Improving the visualization of diabetes data and algorithmic recommendations for healthcare providers

by

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Contents

Abstract

This study investigates how healthcare providers utilize diabetes data reports to inform treatment decisions, aiming to design and evaluate novel interfaces that support clinical decision-making. By observing 10 providers who care for patients with type 1 diabetes, we identified heuristics used in making clinical decisions in our first interview and developed a prototype based on these findings. In the second interview, providers interacted with the prototype and provided feedback on it. We discovered that a well-designed health data analysis tool should aggregate key data points, allow interactive data exploration, and provide algorithmic treatment recommendations linked to evidence. These features can reduce time spent on data analysis, lessen the cognitive burden, and improve patient outcomes. Our contributions include outlining data-based tasks and heuristics, designing and evaluating novel interfaces, and discussing design implications for health data informatics tools in clinical settings.

1. Introduction

Chronic health conditions are an increasingly prevalent problem on a global level (Oostrom et al, 2016). Some of the most prevalent conditions are type 1 and 2 diabetes. 23.7 million people in the US have a form of diabetes which can result in various health complications, such as vision loss, kidney malfunction, and cardiac issues (Center of Disease Control, 2022). An important part of managing diabetes is for providers and patients to periodically review patient data, such as blood glucose levels and insulin dosages, and discover opportunities for treatment changes (American Diabetes Association (ADA), 2017). Wearable devices produce large amounts of data which presents a challenge to device manufacturers of how to design the right software tools that providers can use to efficiently analyze this data. Software that is used in hospitals is often critiqued as having a bad user experience for providers and being cognitively burdensome which can make it difficult for providers to efficiently utilize their time with patients (Jankovic and Chen, 2020).

This study focuses solely on the provider as a user and concentrates on their needs. We conducted this study to gain an empirical understanding of how providers use diabetes data reports to inform care decisions and design and evaluate novel interfaces that support clinical decision-making. For this study, we recruited 10 providers (endocrinologists, nurses, and certified diabetes educators) who have cared for patients with type 1 diabetes (T1D). In the first interview we observed how providers review diabetes data to uncover the heuristics they use to make clinical decisions. We then created a prototype based on insights from these interviews, and let providers interact with the prototype in a second interview to gather their feedback. We observed how providers interact with data interfaces and learned that a well-designed health data analysis tool can improve clinical practice in meaningful ways. More specifically, we found the following:

1. Providers combine quantitative health data and qualitative patient interrogation to uncover patient behavior. Diabetes data interfaces should ideally aggregate key data points from individual days to visualize this patient behavior.
2. Providers value the ability to interact with data to find relevant blood glucose patterns more quickly. Tools should include data interfaces that allow providers to easily filter and search for these patterns which allows them to focus.
3. Providers want to explore data on their own before seeing an algorithmic treatment recommendation and they want to see evidence for each recommendation so that they can check each recommendation and accept or reject it. Recommendations should thus be shown at the end of the data review process and should be linked to relevant data points.

If software tools incorporate these features, it can potentially reduce the time spent on data analysis, reduce the provider's cognitive burden, and let them make better informed decisions to improve patient outcomes. Our contributions are the following. First, we express the different data-based tasks performed and heuristics used by providers to make diabetes care decisions. Second, we design and evaluate novel interfaces that include algorithmic recommendations and create a more efficient decision-making process. Lastly, we identify and discuss design implications for health data informatics tools that aid providers in their clinical work.

2. Related Work

In this section, we summarize existing research on two topics – the data-frame theory of sensemaking and provider behavior regarding algorithmic treatment recommendations.

2.1. Useful Data Visualizations and the Data-Frame Theory of Sensemaking

Diabetes management is a complex undertaking for patients and providers alike. Patients who use continuous glucose monitors (CGM) and insulin pumps continually produce large amounts of data that providers have available when patients come in for an in-clinic visit. This creates opportunities and challenges. The detailed information it provides creates the opportunity to make treatment changes on a detailed level while large diabetes data reports can be overwhelming to look at in the limited time that each provider has available for each patient. This illustrates why it is important to create data visualizations that are useful. Bad data visualizations make it hard to spot relevant patterns, increase the time providers need to review data, and potentially overlook opportunities for treatment changes (Craft et al, 2015). Good data visualizations can increase situational awareness, improve the clinical decision-making process, and maximize utility of patient data. The visualization of health data impacts the provider's reasoning process and the perception of patient behavior which directly impacts clinical decision-making (Craft et al, 2015). Therefore, it is important for manufacturers of medical diabetes devices to understand how providers review data, how different data visualizations impact their perception of that data, and how they use it to make treatment changes.

Providers engage in the process of sensemaking when interpreting diabetes data. The data-frame theory of sensemaking describes this process as having two components: data and frames (Klein et al, 2007). Data are concrete "interpreted signals of events" and frames are "explanatory structures" that construe a relationship between different data elements. Sensemaking within the data-frame theory is the process of conforming data into a frame to reveal relationships between different data elements and interpret the data this way (Klein et al, 2007). People analyzing data construct a frame by noticing salient data elements called “anchors”. Once multiple anchors are found, they are taken together to form a frame that explains a specific event. When new data becomes available that might not fit into an existing frame, the process of modifying a frame or creating a new frame begins so the new information can be included. The construction of a frame involves several sub-processes like seeking a frame, elaborating a frame, preserving a frame, questioning a frame, re-framing, and comparing frames (Klein et al, 2007). In diabetes data analysis, anchors for creating frames include contextual factors (e.g. activity, type of meal, mood) and clinical factors (e.g. insulin, carbohydrates) which help providers to make sense of the factors that impact the outcomes measures such as blood glucose (BG) levels (Raj, 2022). In addition to quantitative data from diabetes reports, providers ask patients contextual questions and gather their experiential knowledge to validate or invalidate the data in question. For the manufacturers of diabetes data reports it is important to understand this process of sensemaking so that they can create data visualizations that provide access to the right information at the right time, connect information across different displays, and show behavioral insights that are relevant for framing BG level outcomes (Raj, 2022).

2.2. Algorithmic Treatment Recommendations

Advances in data science and machine learning have led to the creation of powerful tools that can augment the provider’s ability to analyze data and provide suggestions for treatment changes. When it comes to algorithmic recommendations that provide clinical decision support to providers, the *when, where* and *how* is fundamental. Taking advice on how to make a clinical decision is a high stakes endeavor since it affects the health of a patient and wrong decisions can even have potentially fatal consequences and legal repercussions. One key factor for providers when considering recommendations is thus the explainability of their decision (Panigutti et al, 2022). Researchers found that a recommendation which provides an explanation is perceived as more trustworthy by doctors and more often considered when making a decision compared to a recommendation without an explanation (Panigutti et al, 2022). However, if recommendation systems and their explanations are designed the wrong way, it can lead to overreliance on it without critically engaging with the data (Schmidt & Biessman, 2020; Lee & See, 2004; Panigutti et al, 2022). On the other end, poorly designed recommendation system can lead to algorithmic aversion which is the tendency to discount recommendations. Designers of such systems should therefore design for appropriate trust, not maximum trust (Lee & See, 2004). The authors are calling for user-centered design of recommendation systems where the user is involved from the earliest stage of development (Panigutti et al, 2022).

