young population with T1D, which is at high risk of inadequate adherence to their diabetes regime and is also susceptible to negative emotions, *e.g.*, from difficulties in coping with society and interacting with peers, which could result in blood glucose excursions [21]. Due to the relatively broad adoption of IoT-based devices by this population, however, a promising approach is to leverage IoT technologies to create a system that targets the needs of this particular patient group.

Our contribution → the MyDay IoT-based self-management problem solving app. IoT-based devices (such as Bluetooth-enabled glucose meters) have become common in T1D management protocols. Key challenges remain, however, with respect to (1) integrating real-time physiological data (*e.g.*, blood glucose) with behavior data and (2) communicating behavioral patterns to young diabetic patients in a manner that integrates sensibly and seamlessly with their usage of IoT-based devices. To address these challenges, we developed MyDay [22], [23], an IoT-based self-management problem solving mobile tool designed to provide personalized behavioral treatments (*e.g.*, a just-in-time adaptive reminder for insulin administration) for adolescents with T1D.

As shown in Figure 1, MyDay connects human expertise with smart devices, creating a user-centered system for adolescents with T1D. In particular, by combining IoT communication protocols, Bluetooth BG meters, and mobile device software/hardware components, MyDay integrates real-time BG values, psychosocial (*e.g.* mood and stress) and contextual (*e.g.* location) data that may be relevant in identifying self-care phenotypes. MyDay also creates personalized feedback for self-awareness data sharing and problem solving regarding (1) patterns of T1D self-management and (2) how those patterns relate to different aspects of adolescents' daily experiences.

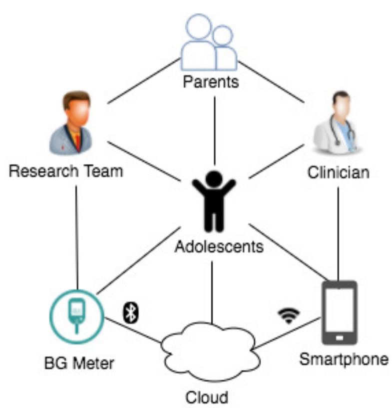

Fig. 1. Integrating IoT Concepts, Technologies, and Human Expertise to Create a User-Centered Self-Management App for Adolescents with T1D

The MyDay app was written in Java for Android and Objective-C for iOS. The MyDay server was written in Ruby On Rails (v4.1) with a firewall-protected PostgreSQL database backend, a web interface for managing users and content, and an API for serving requests to users' mobile devices. To collect blood glucose data, each mobile device was paired with an iHealth's BG5 Bluetooth Low-Energy glucometer [16] via a short-range Bluetooth connection and the meter's accompanying app. The MyDay server used iHealth's open API to communicate with iHealth's secure cloud data storage, thereby automating the data collection process as new BG measurements were collected in real-time. All communications were handled through secure SSL communications with mobile connections managed with temporary authorization tokens.

Paper organization. The remainder of this paper is organized as follows: Section II provides background information on T1D and IoT-based related research; Section III describes the user-centered development process of MyDay that incorporates human expertise into technical decisions; Section IV discusses key design considerations and technical challenges faced, focusing on data collection and integration with IoT-based devices and personalized feedback; Section V examines the design and results from a case study that systematically documented user experience with MyDay; Section VI summarizes the results and feedback from a pilot study that applied MyDay to 31 participants over a one-month period; and Section VII presents lessons learned, clinical implications, and future work from our research and application of MyDay.

II. Background and Related Research

This section provides an overview of T1D and discusses three important aspect to T1D: barriers to maintaining treatment adherence, the importance of problem solving skills for adolescents with T1D, and the ecological momentary assessment data collection method. Related work on applying IoT technologies in T1D research is also discussed and compared with our work on MyDay.

A. Overview of Type 1 Diabetes

T1D is an autoimmune disease where the body produces little or no insulin, necessitating multiple daily injections of insulin or insulin pump therapy for survival. A key issue for individuals with T1D is glycemic control, where T1D patients monitor their blood glucose (BG) levels multiple times per day using BG meters and (less frequently) with the addition of continuous glucose monitoring devices. A 2-3-month average of glycosylated hemoglobin is assessed in clinics via the HbA1c test, which is indicative of overall BG control. In-target glycemic control is critical in delaying or avoiding complications, both short-term (*e.g.*, hypo- or hyperglycemia, diabetic ketoacidosis) and long-term (*e.g.*, retinopathy, kidney disease, neuropathy, cardiovascular disease) [8].

In addition to monitoring BG, other related tasks performed daily by individuals with T1D include counting carbohydrates and insulin self-dosing and administration. Support of self-management behaviors that increase in-target BG values is especially important in adolescents with T1D. These behaviors are important not only because of the long-term health impacts of inadequate glycemic control, but also because this population is at high risk of struggling with adherence to their diabetes treatment regimen [24].

