IDMVis: Temporal Event Sequence Visualization for Type 1 Diabetes Treatment Decision Support

Yixuan Zhang, Kartik Chanana, and Cody Dunne

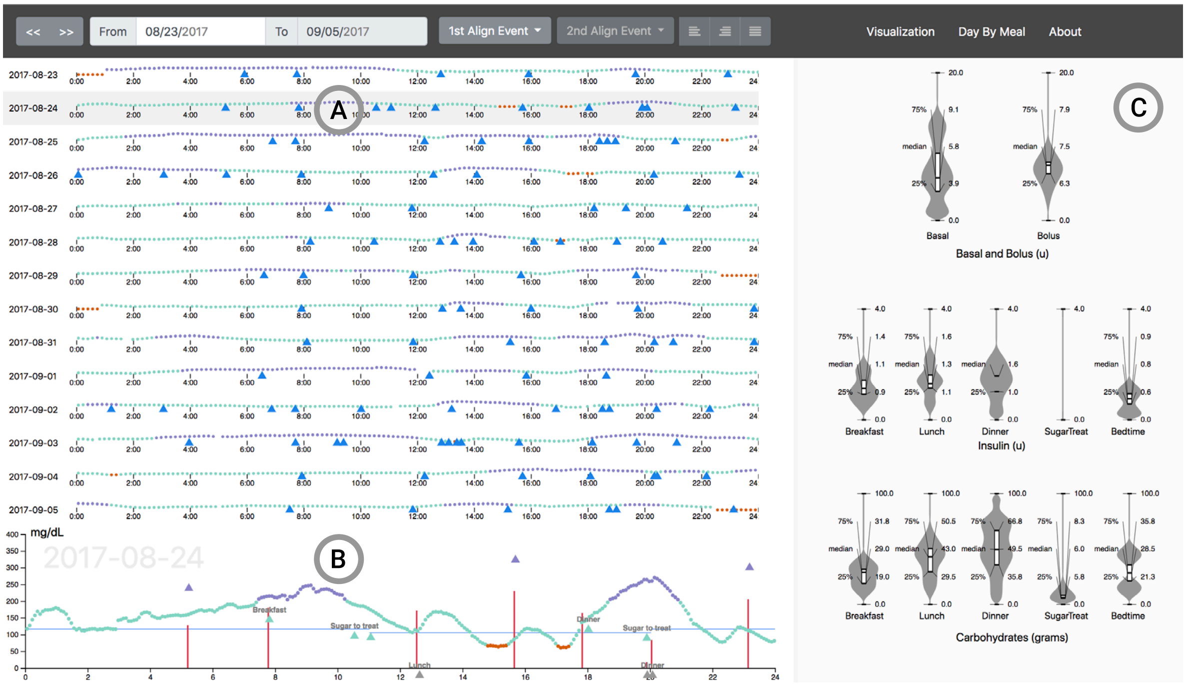

Fig. 1. IDMVis is an interactive visualization tool for showing type 1 diabetes patient data. It is designed to help clinicians perform temporal inference tasks: specifically for recommending adjustments to patient insulin protocol, diet, and behavior. (A) The overview panel displays two weeks of event sequence data at a glance; (B) the detail panel shows additional information for the selected day; (C) the summary statistics panel displays the distribution of insulin and carbohydrate intake overall and for specific events (e.g., breakfast).

Abstract— Type 1 diabetes is a chronic, incurable autoimmune disease affecting millions of Americans in which the body stops producing insulin and blood glucose levels rise. The goal of intensive diabetes management is to lower average blood glucose through frequent adjustments to insulin protocol, diet, and behavior. Manual logs and medical device data are collected by patients, but these multiple sources are presented in disparate visualization designs to the clinician—making temporal inference difficult. We conducted a design study over 18 months with clinicians performing intensive diabetes management. We present a data abstraction and novel hierarchical task abstraction for this domain. We also contribute IDMVis: a visualization tool for temporal event sequences with multidimensional, interrelated data. IDMVis includes a novel technique for folding and aligning records by dual sentinel events and scaling the intermediate timeline. We validate our design decisions based on our domain abstractions, best practices, and through a qualitative evaluation with six clinicians. The results of this study indicate that IDMVis accurately reflects the workflow of clinicians. Using IDMVis, clinicians are able to identify issues of data quality such as missing or conflicting data, reconstruct patient records when data is missing, differentiate between days with different patterns, and promote educational interventions after identifying discrepancies.