The danger of overreliance on recommendations is two-fold. First, it can lead providers to automatically take advice that is wrong and lead to negative patient outcomes. Second, it can lead to the deskilling of providers over time regarding the analysis of diabetes data. Gajos and Mamykinga (2022) conducted a study that explored how people engage with recommendations. They stated: "Learning can only occur when people cognitively engage with the information they receive and process this information thoughtfully" (Gajos & Mamykina, 2022). The results of the study showed that participants made better decisions when recommendations were accompanied by an explanation but they did not learn from their decisions. When an explanation was shown without a recommendation and the participant had to arrive at their own conclusion, they made better decisions and showed learning gains. The authors conclude that different forms of intelligent support from an algorithm such as presenting useful information in an intuitive way may elicit deeper cognitive engagement and prompt individuals to more critically examine recommendations to combine their own knowledge with information contributed by the algorithm (Gajos &

Mamykina, 2022). One such strategy includes cognitive forcing functions which are interventions that take place at the point where the decision is made and encourage the decision-maker to engage analytically with the decision at hand (Bucinca et al, 2021). Strategies are, for example, asking the person to make a decision before showing the recommendation, delaying its display, and letting the user choose when and where to see it. The results of the study indicated that cognitive forcing functions significantly reduced overreliance on recommendation compared to simple explainable AI approaches.

How do clinicians decide if they trust recommendation or not? Two studies found that clinicians want information about the factors that influence the recommendations, beyond simple explainability on a case-by-case basis. Clinicians reported that knowing the subset of features deriving the model outcome and its clinical alignment with their judgement are crucial (Tonekaboni et al, 2019). In addition, clinicians would like to see upfront information about global properties of the model, such as its known strengths and limitations, its subjective point-of-view, and its overall design objective (Cai et al, 2019). They compare these information needs to forming an opinion about a mental model of a colleague who they are collaborating with when asking for a second opinion. Another clinician might have a different medical perspective or standards, and it is important to them to figure out if the other perspective is compatible with their own diagnostic patterns (Cai et al, 2019). These studies show the diverse information needs that providers have and the challenges that designer face when designing algorithmic recommendation systems.

3. Study Context: Type 1 Diabetes

Type 1 diabetes (T1D) is an autoimmune disorder in which the pancreas generates little or no insulin, leading to irregular BG levels. T1D patients rely on insulin to regulate their BG and must engage in lifelong self-management. This involves frequently checking BG levels, counting carbs, administering insulin when eating or between meals, and adjusting insulin dosages based on various factors affecting BG levels (ADA, 2017).

Patients need two types of insulin, long-acting (basal) and short-acting (bolus), with a regimen established in partnership with their endocrinologist (San Francisco Diabetes Teaching Center at University of California, 2021). These insulin types differ in their onset and duration of effectiveness in lowering BG levels. The effect of the long-acting insulin lasts over multiple hours while the short acting insulin acts within fifteen minutes of administration and is usually taken to counter the BG spike that comes from having a meal (ADA, 2021). Medical devices like CGM and insulin pumps can automate some tasks, such as calculating and delivering basal and bolus insulin. An automated insulin injection is called an auto bolus and is given when the pump senses that the patient has high BG levels. Different manufacturers have different names for it, Tandem, for example, calls the automated injection system control IQ. Insulin pumps are configured using insulin-to-carb ratios and correction factors or insulin sensitivity factors, which are determined for each patient (San Francisco Diabetes Teaching Center at University of California, 2021). The insulin to carb ratio is the amount of insulin to be injected for every 10 grams of carbohydrates consumed. The correction factor is the amount of insulin that is dispensed for every unit increase in BG above the target BG number (or insulin to be reduced for every BG unit decrease).

Before a meal, patients must input their current BG number and carbohydrate amount into their insulin pump. The pump then calculates the necessary insulin dosage by using the insulin-to-carb ratio and correction factor. The pump can also be programmed to deliver basal insulin in bursts using different infusion rates throughout a 24-hour period (Scheiner, 2016). The parameters mentioned above and basal insulin settings are continuously evaluated and modified based on the patient's glycemic performance. Data is primarily reviewed using data platforms from device manufacturers such as Tandem, Dexcom, or Medtronic or data aggregation platforms like Glooko and Tidepool. These platforms provide data displays as downloadable PDF reports, containing limited data interpretation features, such as identifying general glycemic patterns. Providers must further analyze these patterns to pinpoint management issues, their causes, and possible care actions to address the problems.

4. Methods

In this section, we present the methods that were used in this study to collect and analyze data. We will also present the design rationale for the research prototype to give the reader an overview of its features.

4.1. Provider Recruitment

Providers were recruited through an adult and pediatric endocrinology clinic from a large teaching hospital and through an email campaign. Providers who expressed interest were contacted to assess eligibility. Healthcare providers (endocrinologists, nurses, physician assistants, and diabetes educators) who have experience with caring for patients with Type 1 Diabetes and with using commercial diabetes management software systems were deemed eligible. Eligible patients were provided with the informed consent form. Participants who agreed to the form were considered enrolled. The study was approved by the university's Institutional Review Board. Recruitment took place over a period of two months and interviews were conducted over a period of three months. We recruited 11 providers and completed the first session with all of them. The second session was only completed with 10 participants since one participant dropped out due to private reasons.

4.2. Data Collection

To identify the tasks and heuristics of how providers analyze diabetes data, we observed data review sessions with 11 providers. These sessions were held on Zoom and were video recorded and transcribed. The average length of the first session was 60 minutes. We obtained de-identified diabetes reports from a previous study with consent of the participants. During the first session, providers reviewed two weeks of data from two patients' diabetes devices that included insulin pumps and CGM. Commercially available data reports provided by the diabetes device manufacturers, such as Dexcom and Tandem were used for data review. Providers were asked to interpret patient data and think out loud while reviewing the report. After that, follow-up questions were asked to uncover additional insights. All providers saw the same two reports, except for the first participant who reviewed one report that was different from the other participants and one that was the same. We then created a novel research prototype in Figma that incorporated new features and visualizations based on insights from these interviews. We showed the prototype to 10 providers to get their feedback. The average length of this remote session was 45 minutes. After the first two participants, we slightly modified the Carbs and Bolus tab to make the visualization more user friendly and removed a feature in the Treatment Changes tab that showed historical settings because it was confusing. During the session, providers were able to interact and review data from a patient with the dashboard prototype and gave their opinion on possible treatment changes while providing feedback on the visualization of the data, user experience of the dashboard, the interactive visualizations, and the algorithmic recommendation system.