Barriers to adherence. Diabetes adherence is hard due to the frequency and complexity of self-management, *e.g.*, tasks must be performed around meals, snacks, and exercise. Psychosocial and environmental factors, such as location, emotional state, social context, and other activities, can thwart diabetes treatment adherence. Moreover, disrupted self-management may be associated with daily living patterns, such as time pressures during certain times of day, social context, or specific activities like sports practice [19]. Adolescents with T1D are also susceptible to negative emotions and difficulties in dealing with society and interacting with others, which could also result in poorly controlled symptoms [21].

Importance of problem solving skills. Problem solving interventions have shown success in helping adolescents with T1D improve their self-management practices and health outcomes through reducing barriers to adherence [18], [19]. Successful problem solving is predicated upon accurately identifying those barriers and patterns of behavior. Based on previous research [18], [25]–[27], improved recognition of how self-management is related to situational, contextual, and psychosocial factors should provide a data-based means to address the first step in problem solving, known as problem orientation, problem identification, and/or problem awareness.

By guiding pattern recognition and problem awareness, MyDay was designed to improve diabetes self-management skills. In particular, it provides IoT-enabled personalized real-time feedback and behavioral problem solving support. Behavioral pattern recognition and problem awareness are cognitively hard for adolescents due to their normative developmental stage of higher-order executive functions, the multifactorial nature of causation, and the repetitiveness of self-management.

Ecological Momentary Assessment (EMA). EMA is a method for providing more accurate problem solving data by systematically studying an individual in (or near) real-time to assess and relate the individual's experiences and environment to health behaviors and outcomes [28]. EMA helps identify novel behavior patterns through data collection at either random or specified critical points over time [20], [28]–[30]. By collecting assessments close in time or at the time of events of interest, EMA helps minimize response bias that may otherwise occur using retrospective methods [28].

Given the pervasiveness of smartphone adoption in adolescents and emerging adults, momentary assessment can be feasibly implemented via mobile and wireless technologies and then streamed to researchers. Adolescents with T1D perform virtually all their self-management practices outside of a medical setting (*e.g.*, they are expected to check their BG, count carbohydrates, and dose insulin while at home, school, or out with friends). To discern and address factors interfering with appropriate diabetes self-management, potential barriers must be identified where and when they occur. EMA is an ideal tool for studying the interaction between person variables and the natural environment of health behaviors [31] and has been successfully used to study diseases like asthma, cancer, eating disorders, and diabetes [32]–[35].

B. Related Work

A number of other studies that have applied IoT technologies in T1D intervention research are described below and compared with our work on MyDay.

IoT-based clinical interventions. Many efforts have been associated with clinical interventions that study the effect of therapy and overall patient lifestyle on glucose metabolism. Philip et al. [11] surveyed various types of sensors used in real-time continuous glucose monitoring (RT-CGM) in youth with T1D across different clinical studies. They observed that RT-CGM can potentially help patients improve in metabolic control of T1D, provided that adequate education and support is provided on sensor therapy and the devices used.

Biester et al. [36] proposed the use of SmartGuard technology in a sensor-augmented insulin pump to trigger an automatic stop of insulin delivery based on predicted low glucose levels. Their study documented reduced risk for hypoglycemia in pediatric patients without increasing HbA1c. Patients must be educated, however, against extra carbohydrate intake in response to an alarm associated with low BG prediction to avoid rebound hyperglycemia.

Prototype portable artificial pancreas (AP) [37], [38] have been developed using glucose sensors, insulin pumps, and radio-Bluetooth connections. Advanced AP systems, such as presented by Kovatchev et al. [39], integrated smartphones with a wireless network for data transmission and remote monitoring. Short-term clinical studies of these systems suggest safety of use in adolescents with T1D, but longer-term studies are needed to monitor their functionality comprehensively.

IoT-based self-management improvement. Another category of related research focuses on health monitoring systems to provide patients with effective means for tracking and displaying important T1D self-management variables, such as BG, food intake, and physical activity, as seen in [40]–[42]. Recent work has involved more personalized approaches, such as individually-tailored notifications and educational support. For example, Li et. al. [43] proposed a predictive model by capturing patient similarities of pooled population data to personalize blood glucose prediction for an individual. Using a mobile-based approach, they collected pertinent daily events, including insulin, meals, exercise, and sleep, and implemented the proposed prediction model as a prototype mobile application to create personalized notifications.

Boulos et al. [12] presented a class of digital intervention in diabetes that gamifies disease management using the Internet together with mobile and tablet devices. Digital games utilize social cognitive theory to increase healthy behaviors and psychological outcomes, promoting better self-care.

The following three aspects distinguish our research on MyDay from prior work described above:

- MyDay does not rely on continuous glucose sensors, which are not widely used by adolescents with T1D.
- MyDay is the first to collect and integrate Bluetooth-transmitted BG data with other relevant health and behavioral data from young people with T1D all in real-time

and provide personalized feedback based on individual BG patterns, psychosocial, and contextual settings.