Index Terms—Design study, task analysis, event sequence visualization, time series data, qualitative evaluation, health applications

1 Introduction

Type 1 diabetes, also called insulin-dependent diabetes and juvenile diabetes, is an autoimmune disease which afflicts 1.25 million Americans. Type 1 diabetes is incurable, and people with type 1 diabetes are estimated to lose over 10 years from their life expectancy [23]. However, with appropriate therapy patients can live long and healthy lives [58]. To optimize health outcomes, patients need to regularly meet their diabetes care team [58]. Clinicians work together with patients to develop personalized treatment plans as well as educate them about diabetes data analysis, proper nutrition, and other self-care needs. Clinicians need to parse varied data, ranging from blood glucose levels to the details of food and insulin administration at each meal and meal timing. A correct reasoning about the interplay between events and blood glucose levels is key for designing an effective treatment plan with the patient. Given the complex interplay between a large number of factors, effective visualization is essential in assisting clinicians to evaluate, reason, make decisions, and communicate with patients.

Current tools for clinician type 1 diabetes management focus on temporal event sequence visualizations which display point data, sometimes

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juxtaposed with separate interval event visualizations [15, 19, 49, 54]. However, disparate juxtaposed visualizations are insufficient for understanding nuanced temporal interactions between many data sources. With long, rapidly changing time series it can be difficult to see the subsets relevant to an event of interest. Many visualizations excel at revealing periodic or cyclic phenomena through carefully chosen folded time scales, but non-periodic patterns can be obscured by a fixed time scale. When considering multiple event pairs across sequences with varied interspersed gaps, it can be difficult to see the overall pattern of relationships between co-occuring events. These problems are compounded by issues of data quality such as missing data, uncertainty in sensor or manual logs, inconsistency between sources with various temporal granularities and level of accuracy, and incorrect timestamps.

In this design study [42] we contribute:

- A novel form of task abstraction for visualization design called hierarchical task abstraction, which marries hierarchical task analysis with task abstraction.
- A data and task abstraction for clinicians performing type 1 diabetes data analysis for treatment recommendation.
- The design and implementation of IDMVis, an interactive visualization tool to support clinicians adjusting intensive diabetes management treatment plans. IDMVis includes techniques for folding and reconfiguring temporal event sequences; aligning by one [57] or two sentinel events of interest and scaling time axes between two aligned events; and for superimposing data from multiple sources to enable temporal inference with uncertain data.
- A summative evaluation of our abstractions and IDMVis with clinicians which validates our approach and elucidates how visualization can support clinicians make treatment decisions.

2 Background on Type 1 Diabetes

Type 1 diabetes is an autoimmune disorder resulting from the progressive destruction of the pancreatic beta cells (insulitis) [58]. Beta cells are responsible for producing the hormone insulin which regulates blood glucose. Without beta cells producing enough insulin, blood glucose levels rise and cells are unable to get energy from the blood stream. If untreated the patient will enter ketoacidosis, a coma, and eventually die. The only treatment for type 1 diabetes is insulin injections, usually multiple times per day with intensive diabetes management [58]. The goal is to lower average blood glucose and keep it within a target range, e.g. 80–180 mg/dL (USA) or 4.4–10 mmol/L (UK and many other countries) [4]. In this paper we use mg/dL. Blood glucose lower than 70 mg/dL (hypoglycemia) puts the patient at risk for seizures, coma, and death; blood glucose above 180 mg/dL (hyperglycemia) increases the risk of long-term complications to most major organ systems.

The patient or their caregiver(s) take over the role of the beta cells by monitoring and adjusting blood glucose levels. Monitoring is done by testing blood with a glucose meter (**SMBG**) 4+ times a day [41] and/or measured more frequently by a continuous glucose monitor (**CGM**) sensor inserted into body fat for 1–3 weeks [11]. To lower blood glucose levels, insulin is injected into the body via an insulin pump, syringes, and pens. To raise blood glucose levels, food is consumed.