4.3. Data Analysis

We analyzed the recorded videos and transcripts of the first session to understand the tasks that providers engage in and the heuristics they use when reviewing diabetes data. We used this data to create features that were included in the research prototype. After the second session was completed, we conducted an in-depth analysis of both sessions' transcripts and videos and used descriptive coding to identify common themes across both sessions. After that we used Miro to perform affinity diagramming. For this, the most relevant quotes were pasted into Miro and organized spatially by similar themes. These clusters were then organized into metaclusters which revealed the most important findings. You can find these findings in the section 5.

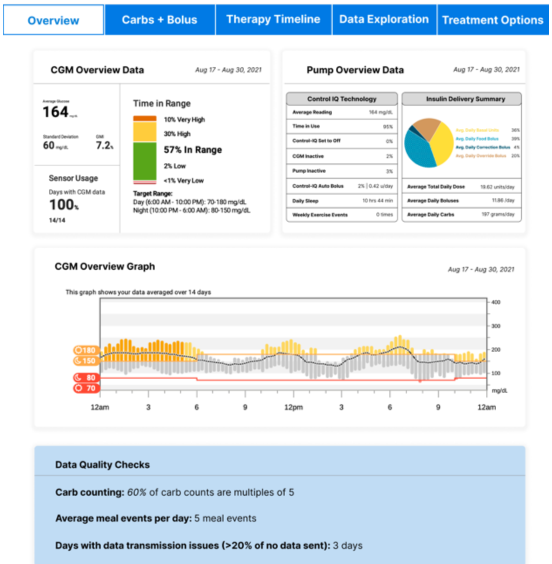


Figure 1. *Overview tab*

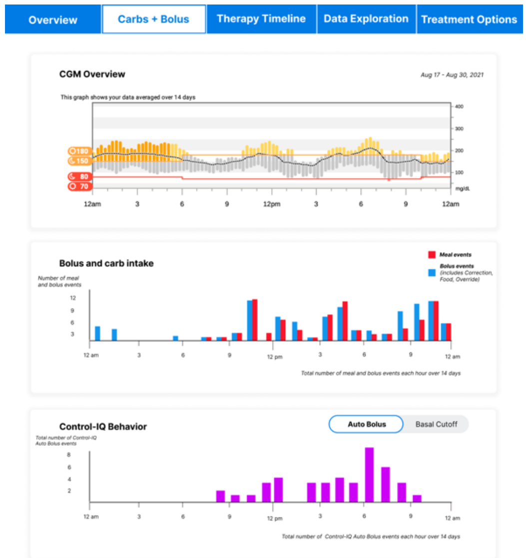


Figure 2. *Carbs and Bolus tab*

Figure 3. *Therapy Timeline tab*

Figure 4. *Data Exploration tab*

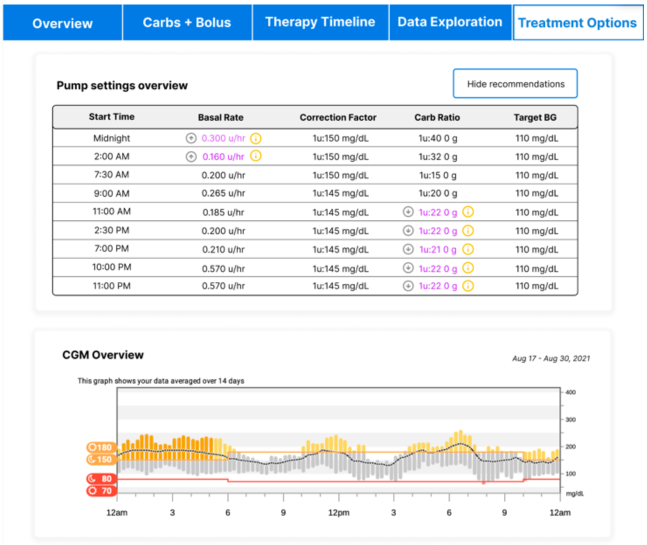


Figure 5. *Treatment Changes tab*

4.4. Design Rationale

Based on insights from session 1, we designed a research prototype in Figma that simulated a working web dashboard with real patient data. The dashboard included five tabs that allowed for quick navigability between them: Overview, Carbs and Bolus, Therapy Timeline, Data Exploration, and Treatment Changes. The Overview tab (see Figure 1) included general "data checks" from both pump and CGM data since providers expressed their wish for combining data from the two reports. This allowed them to get a general picture of the data before analyzing it in detail. The Carbs and Bolus tab (see Figure 2) aggregated carbohydrate and bolus data, including the auto bolus data, to make it easier to spot eating and bolus behavior of a patient. This was based on heuristics we discovered in session 1 where providers analyzed individual days of the therapy timeline to discover meal times, bolus coverage, and auto bolus behavior. The Therapy Timeline tab (see Figure 3) included the therapy timeline and logbook from the pump report. We kept the visualization the same since it was well liked by providers and we did not see the need to completely redesign it. The Data Exploration tab (see Figure 4) allowed providers to filter pump and CGM data by pattern and time of day. For example, you could choose "Evening Highs" to see only days where the patient had high BG levels in the evening. This was an experimental feature to see if providers like to filter data so they can focus their attention on the most relevant days. It also showed potential causes like "Basal Rate" that might induce the anomaly in BG levels. The Treatment Changes tab (see Figure 5) showed the pump settings combined with a button that allowed providers to show and hide treatment recommendations. The recommendations only showed in which direction a parameter should change without suggesting a specific number because diabetes management is so complex since there are many different factors that providers take into account. Clicking on a button next to each recommendation led the provider to a filtered pattern view which corresponded with the recommendation in question so they could validate a recommendation. The algorithmic recommendations and filtering was done using the "Wizard of Oz" technique and only simulated these features based on learnings from session 1 without actually employing a working algorithm.

5. Findings

In this section we describe the findings from both interviews with providers and describe their behavior when analyzing diabetes data and their feedback regarding the prototype.