- MyDay engages health communications via insightful and graphical feedback to help adolescents with problem solving and improve T1D self-management.

III. Iterative Design Process for the MyDay IoT-based App

This section describes MyDay's user-centric design cycles to provide a detailed workflow of how to connect IoT technologies with humans in an actual clinical study setting. This workflow actively engages human intelligence by incorporating feedback, suggestions, and observations (*e.g.*, what worked or did not work in each cycle) from our multi-disciplinary research team, adolescent participants, and parents into the subsequent cycle. Our research team consisted of experts in pediatric psychology, pediatric endocrinology, health communication, biomedical informatics, childrens media, and computer science, collaborating to create the initial specifications for the tool, select feasible IoT-based devices to use, prioritize and incorporate adolescent feedback.

Table I outlines the five design cycles, each providing technical and behavioral support and feedback subsequently incorporated into the MyDay design iteration.

TABLE I
Overview of Five MyDay Design Cycles.

Design Cycle	Goal	Feedback Obtained from
1	Conduct rapid design feedback iterations on paper before development on mobile devices	Research team
2	Obtain feedback on the assessment items, response options, and feedback graphics before database and API development	Adolescent participants
3	Obtain feedback on usability, comprehension of the intent of the questions, engagement, and suggestions for how to improve	Adolescent participants
4	Obtain feedback on experiences using the app and an infographic-style feedback summary of data	Adolescent participants
5	Test on-demand real-time visual feedback that integrated BG and psychosocial-behavioral-contextual data	Research team

A. Design Iteration 1: Concept Study

During the initial concept study of MyDay for use on mobile devices, the team conducted several design iterations that were reviewed by the research team, who suggested changes to the app. Mock-ups of the main data entry home page and examples of assessment questions are shown in Figure 2. Several feedback graphics were explored to integrate many influences or factors simultaneously. Complex graphics were deemed as too complicated and replaced with simpler and more intuitive feedback graphics to enable rapid understanding of the depicted relationships.

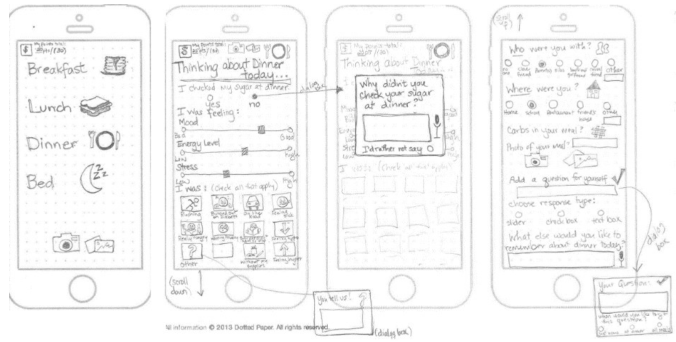

Fig. 2. Initial Data Entry Screen Design of the MyDay App

Few assessments of psychosocial constructs have been validated for EMA. Self-reported psychosocial assessment instruments are often multifactorial and include a number of items that would be burdensome within a momentary assessment. Assessment items, however, were crafted based on previous validated approaches to the extent possible. For example, mood was assessed using the validated two-dimensional valence (negative/positive) and arousal (high/low) [44].

B. Design Iteration 2: A Working Prototype

Before committing time and resources on the software and database, the general format for the assessment, response options, and feedback graphics were tested with adolescents using wireframes, which are visual guides that depict the skeletal framework of an app and/or website. A group of six adolescents (67% male; Age (years): M = 15.0, SD = 1.1; HbA1c not obtained for this sample) were recruited within a pediatric diabetes clinic. Depending on which mobile platform teens typically used, they were shown an iOS- or Android-version of the assessments, as shown in Figure 3.

Each teen was then led through a semi-structured interview about the overall interface design, item language, types of feedback and data visualizations they would like, app data sharing (how and with whom), and their perceptions of how they could use the data to solve diabetes-related problems. Their feedback was incorporated into the design and used to create functional prototypes of the MyDay app.

C. Design Iteration 3: In Vivo Testing Round 1

The first functional version of MyDay was tested by four adolescents (50% male; Age (years): M = 15.5, SD = 1.7; HbA1c: M = 8.0%, SD = 2.9%) recruited from the pediatric diabetes clinic described above via clinician referral and interest cards. Each adolescent was given a Fitbit wearable activity tracker [45] to place around their wrist to measure daily physical activity. The goal was to link their activity patterns to BG changes and self-management behaviors via Bluetooth, but these activity tracker data were not integrated into the MyDay system due to concerns regarding feasibility of wearable tracker use, as described in Section IV-A.

Research staff met with each adolescent to help them install MyDay. They initially used the adolescent's Unique Device Identifier (a device-specific 40-character value) to create an installation link. During subsequent rounds of testing, iPhone and Android users could install MyDay via their respective app stores. Participants were then shown how to use the app and after a usage period of 8-9 days participants discussed their experiences using the app with research staff.