However, blood glucose level is determined by a complex interplay of factors beyond food and insulin [10, 58], which complicates treatment. In **intensive diabetes management (IDM)** [58], treatment plans integrate several components into a patient's lifestyle including blood glucose monitoring, carbohydrate counting to match food with insulin, intensity and duration of physical activity, and self-adjusting insulin protocols. Two constants—the insulin to carbohydrate ratio and insulin sensitivity—are carefully titrated for individual times of the day and/or weekdays. These constants, as well as other factors such as dietary choices and timing of doses, are reassessed on a monthly or weekly schedule. Patients are usually given insulin in two forms: long-acting **basal insulin** and fast-acting **bolus insulin**. There are many other factors to consider when designing a treatment plan that we will not list here for space considerations. See [40] for a detailed discussion.

In order to make evidence-based treatment adjustments, patients and their caregiver(s) are asked to start monitoring blood glucose levels and events throughout the day in a paper or electronic logbook. Logs typically include blood glucose levels before and after meals, the amount of insulin injected, and grams of carbohydrates ingested. Sometimes additional factors affecting blood glucose are recorded, such as grams of protein and fat ingested, specific foods eaten, and sickness, exercise intensity, and errors. All entries are datetime stamped manually or electronically. Additionally, medical device data can be downloaded over USB by desktop applications or automatically by Bluetooth to phone or web apps. However, devices vary widely in their accuracy and the data from devices and logbooks is often incomplete or erroneous.

Frequent visits with the patient's diabetes management team are required for treatment adjustment, education, and ensuring treatment adherence. The clinicians involved generally include a **certified diabetes educator (CDE)**, dietitian, endocrinologist, and social worker. All but the social worker are directly involved in extensive data analysis with patients or their caregiver(s), which usually consists of performing temporal inference tasks on 14 days (see Section 9.2) of collected logbook and device data. From our interviews (see Section 8) we learned that CDEs meet with their patients on average every three to six months—if patients meet their HbA1c goal. HbA1c [58] is a common blood test used as a proxy for how well diabetes is controlled. Patients above their goal are recommended to visit their CDE monthly or even weekly. Patients usually visit their dietitians and endocrinologists once and twice a year, respectively. During a clinical visit, the length of time spent on data analysis can vary from 15–60 minutes.

3 Related Work

3.1 Temporal Event Sequence Visualization

Many techniques for visualizing temporal event sequences have been proposed. Here we discuss those techniques particularly relevant.

Temporal folding, or splitting, a sequence into periodic units like hours, weeks, months, or years can be used to find cyclic phenomena. Folding can reduce pattern variety facilitating visual analysis [17]. **Aligning** sequences by **sentinel events** of interest helps users identify precursor, co-occurring, and aftereffect events [57]. E.g., alignment has been successfully applied in LifeLines2 [57] for clinical events and in CareCruiser [20] by aligning treatment plans. When aligned by a single event we can maintain a consistent time scale between folded or reconfigured units of event sequences. However, it can be valuable to explore the sequence between two separate sentinel events. Current approaches do not support multiple sentinel event alignment or techniques for scaling timelines between them.

Viewing multiple folded and aligned units of event sequences simultaneously and in their entirety would require considerable screen space. However, aggregation can obscure rapid changes and outliers. Overview and detail approaches are beneficial in these cases [2, 45].

Many temporal event sequences of interest suffer from issues of incompleteness, uncertainty (both data uncertainty and temporal uncertainty [1, 25], and inconsistency between sources. To overcome these barriers, our solution is to combine infrequent, accurate readings in the same composite visualization with frequent, inaccurate readings—as well as other manually or automatically logged factors of interest.

Take-away: Our study builds upon this prior work by developing the techniques needed for decision making using temporal event sequence visualizations of a long stream of multidimensional, interrelated data. In particular, we use temporal folding [17] combined with novel dual sentinel event alignment and time scaling to support temporal inference about intervals preceding, between, and following the events.