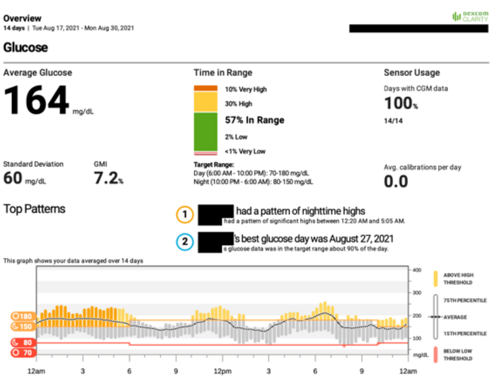


Figure 6. *CGM Overview page*

Figure 7. *Pump Overview page*

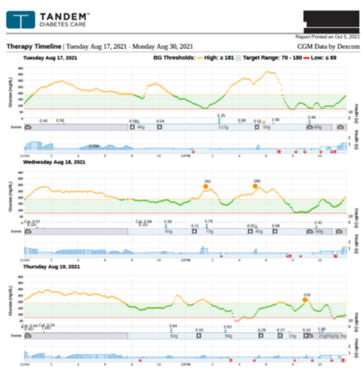


Figure 8. *Therapy Timeline*

5.1. Data Exploration

Session 1 revealed how providers reviewed diabetes data to uncover patient behavior and find opportunities for treatment changes. Most providers first look at the CGM report and then at the pump report but spend more time on the pump report since it incorporates CGM data as well as pump data. The most important part of the CGM report was the first overview page (see Figure 6) which showed the date range of the report, time in range, the amount of time the CGM was used, average glucose levels, standard deviation, and a graph that aggregates the CGM data by the time of day. These data points were "data checks" to make sure that the data quality is solid before performing a more detailed analysis. Most commonly providers then opened the pump report overview (see Figure 7) and performed further data checks. They looked at time in use of control IQ, activation of sleep and exercise mode, the ratio of basal to bolus, control IQ auto bolus, and average total daily dose of insulin. Most of the time thereafter was invested in the therapy timeline (see Figure 8). This might have several reasons. The timeline includes both CGM and pump data, including BG levels, boluses, carbs, auto bolus, and basal for each day. All this data combined allowed them to identify patterns of behavior that would lead to possible treatment changes. The timeline gives a full view of behavior from day to day. On one hand, this allows the providers to spot very minor details and allows them to see how it changes from day to day. On the other hand, it can be overwhelming to look at this much data if they are only looking for specific patterns. An alternative visualization of the therapy timeline is the logbook that was traditionally used in diabetes management. Most providers reported that they don't use the logbook format anymore to analyze data. P04 mentioned that she likes to print out all the logbook data and manually highlight patterns but this is mostly because she learned it that way a long time ago and prefers to still do it that way. The Overview tab was deemed useful in Session 2 because it combined the most important data points for CGM and pump data. The data check box at the bottom of the page was not perceived as useful by most providers because the data transmission issues check is already covered in the CGM data check at the top, the carb counting that shows multiples of 5 is not seen as an issue by most providers (relating to ghost carbs), and the average meals per day can be seen in the Carbs and Bolus tab.

The concrete behaviors that providers are trying to find out are: carb counting, meal times, bolus timing (taking boluses before meals) and turning on exercise and sleep mode on the pump. If a provider sees something unusual in the data, they like to ask questions to gather more information about what happened on a certain day. For example, P06 saw an unusual BG spike in the morning and remarked “So what I would find out is here I would probably start out with breakfast. What time do you eat breakfast? Because you're jumping way up after breakfast. And then how much are you bolusing?“. Noticing another anomaly, P03 would ask: “So I probably, you know, ask a quick question like, do you guys happen to remember what happened on this day? You know, are we at a party maybe or having different food choices or something just to kind of tease out what might be happening on some of these days where we're going a little more hog wild and have higher numbers.“ The combination of quantitative data and qualitative interviewing allows providers to form a coherent picture about patient behavior and potential causes for anomalies in BG levels. In session 2, the feedback on the Data Exploration tab was very positive. Providers liked that it showed relevant and actionable high and low BG patterns so that they did not have to look through each individual day to find them. They also liked the highlighting boxes around patterns to draw their attention to the right location in the graph. The filters allowed them to spot trends sorted by time of day. Two providers remarked that they would still like to see the full timeline to see consistency of behavior and patterns and make sure that the algorithm has definitely found all the relevant patterns. Seeing a filtered view for a specific pattern gives them a way of more quickly identifying causes and develop ideas for treatment changes.

In session 1, providers looked at the therapy timeline to figure out when the patient ate, if they are putting in carbs correctly, if they bolus before they eat, and if there are certain patterns for auto bolus injections. This was done by looking at each day individually. By aggregating carbs and bolus event data and auto bolus injections in the prototype, providers were able to derive these insights from two graphs more quickly in session 2 using the Carbs and Bolus tab. They were able to see the main meal times, if the patient covered their meals with boluses, and at what time a high frequency of auto bolus injections occurred. One insight, for example, was that the pump gave a lot of auto bolus injections at 6 pm after the patient only had few meals, which could mean that the carb ratio needs to be adjusted. P01 thought out loud while looking at the graph: „But then you can see they're bolusing there for food and then they're ending up with a lot of auto bolus afterwards. So it's kind of a sign either that their carb coverage is not adequate, especially because it's so close to after the bolus. It could even just be that their timing is off, like their bolusing post-meal rather than pre, so the auto bolus is correcting because the sugar is shooting up fast and so then it ends up doing the auto bolus right away after." Some providers remarked that the graph would be even more helpful if there was some way to show if the bolus was taken before or after the meal. By aggregating the data this way it made it easier to develop an idea of patient behavior before diving into the more detailed therapy timeline. However, not every provider found the carbs and bolus graph helpful because it was a new kind of visualization. They said that it might be helpful but you would realize it over time and need to get used to it. Most providers did not notice the additional Control IQ graph at the bottom of the page which showed the automated basal cutoff. When they saw it, they usually did not derive any value from it.

Three providers wished for the three graphs (CGM overview, aggregated carbs and bolus data, auto bolus data) to be displayed at the same time on the screen so that they could quickly compare them.