Data from this round of *in vivo* testing were primarily qualitative; while the responses entered for each of the four daily EMA entries were recorded, the main interests in this round of feedback were (1) MyDay's usability, (2) comprehension of the content, (3) understanding feedback, (4) engagement with the app, and (5) suggestions for improvement of the app. Modifications from the first round of prototype testing were implemented rapidly so a new round of field testing could begin as soon as possible.

D. Design Iteration 4: In Vivo Testing Round 2

For this next iteration, eight adolescents (50% male; Age (years): M = 15.3, SD = 1.7; HbA1c: M = 9.6%, SD = 3.2%) were recruited using the same method. Each participant used MyDay between 7-14 days, and Fitbit activity trackers were given to the first five enrolled participants to wear during participation. As in the previous round of testing, research staff met with participants at the start of their time using the MyDay app to introduce the study. The participants were again interviewed by the staff at the end of their period of use to record their experiences.

To test a range of feedback graphics simultaneously, each participant was shown an infographic-style feedback summary of their data from the app during their interview. This draft summary, called "All About Me," was a visual representation of aspects surrounding their diabetes self-management, such as where they were when their BG was high, the number of discussions they had about diabetes that week, or what barriers were in place when they missed a BG check. A sample of an *All About Me* infographic is shown in Figure 4. This and other early feedback interfaces were ultimately transformed into the interactive feedback screens shown in Figures 7 and 8 based on user and parent input.

E. Design Iteration 5: Intensive Internal Testing

The remaining development of MyDay consisted of (1) implementing the complete suite of on-demand real-time visual feedback that integrated BG and psychosocial-behavioral-contextual data, (2) integrating the iHealth [16] API to incorporate Bluetooth BG meter data with meal and bedtime data collected from MyDay, (3) creating a system for matching BG meter data to the correct MyDay assessment, and (4) implementing a method for users to share their data and graphical feedback. To provide rapid feedback on the validity of the BG data going into the system, an internal testing cycle was conducted with staff testing their BG levels and utilizing test solutions to indicate high and low glucose. Moreover, we

Assessment Type	Data Collection Elements
Meal, Bed, and Snack	My blood sugar BEFORE mealtime was: / I did not check
Meal, Bed, and Snack	Carbs: / I did not count / I did not eat
Meal, Bed, and Snack	What time did you eat?
Meal, Bed, and Snack	Photo of what I ate: / Image Review
Meal, Bed, and Snack	Did you take insulin?
Meal and Bed	Around this time, I was feeling: / Mood (Bad – Good) / Energy Level (Low – High) / Stress Level (Low – High)
Meal	People — I was with: no one, casual friends, parent(s), strangers, sibling(s), other
Meal	Place — I was: at home, at a restaurant, at school, at a friend's house, at work, on the road, other
Meal	Barriers — I was: Rushing, Tired of diabetes, Feeling sick, On the road, Really hungry, Wanting privacy, Feeling low, Feeling high, Having a lot of fun, Tired, Busy (didn't want to stop), Without my supplies
Bed	Today I had an experience about diabetes that made me feel:
Bed	If you did, who was involved?
Bed	Do you want to remember anything else about this experience?
Bed	What was the best thing about today?
Bed	What else would you like to remember about today?

Fig. 3. Data Collection Elements and Assessment Types

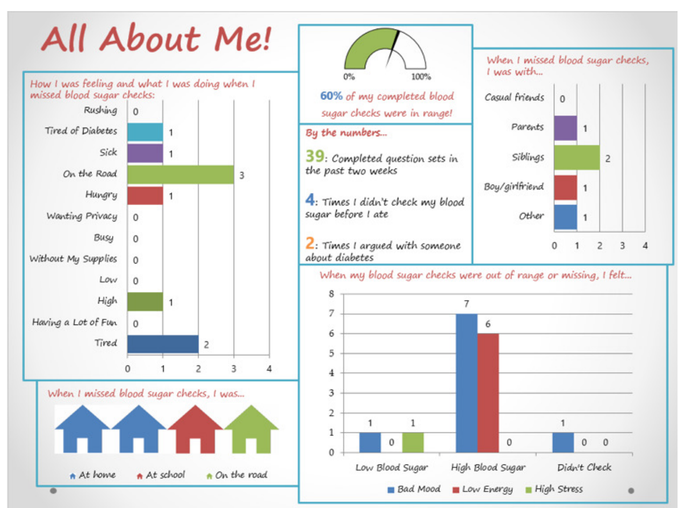

Fig. 4. Initial Draft of *All About Me* Infographic

tested the broadest range of mobile phone types and operating system versions within a controlled testing environment.