3.2 Electronic Health Record Visualization

Electronic health record visualization is often closely aligned with the problems of temporal event sequence visualization—the health state of a patient inherently changes over time. Early approaches focused on a single patient and displayed both point and interval events, e.g. the Time Line Browser for diabetes data [13] and LifeLines for a personal medical history [33]. KNAVE I [43] and II [44] augmented dynamic exploration of a patient's record with domain-specific abstractions and ontologies. For multiple patient records or cohorts, VISITORS [26]

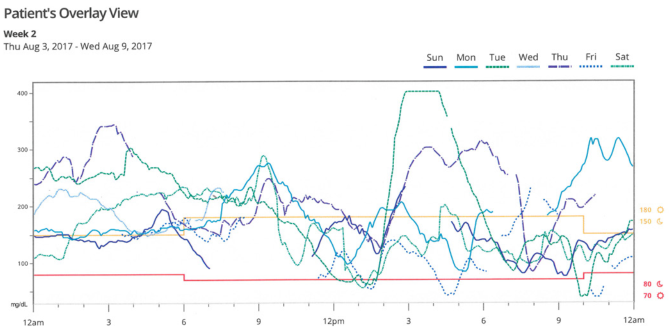

Fig. 2. A screenshot of Dexcom CLARITY shows blood glucose levels for seven days superimposed with a different color for each day [15].

(succeeding the KNAVEs) and LifeLines2 [57] (succeeding LifeLines) provide aggregation and cohort analysis visualizations.

The comprehensive survey of electronic health record visualizations by Rind et al. [37] includes many temporal visualizations. Their taxonomy groups techniques according to data types integrated, of which we use both categorical and numerical data. Our categorical data includes nominal and ordinal components, and our numerical data includes both interval and ratio components—see Section 4 and Table 1. Many of the surveyed systems support multiple variables via separate windows or juxtaposed visualizations, notably excepting the Time Line Browser [13]. We believe this is insufficient for exploring the intricate interrelationships and uncertainty in type 1 diabetes data. Our work focuses on superimposed distinct visualizations of multivariate data.

More recently, Rind et al. [36] discusses the difficulties in designing visual analytics tools for temporal electronic health records that include poor data quality and uncertainty. General techniques for data cleaning or wrangling are outside the scope of this paper. However, we hope that our work will form the basis for tools that will bring effective personal visualization into the collaborative analysis between the patient, family, and clinician. The eventual goal is to increase data logging compliance, completeness, and accuracy by leveraging the personal visualization's facility for promoting self-reflection and reminiscing [53].

Take-away: In the context of type 1 diabetes, our work focuses on superimposed distinct visualizations of multivariate data combined with temporal folding and sentinel event alignment to promote reflection and reconstruction of data. Existing personal electronic health record visualizations are constrained by data and domain scenarios and/or do not support these visualization approaches. Multiple record or cohort visualization tools are not designed to facilitate such personal visualization.

3.3 Type 1 Diabetes Visualization

Paper diabetes logbooks are widely used despite many available electronic options. A logbook is usually arranged as a table of days by common events such as meal and bed times. Clinicians use the table to understand blood glucose trends between these events and overnight.

Data from diabetes medical devices is usually viewed through vendor web, phone, or desktop applications. These devices include continuous glucose monitors (CGMs), insulin pumps, glucose meters, ketone meters, and Bluetooth-enabled insulin pens. E.g., Dexcom CGM data can be viewed in CLARITY [15], which provides small multiple time series for individual days, a 7-day superimposed line chart (Figure 2), 14-day percentile charts, and aggregate statistics. Tandem insulin pump data can be viewed in t:connect [49] which shows one day at a time or multiple days superimposed—as well as aggregate statistics. The benefit of superimposing time series from multiple days is to allow direct comparison without changing the view [22]. However, these line charts may cause significant visual clutter and conflicts [22]. Superimposing distinct views can sidestep this problem [6].

Performing temporal inference using disparate applications for each data source is challenging. Despite several advances in data integration and visualization, device interoperability and data integration remains problematic [56]. Existing tools for integration include the open source Tidepool [54,59] and Nightscout [51] as well as the commercial Glooko [19]. These tools combine several visualizations: day-by-time scatterplots/tables, multi-day percentile charts/box plots, small multiples for individual days, aggregate statistics. Each can display continuous glucose monitor, glucose meter, and insulin pump data.

In addition, many research prototypes have been developed for visualizing diabetes data—e.g. Time Line Browser [13]—and for encouraging self-tracking activities and reflection—e.g. by integrating photos of meals on a timeline [18,46]. More recently, Katz et al. [24] investigated how a variety of visualizations help users reflect on type 1 diabetes data and suggest that line charts provide value in understanding frequency and variation of blood glucose tests and that overview statistics visualizations can help assess overall performance.