Providers are concerned about patient behavior that interferes with the pump “doing its job”. This includes putting in so-called “fake” or “ghost” carbs to get insulin and overriding the pump to get more or less insulin. P01 remarks “So they'll tell me, oh I wasn't actually eating 16 grams of carbs, I just put in 16 grams of ghost carbs because I wanted the pump to get me insulin. So I need to know, like I need to walk through it with them.“ Putting in ghost carbs or overriding the pump too much is problematic because it paints an inaccurate picture of the therapy timeline and what the patient is actually doing. It also distorts how many carbs they are eating and how much insulin they should be getting which means that it is harder to figure out what treatment changes are needed. Overriding can be spotted fairly easily in the pump report by looking at a simple pie chart but figuring out when a patient puts in ghost carbs can be harder and needs interrogation about specific instances. The pump follows a certain algorithm that carefully considers the carbs that a patient is taking in and current BG levels to calculate the exact dose of insulin needed. When you manually override this algorithm a lot, it can cause issues, as P03 explains: “Yeah and here seeing that 50% of the bolus has got overridden, that would be a point of emphasis for me with the parent to be like, okay, what can I adjust in your pump so that you don't feel like you're adjusting this bolus yourself? And kind of point out that the safest thing we can do for this kid is to try to make sure that we're doing everything as consistently as we can. Trying to take human error out of the equation.“ P09 echoes this point: “I'm thinking why do you override? Do you override up, do you override down? Why do you do that? If you do that, then you are fighting the algorithm. So I don't care for that. That's not helping the patient.“

This section showed how providers engage with diabetes data in commercial reports and in our prototype to accumulate insights that will help them to make the appropriate treatment changes. In the next section, we will explain how data reports are used in the daily clinical workflow.

5.2. Clinical Workflow

Every clinician has their own way of collaborating with Clinical Diabetes Educators (CDEs). They usually have a specific way of collaborating and know what the other party does to complement each other and optimize the diabetes care for each patient. CDEs usually pay closer attention to carb counting and insulin cartridge changes, while the clinician is more focused on pattern recognition and making actual dose changes. Sometimes CDEs give recommendations to the clinician about dose changes which they may or may not accept. Some health systems do not have CDE staff, so clinicians there perform all the necessary tasks with patients.

The process of analyzing diabetes data differs from provider to provider. Everyone looks at different parts of the report and may come to different conclusions from the same data. Providers can sometimes customize a PDF report before downloading it. There are 3 ways of looking at the data: digital PDF, printed PDF, or interactive dashboard. Most providers use digital PDFs. Since the process of reviewing diabetes data differs from provider to provider, a long PDF report that includes a lot of components can be a cumbersome way to review data because it can take a long time to find the graph that is most useful to one provider. It is possible to customize reports to a degree but most providers did not find it very helpful because you still need to scroll a lot if you want to go back and forth between different visualizations. The dashboard prototype was well received for its user friendliness and ability to navigate quickly between tabs so that you can find the graph you need quickly and switch between them easily. P08 said “I like the tabs. I think it's well structured. I like it in terms of having the raw data, I like the ability to move around.“ P03 agrees: “I like it a lot better than scrolling and trying to find something.“ This speaks to the user friendliness of interactive dashboards and illustrates the challenges that providers face when using PDF reports in their daily clinical workflow.

Some providers like using interactive dashboards but often cannot use them because of software design limitations, internal IT regulations, or documentation purposes. This means that they have to download PDF reports and manually take screenshots and type up treatment changes in order to document them in the EHR. Tandem, for example, does not show the therapy timeline, which is the most important part of the report, in the online dashboard and thus forces providers to download a PDF report. There are also different logins for different manufacturers, which can be inconvenient because sometimes patients need to send certain “share codes” to providers that allow them to login. IT administrators at health systems can block the usage of software that is deemed unsafe for any reason. P01 shared his frustration about the way healthcare administration works in large health systems: “So then unfortunately I will say I love the visualization, but unfortunately sometimes what we actually use in clinic comes down to that, right? Like it doesn't come down to what the doctors think is best visualized, the decision is a business decision that's not made by any of the doctors. The IT people at our health system get to make the choice. And they do that without our input.“ This illustrates how difficult it can be to get useful tools which aim to improve clinical workflows in the hands of providers. Even if there was a software that had the ideal user experience and would be very efficient for clinical staff to use for accessing, analyzing, and documenting diabetes data, it would still need to overcome a lot of barriers until it was actually in clinical use.

5.3. Algorithmic Treatment Recommendations

In session 1, we observed that providers formed their opinions about patterns while looking through the data and asking the patient questions. They identified patterns and formed a mental model about causes that most likely cause anomalies in BG levels during this process. On the last page of the pump report the pump settings are shown (see Figure 10). These settings form the basis for making treatment changes since the provider can see the actual settings and make adjustments as necessary. The parameters that are available to change are carb ratio, correction factor, and basal rate (depending on the device manufacturer). Changes are usually documented by manually typing in notes in the patient chart and then taking screenshots of the PDF report and pasting them into the patient chart as well.

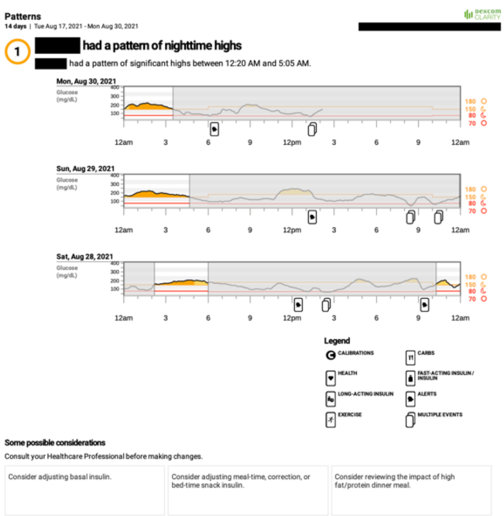
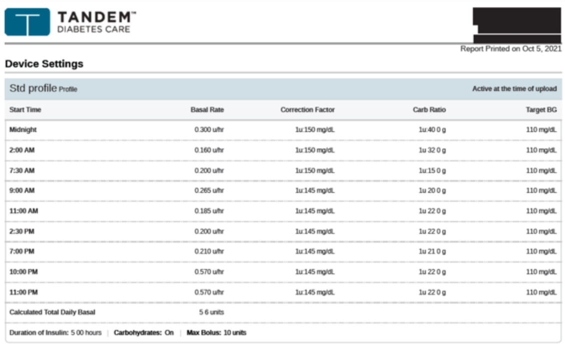


Figure 9. *CGM Recommendations*


TANDEM™ DIABETES CARE

[redacted]

Report Printed on Oct 5, 2021

Device Settings

Std profile Profile — Active at the time of upload

Start Time	Basal Rate	Correction Factor	Carb Ratio	Target BG
Midnight	0.300 u/hr	1u:150 mg/dL	1u:40 0 g	110 mg/dL
2:00 AM	0.160 u/hr	1u:150 mg/dL	1u 32 0 g	110 mg/dL
7:30 AM	0.200 u/hr	1u:150 mg/dL	1u:15 0 g	110 mg/dL
9:00 AM	0.265 u/hr	1u:145 mg/dL	1u 20 0 g	110 mg/dL
11:00 AM	0.185 u/hr	1u:145 mg/dL	1u 22 0 g	110 mg/dL
2:30 PM	0.200 u/hr	1u:145 mg/dL	1u 22 0 g	110 mg/dL
7:00 PM	0.210 u/hr	1u:145 mg/dL	1u 21 0 g	110 mg/dL
10:00 PM	0.570 u/hr	1u:145 mg/dL	1u 22 0 g	110 mg/dL
11:00 PM	0.570 u/hr	1u:145 mg/dL	1u 22 0 g	110 mg/dL
Calculated Total Daily Basal	5 6 units			