Seven research team members (each using a different combination of mobile device type, mobile platform, and operating system version) were given the Bluetooth BG meters and asked to submit data on a regular basis using MyDay and the meter. Submitted values were varied to test different patterns of emotional states and environmental factors, with standardized glucose solutions used to simulate out-of-range BG.

Submitted data entries were retrieved from the heterogeneous IoT devices via Bluetooth and Wi-Fi. These data were securely transmitted to our research staff for analysis. These entries were also recorded manually in a paper form so the data being displayed in the feedback could easily be compared to what should have been there.

During this evaluation process, the team continuously tested the accuracy of the data being returned from MyDay, the clarity and ease of understanding of its provided graphical feedback, and the stability of the system performance under different potential use situations. Complex scenarios were tested to ensure the feedback graphs were updated as intended.

For example, some research system testers did not upload meter data for several days to see how graphs updated after the time delay. Others neglected to submit a meal time or skipped items within an assessment to test out various displays. This round of internal testing resulted in a final prototype of the MyDay system that was deemed ready for a larger-scale pilot test, as discussed in Section VI.

IV. Technical Considerations and Key Challenges

This section presents detailed design modifications based on results from the iterations and lessons learned from the iterative design process described in Section III. We identify key challenges faced and mitigation solutions attempted as we applied IoT concepts in adolescent T1D intervention via MyDay and experimented with different visualizations to promote adolescents' interactions with the tool. The discussions focus on three aspects of the system: (1) data collection of EMA assessment, (2) real-time BG integration, and (3) providing personalized real-time feedback. The technical specifications of the system are descried at the end of this section.

A. Data Collection of EMA Assessment

MyDay's administration interface provides flexible creation of data collection content, format, frequency, and timing. Data collection based on photos, rewards for data entry in the form of points, and data entry notifications were administrative features modified based on research and implementation needs.

All daily assessments were available for data entry before or after a notification time for a full calendar day, from midnight to midnight; early rounds of testing showed that adolescents have highly variable daily schedules, even during the school year. Users received four reminder notifications on their devices per day to submit the assessments. The timing of each notification was tailored to each individual's indicated approximate mealtimes and bedtime. This daily assessment entry deadline was problematic for some users, especially over winter and summer school breaks when they were awake past midnight more often. During the initial 2-3 days of the protocol these data were monitored, and the case study participant described in Section V was contacted for troubleshooting if there were apparent missing data.

Each mealtime assessment asked the same set of questions. The assessment was kept as brief as possible with the goal of completing an assessment in less than one minute to help maintain engagement and minimize response burden. The fourth assessment, at the end of day, contained more retrospective items that considered the day as a whole and attempted to promote positive psychology.

A question was added to each mealtime assessment about the time of the meal, to allow the system to link the correct BG meter reading to each meal. For the bedtime assessment, the system used the last glucose value of the day after 8:00 p.m. If a bedtime value also matched a mealtime value (*e.g.*, a check at dinner after 8:00 p.m. with no later checks), the BG value was recorded as a mealtime BG value and the bedtime assessment for that day recorded as a missed BG check. The MyDay system scanned for matches any time new data, EMA or BG, were added to the server or when a new MyDay assessment was added. The system looked for unmatched glucose values that would fit the data entry criteria, and when new BG data were added, it searched for MyDay assessments that did not currently have an associated glucose reading. This process is shown in Figure 5.

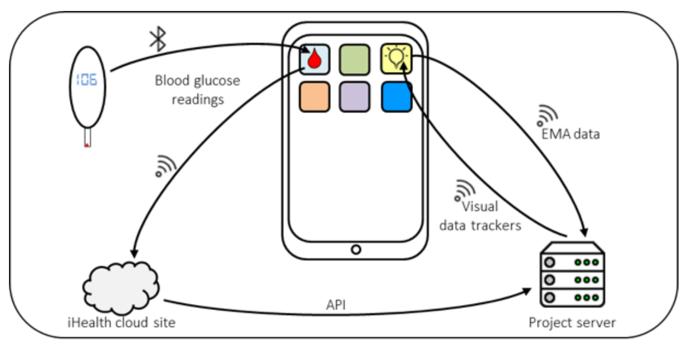

Fig. 5. Process of Blood Glucose Data Integration

An on-demand "Snack" assessment, which is an abbreviated version of a mealtime assessment, could be completed an unlimited number of times per day to gain information on non-mealtime BG and ecological factors. An "I did not eat" option was added to encourage participants to complete a mealtime assessment even when a meal was not actually eaten. In general, habitually skipped meals are a risk factor for worse glycemic control.

Young participants were frequently unable to use the Fitbit at the very times when they were most active. For example, a dance instructor would not allow one adolescent to wear the tracker during class, and a football player's Fitbit frequently fell off during practice. Though physical activity plays an important role in BG patterns, the research team decided to stop asking participants to use a Fitbit activity tracker, focus on other potential issues that influence self-management and glycemic control, and revisit how to better integrate exercise issues in subsequent versions.