Duration of Insulin: 5 00 hours | Carbohydrates: On | Max Bolus: 10 units

Figure 10. *Pump Settings*

Providers are comfortable using their own heuristics to come to conclusions while looking at the data and then making treatment changes as necessary. Using algorithmic recommendations, however, is a divisive topic. In Session 1, four providers were very skeptical of using recommendations because they did not trust its accuracy and they felt like it would not be necessary since they are capable of doing the analysis quickly on their own. P01 remarked “Algorithms? I don’t trust them.” P11 said “I feel like it would be a lot of work to do something like that for something that I could gestalt in less than a minute.“ It seemed like some providers had the concept of an algorithm in their mind that they need to follow at all times. Other providers viewed recommendations as a tool that gives them suggestions which they may or may not follow. P06 mentioned that “It‘s hard to know because you know, so much about sugar management is trial and error. But it'd be great to have something to guide me. I would use it as a guide. I wouldn't use it as an absolute.“ The importance of patient health and algorithm accuracy also came up when P04 claimed that “I lose sleep over dose changes sometimes. I couldn't do a 60%. It's not high enough. You'd have to gimme a better, like it's going to be 80 plus percent the right thing.“ Another issue with using recommendations is the legal framework that providers operate under. Providers expressed that they need to be able to own their decisions because they are liable when something goes wrong. P07 was open to the idea of recommendations but had concerns about the legal implications: “I mean, that is obviously the holy grail, right? Of trying to do this automatically, right? […] But you know, when it comes to giving medicine and insulin, that's where the problem is, of course there's legal issues. That's a whole different ballgame, right?“ Furthermore, 5 providers argued that the algorithm would be lacking important contextual information about patient behavior. Without information like exercise times or types of meals the patient eats it would be hard to holistically assess the situation. Providers did not make any suggestions as to how they could collaborate with the algorithm to extract this information from patients and include it in the algorithmic assessment. P11 said: “I don't think I need an algorithm to tell me based on the look of this tracing what big picture changes

I need to make. And I think that a lot of the nuanced changes that I would make would be based on patient behavior and talking to them about what is going on at each one. So I don't know if a program would be able to capture that.“ Another concern was that the algorithm would not be able to educate patients on the right behavior. This opinion seems to stem from the perception that an algorithm could exist that covers the complete patient visit - from analysis, to treatment changes, to education – without the provider intervening or being present. P07 voiced this concern: “I'm just thinking, you know, this insulin thing is not the main thing. It's about behavior of the patient. And what you're trying to instill is the right behavior. So things like pre-bolus behaivor, you know, that they need to give the insulin 15 minutes before eating and they need to enter the carbs, all of that stuff, you need motivational interviewing. The program's not going to do that for you.“ He also noted that the personal connection with the patient is very important and that an algorithm cannot be empathetic and build that relationship: “Not only do I know where they exercises at 2:00 AM at 3:00 AM. I know their cat‘s and dog‘s name. No, I'm not joking. So, you know, in MyChart, there is a post-it note. You can put a small note that only you can see. And I always put those personal details there. Like, you know, cat's name, dog's name, something, you know, this guy like sushi a lot. Okay, I know that. So next time I talk to him, I'll say, how is your sushi? So these are just forming connections.“ This illustrates that some providers might fear that the algorithm could take over many functions of the provider’s job. There is a need for clear explanations of what algorithmic recommendations can and should do to address these concerns.

In Session 2, we showed providers the prototype which included the pump settings on the last page. A button on the top of the page allowed providers to show or hide recommendations. The recommendations showed the provider in which direction they should change a parameter, for example the carb ratio, but not the exact amount to what it should be changed. For every recommendation, providers could click on a button next to it that would take them to the filtered pattern view which corresponds with the recommendation so that they can look at the relevant data to accept or reject it. All providers had positive reactions towards this feature. This might be the case because they are looking at the data themselves first and have a mental model in place before seeing it. When they are presented with the recommendation, they can quickly verify it and compare it to their own opinion. P08 said "I like the tech supporting me in terms of looking at patterns and showing me patterns to recognize. And I particularly like the prompts to say these are considerations in terms of making adjustments so that I can cross check." Providers usually went through the recommendations one by one and checked the data to see if they would accept or reject it. They either agreed with a recommendation because they had the same change in mind, disagreed with it because they did not see the necessity of that change after reviewing the data, or agreed with it after looking at the data - but they had not thought of it before. The third case is interesting because it augments the provider's ability to make treatment changes that they might not have thought of. P04 described it like this: "Some of it I was like, oh yeah, I don't know that the increasing of the basal rate at night did not really cross my mind because my thought when I was looking through it is that they were high going into midnight and we needed to fix what's happening in the evening before doing the basal. I don't think going up on it would be wrong but it wasn't something that registered with me to do." Another case is reported by P05: "So again, if it recommends something, I'm like, why is it doing 11:00 AM? I didn't notice an 11:00 AM problem. I can click on the little i-icon, and it takes me back to, oh yeah, it actually did have midday highs. I had forgotten. I was just thinking about these two highs. So it's just like a human thing, right? I was just like focusing on the nighttime, but I forgot. The program told me daytime was also a problem and it brought me right to that. Now I feel comfortable making a change. And it tells me, you know, I should decrease this number, which I like. Actually I like that it doesn't give me the number, just tells me the direction. Because again, I take into account the age of the patient, how scared they are of hypoglycemia by how much I tighten this number." This illustrates several points. With the interactive recommendations in the prototype, providers are able to look at data that is relevant to each recommendation before making a change. They can also ask the patient questions to take contextual factors into account. And they remain the source of authority for making clinical decisions. In session 2, no provider voiced concerns about contextual patient behavior information, legal repercussions, or poor algorithm accuracy. This might be the case because they felt like they were in charge and the algorithm was only giving suggestions that they could verify without it being the ultimate decision maker.