B. Real-time Blood Glucose Integration

A key challenge faced by technology designers, researchers, people living with diabetes, and their families is the lack of simple and direct access to BG data from devices [46]. Self-reported BG logs have been shown to be inaccurate, with individuals often misreporting values, forgetting to enter data, omitting undesirable readings, or making up values [47]. Real-time BG data integration into MyDay was made possible by the iHealth BG5 Bluetooth glucometer [16], a commercially-available Bluetooth Low-Energy meter. This glucometer eliminates the need for self-reported BG data by automating the BG logging process, and is therefore a feasible smart sensor for us to integrate into our IoT-based system.

Using the most recent version of the system, iHealth's relatively new meter with an open API was incorporated to our secure server that integrated real-time BG data to provide feedback in the MyDay app. The glucose meter connected to an Android phone or iPhone via a short-range Bluetooth connection. By pairing the meter to our test users' mobile device via Bluetooth, the accompanying meter's app service automatically pushed de-identified data to the iHealth secure cloud site via a cellular or Wi-Fi data connection. When a BG test was performed while the meter was synced to the smartphone, the meter's accompanying app automatically uploaded the value to the company's secure cloud server.

The Bluetooth meter did allow for standalone BG monitoring and caching when the meter was not paired to a mobile device. Those cached values were pushed to the company cloud site the next time the user paired the meter. Every time new values were updated, our system requested the meter API to securely send the value to our MyDay server that recorded the data to the MyDay database.

All glucose values were collected, although the MyDay assessment focused on mealtimes and bedtime. To be considered a mealtime glucose value, the MyDay system looked for the most recent glucose reading within one hour before the user-reported time of the meal. This window was based on the recommendation of diabetes clinicians on the research team. The iHealth API was used to acquire glucose readings in real time and subsequently integrate the data into the MyDay app's graphs and logbook.

C. Personalized Real-Time Feedback

Upon collecting and integrating the heterogeneous data sources, personalized feedback was created to close the loop of the IoT system by providing intelligence back to users. MyDay created personalized feedback to communicate patterns of BG and how they relate to adolescents' behavior. The ultimate goal is to help these diabetics become aware of how and where they could improve problems in their self-management.

TABLE II
DESCRIPTIONS OF GRAPHICAL FEEDBACK DOMAINS.

Feedback Menu	Description of Graphical Feedback
Home	Overall summary and week by week comparisons of low, in range, and high BGs
Good News	Badges for meeting the criteria for BGs in range, low stress, high app use, good BG average, and high number of BG checks; best things from the past 7 days
Highs	Overall high BGs and by day of the week and time of day
Lows	Overall low BGs and by day of the week and time of day
People + Places	Top 3 most frequently reported people and places displayed with BG highs, lows, missed BG checks, or skipped meals
Stress, Energy, Mood	High stress, low energy, and bad mood displayed with BG highs, lows, missed BG checks, or skipped meals
Whats Going On	Top 3 most frequently reported barrier icons displayed with BG highs, lows, missed BG checks, or skipped meals
Missed BG + Meals	Meals eaten with no BG check, skipped meals, and missing app entries

In earlier rounds of testing, adolescent participants were shown a sample of a draft summary "All About Me" infographic during enrollment and were told that they would receive a custom version using their own data. In obtaining iterative feedback from adolescents, however, the asynchronous graphical feedback was viewed as limited in promoting engagement because it was too far removed from actual events. Individuals who used MyDay for more than one week reported losing interest in submitting EMA assessments because they could not see how their data trends were changing over time.

The original intention was to provide an *All About Me* data summary to each user on a weekly or biweekly basis. User feedback prompted thinking about ways to provide more immediate feedback within the app via graphical communication. Moreover, participants repeatedly commented that they would benefit from more types of immediate and real-time feedback regarding their data from the MyDay app. Some examples are:

1) "It would be cool if you could (see different graphs by day)."
2) "Show (graphs) by day and kind of just scroll down to each meal?"
3) "It would be kind of interesting to see how many times when I was rushing, how many times I was high versus in range versus low. Compare those contexts."

Due to all received feedback, substantial changes were made to MyDay's approach to graphical feedback by integrating a greater variety of feedback that was viewable through the app itself. A menu with the following eight tabs was introduced: *Home*, *Good News*, *Highs*, *Lows*, *People + Places*, *Stress + Energy + Mood*, *Whats Going On*, and *Missed BG + Meals*. Integration of BG values with psychosocial and emotional data was provided as feedback within feedback in the app, and all BG values were recorded to the MyDay logbook. After the data from different sources were matched, the app provided

Fig. 6. Early Screenshots of Personalized Graphical Feedback Derived from IoT Device Collection and Analysis

immediate feedback on various combinations of BG data and relevant factors such as time of day, day of the week, social context, physical context, and mood and stress, as described further in Table II and shown in Figure 6.