There is a recommendation page in the Dexcom report (see Figure 9) that stands in contrast to the recommendations shown in the prototype. The recommendations are shown on page 3 of the report and only show a limited amount of relevant BG patterns. In addition, recommendations at the bottom are displayed in written text. Recommendations are shown too early in the decision making process so providers often quickly glance over them without registering them since they have not looked at the relevant data themselves first. There is also not enough data to back up the recommendations. Furthermore, the recommendations are not embedded in the location where providers make decisions so they would not go back and forth between the pump settings and the CGM report. Another case where we saw issues with written recommendations was the data exploration tab. Providers were not very fond of the probable causes shown at the top of the data exploration tab. They were shown before they went into the data below, so they glanced over it quickly to look at the data first. It was also written and did not highlight a specific pattern. It is hard to establish a specific cause for a specific pattern in diabetes care, so often providers would dispute probable causes that were shown. The recommendations that were shown in the pump settings did not include written probable causes, but had implicit causes that would lead to a specific recommendation. These were much more well received because providers would not argue about the specific cause but could just check the data and simply reject or accept it.

We asked providers if they have certain information needs regarding how the algorithm is created and what factors it takes into account. Only P05 explicitly requested background information on the algorithm, saying “if I was going to adopt this, I would just want a document I could read once about how the algorithm makes decisions so that I know why it's suggesting what it's suggesting and then I would feel more comfortable using it as a way to speed up my clinic.” Every other provider said that they could simply check each recommendation themselves and thus form an opinion about how good the quality of the algorithm is over time. Based on the feedback from providers, the use of recommendations could go three ways. Either the recommendations are not useful which would lead providers to abandon them over time. P05 was part of a trial that piloted an algorithmic CDS at their health system. She said “they came here and we were going pilot the system for them and we did it, but, you know, probably every other patient there was an error message or something that came up. So, you know, you get frustrated and you're like, I'm just going to do it myself and just look at the data.“ Or they could be very good which could lead to an overreliance on them over time and a possible deskilling of their ability to analyze data manually. P01 voiced this concern: “I like that it's making a suggestion. And then I guess my only fear though is that if the computer starts telling people that these are the right directions that things are supposed to head in that people won't actually look at it that closely and they'll just accept it because it's like 20 minute office visits.“ The third option might be a middle ground where recommendations are good but the software only shows them at the end or employs another kind of cognitive forcing function, so providers analyze the data themselves before looking at the recommendations.

6. Discussion and Design Implications

The findings in this study reveal many important design implications for manufacturers of medical diabetes devices and data reports or dashboards. We found that, concurring with existing literature, when a data analysis tool takes the needs of providers into account, the time spent on looking at the data gets reduced and providers can identify opportunities for treatment changes that may have otherwise been overlooked (Craft et al, 2015).

It is evident that pump and CGM data should be combined into one report to remove the burden of handling two reports. Most CGM data is already included in the pump report, so there are just a few data points and one graph that needs to be added and then the CGM report would not be needed for data review anymore. The feedback in session 2 has shown that good data visualizations can help providers to find anchors for data frames more quickly (Klein et al, 2007). They can use graphs with aggregated data like the carbs and bolus graph to create and re-create frames instead of scrolling through many pages of data. The carbs and bolus graph was useful because it took the heuristics of what providers are looking for and showed aggregated data in a way that made it easy to extract insights from it. Manufacturers should look for similar ways to aggregate data that allows providers to quickly spot certain trends without needing to scan all of the individual days. Most providers appreciated the opportunity to have a dashboard that let them explore the data in an interactive way. The filtered pattern view allowed providers to focus on the days that have concerning patterns and blend out the rest. The benefit is that you can compare these patterns and see similarities more easily. The downside is that you may not see the day before or after or miss inconsistencies when blending the other days out. Interactive dashboard were clearly preferred over static PDF reports because dashboards let providers navigate to the relevant data interfaces more quickly without endless scrolling. This means that device manufacturers should improve their dashboards to improve usability and include all the necessary components that providers need to review diabetes data. Health systems should work with manufacturers to address cybersecurity concerns so that providers can use software that is useful and that speeds up their workflow. Otherwise providers are relying on outdated technology which slows down clinical work, increases provider burnout and worsens patient outcomes.

The findings indicated that many providers were skeptical of using algorithmic treatment recommendations and deemed it as not very useful when it was brought up in the session 1. In session 2, most providers praised the recommendations feature when seeing it in the prototype and could imagine using it in their clinical work. This could mean that it is hard for providers to imagine the way recommendations are presented and how they could be integrated into the data review process. They were open to using them as a guide rather than as an absolute source of truth. The findings showed that the when, where and how is very important when it comes to showing recommendations. An important part of the system is backing up an recommendations with data that the provider can review. This explanation allows the provider to verify a recommendation and accept or reject it. This finding is in line with existing literature that stresses the importance of explainability for medical decision support systems (Panigutti et al, 2022). The findings from session 2 stressed that recommendations should be shown at the end of the process, after providers have formed a mental model about patterns, patient behavior, and possible treatment changes. It is also helpful to show recommendations only on demand, for example with the click of a button.

These cognitive forcing functions allow the provider to critically engage with the data first before seeing the recommendations. This is important because it allows providers to spot wrong recommendations and hone their data analysis skills. The significance and positive effect of cognitive forcing functions is in line with previous research by Bucinca et al (2021) and Gajos & Mamykina (2022). Overreliance on recommendations is a real danger and could lead to deskilling of providers regarding diabetes data analysis. Systems should thus be designed for appropriate trust and include cognitive forcing functions while still building features that allow the provider to save time in the process, as has been previously expressed by Schmidt & Biessman (2020), Lee & See (2004), and Panigutti et al (2022). Our findings indicate that explainability of recommendations is desired by providers. However, we did not find evidence for the need to see upfront information about global properties of the model, such as its strengths and limitations. Providers seem to build trust in recommendations over time, based on how often they accept or reject recommendations in their daily practice. This finding is contrary to previous research by Tonekaboni et al (2019) and Cai et al (2019) in which they claimed that providers want to see global properties, strengths, and limitations of the recommendation system before they start using the model. Once trust has been built and a stable provider-algorithm relationship has been established, human-machine teams could bring out the best in each other because the provider could spot errors in algorithmic recommendations while the algorithm could give the provider inspiration and highlight treatment changes that might otherwise have been overlooked. Building the right kind of systems for interaction between provider and machine is important to manage the sensitive topic of medical authority. When algorithms are serving the provider, humans are in charge and make the ultimate decision. When systems are designed for maximum speed, efficiency, and outsourcing of cognitive tasks, the source of authority might transition to the algorithm where the human only accepts suggestions and does not engage cognitively with the data anymore. Providers expressed that the personal connection between provider and patient is very important. The goal of algorithmic recommendations is not to interact with the patient across the whole visit. The goal is to have a tool that the provider can use to make better decisions more quickly and spend less time looking at data. This will free up time during a visit and allow providers to spend more time forming personal connections with patients and educate them on diabetes with empathy.

7. Limitations

Given the challenges of recruiting from a clinical population, the study involved a small number of participants. Our findings may or may not generalize to a larger sample. In addition, most of the providers came from the same health system which limits the diversity of perspectives on diabetes management. We used only PDF reports and did not include an interactive dashboard from an existing provider in session 1. It would have been interesting to observe how providers engage with dashboards to assess their usability. Another limitation is that we used PDF reports from just two device manufacturers. Using reports from other manufacturers would have allowed us to gain additional insights before creating the research prototype. It would have been useful to create several different prototypes and assess how providers engage with each one differently to find out which features are the most useful ones. Overreliance on recommendations is dangerous given the current state of the technology. If algorithms advance to a state where the level of accuracy and quality of treatment is better than any human provider, there will be a need for discussions about how the medical and legal framework regarding algorithmic recommendations needs to be changed. Furthermore, additional research is needed on how software tools can help both patients and providers collaborate to look at the same visualization and make sense of it together.

8. Conclusion

Software tools can make providers more or less efficient when providing care for patients, depending on how well they are designed. This study showed that providers value interactive data visualizations that allow them to explore diabetes data and gather insights on patient behavior efficiently. We discovered essential heuristics that providers use when reviewing diabetes data and created a prototype that leverages these heuristics to improve the data analysis process by combining data checks, aggregating important data points, enabling quick navigability between interfaces, filtering for relevant patterns and providing algorithmic recommendations in the appropriate location. We found that providers were skeptical of the abstract concept of algorithmic recommendations but when faced with concrete recommendations that they were able to individually verify they valued it as a guide that they draw inspiration from. Providers did not see the need to see global properties of the recommendation system upfront and instead judge its value by how often they accept or reject recommendations over time. Our work contributes to the understanding of how providers analyze data to manage diabetes and the needs they have for considering recommendations. We hope that this work inspires diabetes device manufacturers and software designers to create tools that put the user at the center of the design process so that providers can provide better care for their patients.

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Appendix A

Interview Guide for Session 1

General Questions

- What is your position at your health system?
- How many years of experience do you have?
- Which T1D population do you typically work with?

Data Review

We have examples of reports from existing diabetes software management systems including a continuous glucose monitor (CGM) and an insulin pump for you to review.

Please walk through the report while thinking aloud to identify management changes you might make for this patient.

Reports: Patient from report #5 is a 20 year old female, and patient from report #9 is a 7 year old female

- What patterns do you see in the data?
    - Among the multiple patterns that you see, how do you prioritize them for intervention?
    - Do all of these patterns need to be fixed?
        - Why?
        - Why not?
        - How did you come to this conclusion?
- [for a certain pattern] What are some of the potential causes?
    - How did you find the potential causes?

    - What data did you use to identify the causes?
        - Patient behaviors, system behaviors, outcomes, etc.
    - What data do you need to identify the causes?
    - How do you connect different types of data? What makes this challenging, if at all it is challenging?
- How would you fix this pattern, if you would?
    - How did you come to this conclusion?
- What are the challenges of making decisions from patients' data?
    - What would be a difficult case as per you?
    - How do you handle difficult cases - e.g., patterns with more number of possible changes to make, cases that have limited data available, cases where you may disagree with the patient or with the data
    - Which challenges do you face when inferring causes and thinking about recommendations?
- What uncertainty do you face in making decisions from data?
    - How do you deal with the uncertainty? E.g., cases where you are uncertain of a potential cause
- In the face of these challenges, what will help you make decisions?
    - E.g., knowing what do other providers recommend? What do other similar patients benefit from? Having a cheat sheet of clinical standards?
- Are there any parts of the report that you never look at?
    - Why not?
- From your perspective, how do you think you look at these reports differently than a diabetes educator?

[transition after the previous question] Design Ideation

- With analyzing and interpreting data, what support do you need?
- What kind of a computational assistant could you imagine?
- Do you have any challenges when looking at two different reports for CGM and the insulin pump? Could having one common report address these challenges?
- What types of evidence would you want a tool to help you identify?
    - Help in terms of validating your inferences, identifying episodes and causes, handling uncertainty, or identifying alternate treatments
- What could be negative consequences of having an automated data analysis tool for clinicians?
    - Could you imagine having algorithmic recommendations with explanations that give you hints what to do? Or rather just hints at what parts of the data to look at and visualize it in an intuitive way?

Appendix B

Interview Guide for Session 2

Intro

Here are data interfaces to help you understand patient data – detecting patterns and explaining them. As a part of this activity, I would like you to look at these one by one and think aloud to share thoughts that come to mind as you browse these. I will give you some general information about each tab before you start so you have an idea of what it includes. Then you can explore each tab at your own pace, you can open them in the order you like.

Brief information about each tab

- Overview: gives you most important general data about CGM and insulin pump

- Carbs and bolus: gives you a novel way of looking at bolus and carbs data, including Auto bolus
- Therapy timeline: shows you the standard therapy timeline
- Data exploration: an interactive way of exploring episodes and patterns of high or low blood sugar
- Treatment options: shows you pump settings and recommendations for treatment changes
- Patient is a 7 year old female

General feedback at the end

- What information would you like to know about how the algorithm makes recommendations?
- How was your overall experience of reviewing diabetes data with these data interfaces?
    - What did you like about them?
    - What did you not like about them?
- Would you like extra information somewhere? Is there anything missing that you would like to see?
- How do you like the order of the tabs? Would you change the order of them? How would you rank their importance?
- Did you prefer the interfaces that are static and that you can browse or did you like the interactive explorative ones?
- How was this experience different from looking at the PDF reports? (Cognitive load, ease of use)
- How could this be integrated in the clinical workflow?

- What treatment recommendation would you give this patient?

Questions while looking at the prototype

- Summarize what insights you got from each data interface.
- Is the data insights box on the overview page helpful?
- How would the novel visualization of carbs and bolus behavior help you? What do you think about the Control IQ aggregated data?
    - Did this visualization give you any specific insights?
- How could the data exploration tab be improved? Does the organization in patterns and possible causes make sense?
    - Why did you like or not like this interactive approach to exploring the data?
    - Are the probable causes useful information to you?
    - Is there any extra information you would like to see here?
- What do you like/not like about the treatment options tab?
    - Are the graphs on the bottom helpful to figure out treatment changes? Why or why not?
    - Observe: how do they interact with the treatment suggestions? Do they click the i-icon or do they browse manually?
    - Are previous settings helpful?
    - What is your opinion about the treatment suggestions? How would you approach these suggestions? What would you like to learn about the algorithm (or would you like more explanations)?