All available BG values, as opposed to only mealtime BGs, were used in the data visualizations when possible. Some graphs depended on self-reported mealtime data, however, so they were limited to those time points with self-report. With a few exceptions (*e.g.*, missed app entries and skipped meals), the feedback focused on integration with BG data because it was the most salient data to help users identify patterns in their diabetes self-management. In particular, BG data helped users see where they were, who they were with, how they were feeling, or what was going on around them when they missed BG checks or when their BGs were out of target range.

MyDay graphical feedback was a major focus for the architecture of the app's assessment questions and design. The graphical information within the feedback was organized to facilitate best practices in personalized feedback: rapid understanding, reveal novel patterns and associations, provide meaningful information, and provide real-time updates [48]. Participants also received feedback on how many entries they completed in the form of points and could look at a gallery of photos they had taken at any time. Any of the eight feedback pages and the points, logbook, and gallery pages could be spontaneously shared via text, email, or social network.

V. Case Study

This section describes the design and results of a case study conducted to provide in-depth *in vivo* data and user feedback on MyDay. The goals of the case study were to

- examine the feasibility of data collection and behavioral sampling schedule (at each meal and bedtime) over the course of four weeks and
- explore engagement with the app and its features such as the graphical feedback and sharing.

A 14-year-old male with T1D agreed to use the app to help identify technical, communication, behavioral, and implementation issues for one month. Multiple relevant patterns were identified in his use of the app and in his graphical feedback that indicated protective and risk-related patterns.

By the end of the one-month study period, the case study user had completed 87% (95/109) of expected entries. Eleven of the fourteen missed entries occurred at bedtime. This user reported going to bed after midnight most nights and forgot to enter bedtime information before the next calendar day.

He checked his BG 70 times over one month for an average of 2.3 checks per day and missed 42% of his expected mealtime BG checks. The case study took place during summer, so not surprisingly his data patterns did not change from weekday to weekend and indicated that he was at home for every entry. Most (58%) of his high BG values were at nighttime. Eighty percent of his morning BGs were low, which is over three times more often than any other time of day. He also reported skipping most meals at breakfast (8/27) compared to lunch (5/27) or dinner (0/27).

Regarding feedback about the app itself, this participant reported he liked seeing the overall BG feedback on the home page with his low, in range, and high blood sugar percentages combined. He thought the icons used throughout the app were easy to understand. The feedback helped him identify self-management patterns, such as he was ”always low in the morning” and “high at dinner.” Another data pattern relevant for problem solving was that he missed mealtime BG check 9/28 times when he had low energy. He reported that the Stress + Energy + Mood feedback page was most interesting because he realized stress affected his numbers and thought the feedback in general was ”really cool.”

Research staff also interviewed the case study participant's parent to obtain general feedback and insights regarding her son's use of MyDay and to explore ways that a parent and teen spontaneously interacted about the data and app. The mother reported that MyDay was "awesome" because it was used on the phone, something her son always has with him, and is a discrete way to keep his information close by. She also reported that the MyDay app could be helpful for her son's awareness of self-management and problem solving around diabetes because it was personalized and worked with his data.

After analyzing the graphical feedback in the app, the parent and teen reported discussing how his BG values were higher than expected and how it helped him adjust his self-care to address that issue. The parent reported that she was "somewhat" involved in her son's use of the MyDay app in the past month, *e.g.*, they looked at the graphical feedback twice and she reminded him to complete entries some in the first week. When asked what she would tell another parent whose child is going to use the app, she replied they would like it and that it is the "the way of the future."

VI. Pilot Study

After digesting the detailed feedback from the case study reported in Section V, we then conducted a more comprehensive pilot study, which is described in this section. This pilot consisted of 31 adolescents users of MyDay who participated in this study for one month. After the study period, adolescents and their parents completed interviews about MyDay.

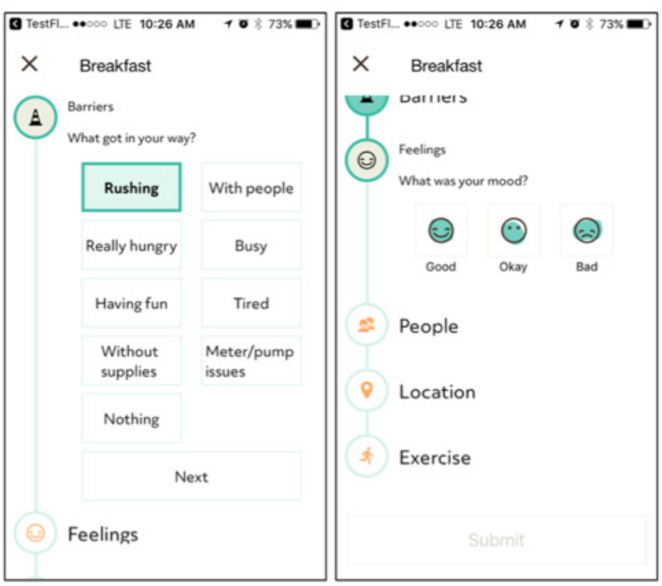

Fig. 7. Example Assessment Screenshots of the MyDay App Updated Based on the Pilot Study

Eighty percent of parents found the MyDay app helpful in creating diabetes awareness for their child. Likewise, 93% of parents found trackers in the app useful in encouraging parent-child collaboration about diabetes. Only 20% of teens spontaneously shared their tracker information with their parents, but 90% of the parents expressed their desire to receive their child's tracker data automatically.

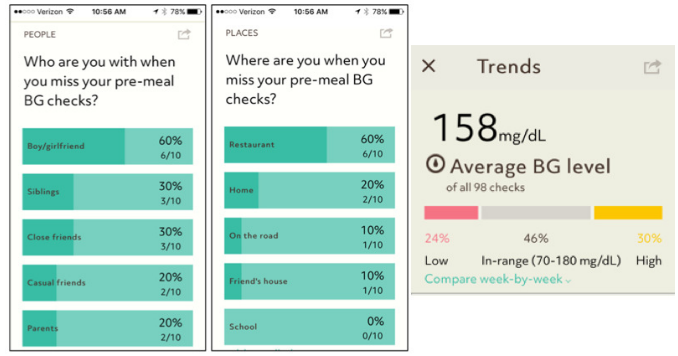

Fig. 8. Example Feedback Screens in the MyDay App Updated Based on the Pilot Study

Most parents observed that their teens considered the BG feedback and graphical visualizations of data trends to be the most valuable components of the app. Parents also provided suggestions for improving MyDay in terms of its data visualizations and data sharing capabilities. The research team then evaluated the technical feasibility of gathered feedback and made corresponding changes to enhance the MyDay app.

Figure 7 presents example screenshots of data collection inputs based on user feedback now incorporated within the latest version of MyDay. The example inputs in the figure capture the psychosocial barriers that contributed to an adolescent's pre-meal missed BG measurement and their mood at breakfast. Figure 8 shows example feedback screens in MyDay developed based on feedback from the pilot study. Using illustrative bar charts with corresponding statistics, MyDay provides clear and collective feedback to indicate the location and social contextual factors associated with missed BG checks. By integrating Bluetooth BG meter data, MyDay also provides overall BG monitoring and enables weekly comparisons of BG values, motivating the development of problem solving skills in adolescents with T1D.

VII. Concluding Remarks

Adolescent and parent feedback and data from the iterative design cycles and a case study showed how MyDay integrated bio-behavioral information for real-time personalized feedback to help adolescents with T1D. MyDay represents an example of an IoT-based, hybrid human-reported and automated data collection system. It enabled users to predictably and regularly schedule multiple daily momentary assessments and provided useful insights for teens about their self-management patterns.

The case study and initial pilot study described in Sections V and VI, respectively, confirmed initial acceptability, feasibility, and utility of MyDay in identifying novel behavioral targets for problem solving. The user-centric design process described in Section III yielded a readily accessible and comprehensive app to help teens with T1D identify personally relevant data patterns and behaviors that can positively impact their self-management practices and BG values. As next steps, the app and interactive feedback will be further integrated into a behavioral problem solving support system.

Based on our experience applying IoT technologies to create the MyDay T1D self-management tool, we learned the following lessons:

- Integrative physiological and behavioral feedback using real-time IoT technology enhanced the potential impact of MyDay's feedback on health behaviors
- IoT allowed MyDay to support just-in-time communication, thereby enhancing awareness and behavior change. Ultimately, these capabilities will help (re)invigorate the science of human feedback in healthcare
- The evidence base for, and potential of, momentary assessment is growing rapidly. With the adoption of ubiquitous IoT computing devices (*e.g.*, mobile, wearable devices and smart sensors) and Internet connections (*e.g.*, Wi-Fi and Bluetooth), these data are becoming much more accessible and affordable.

Our work with MyDay is ongoing and we are in the process of developing a means to offset the self-report burden by using background data collection, proxy variables or physiological assessment for some relevant factors like stress, GPS for location, more unobtrusive sensors for physical activity tracking (as we have demonstrated in another mHealth case study [49], [50]), or inference of social context using multiple time-location variables. The validity and reliability of many proxy variables have not been well established. It is also likely that a relevant core set of human experiences will never lend themselves to accurate assessment using unobtrusive proxy variables or triangulation using background data from IoT devices.

Future development and evaluation work planned for MyDay include (1) integration and experimental testing of the app and data within a problem solving system to support data interpretation and implementation of goals identified from the EMA, (2) collaboration with clinicians to explore clinical utility and associated modifications needed for clinical workflow implementation [19], [51], and (3) advanced learning of the data to produce an intelligent model that can autonomously provide more adaptive communications, such as a just-in-time reminder for insulin administration. Integration into clinical practice will require additional clinic-based design cycles and integration of data valued by clinicians.

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