Take-away: Temporal event sequence analysis of the last 14 days of data is a critical part of diabetes treatment (see Section 9.2). Current diabetes data visualization tools do not provide multi-day overviews of event sequences integrated from multiple sources. Nor do they support sentinel event alignment for identifying precursor or aftereffect events. Existing superimposed line charts are cluttered and challenging to read.

3.4 Task Analysis and Abstraction

Task Analysis: Among the many types of task analysis detailed by Diaper and Stanton [16], **hierarchical task analysis** is a popular approach [39]. It incorporates a set of goals and low-level tasks in a hierarchical manner to help researchers understand not only the necessary tasks but also the goals and process [5,38,39]. It has been applied successfully in health applications, e.g. for hemophilia care [50].

Another popular analysis framework is cognitive work analysis [55]. It is similar to hierarchical task analysis in that they both involve process observation, but there are marked differences. Salmon et al. [39] explicitly compared them theoretically and methodologically and concluded that cognitive work analysis describes systems formatively based on constraints imposed on activities, whereas hierarchical task analysis describes systems normatively using goals, plans, and activities. The derived outputs differ, but are also highly complementary. In this paper, we focus on analytic goals and thus use hierarchical task analysis.

Task Abstraction: There are many existing task abstraction systems and methods in the visualization community. Most of them focused on high or low level task abstractions [9,27,35]. However, a recent qualitative study of 20 IEEE InfoVis design study papers showed that most existing task abstractions cannot easily bridge between high-level goals and low-level tasks [27]. A few abstraction systems mentioned the sequential and hierarchical structure of tasks. For example, Springmeyer et al. [48] reported a characterization of the scientific data analysis process that applied hierarchical structure and decomposition of activities. The multi-level typology of task abstraction introduced by Brehmer and Munzner [9] discussed how their typology can be used to compose complex tasks into sequences of simpler tasks (why-what-how). However, both of these approaches omit relevant non-visualization tasks that are crucial for understanding the analysis process (e.g. see Section 5.1).

Instead of proposing a visualization task classification system, we propose a systematic approach that brings real-world problems and visualization design closer by marrying hierarchical task analysis rooted in human-computer interaction with visualization task abstraction: forming **hierarchical task abstraction**.

Take-away: Effective task abstraction requires bridging high-level user goals and their low-level tasks. Before conducting task abstraction, performing a hierarchical task analysis can help visualization designers understand user goals, processes, and interrelated tasks.

4 Data Abstraction

The data recorded by a type 1 diabetes patient usually consists of datetime stamped events from a logbook and diabetes medical devices (see Section 2 for more detail). For this design study, we focus on the more commonly collected data which is summarized in Table 1.

Table 1. Data abstraction summary

Key Term	Data Abstraction	Example
Data from devices		
CGM	Quantitative (Ratio)	100 mg/dL or 5.5 mmol/L
Basal insulin	Quantitative (Ratio)	.267 units/hr
Data from logbooks		
SMBG	Quantitative (Ratio)	100 mg/dL or 5.5 mmol/L
Bolus insulin	Quantitative (Ratio)	2.3 units
Event tag	Nominal	Breakfast
Carbohydrates	Quantitative (Ratio)	33 g
Meal contents	Text	"*Peanuts, tofu, broccoli, milk*"
Notes	Text	"*Overdose by .5u as rising fast*"

Data from devices: CGM data provides near-real-time glucose readings for type 1 diabetes patients (approx. 288 readings per day). A single CGM data sample is a number, in the unit of mg/dL or mmol/L, and an associated timestamp. Basal insulin can be administered by an insulin pump using fast-acting insulin or injection using long-acting insulin—the examples in this paper show data from an insulin pump. Each datum contains an insulin delivery rate in the unit of units/hr and associates two timestamps for when the rate starts and ends.

Data from logbooks: Each entry in the logbook represents a daily event such as breakfast, lunch, dinner, or exercise, as recorded in the "Event tag" field with a corresponding datetime value. For different types of events, type-specific information is recorded in the logbook. For example, a meal would have grams of carbohydrates and meal contents. Patients (or their caregivers) often add notes to events to explain abnormalities in measurements or treatment. Notes can help with later reflections and analyses of the event sequence.

5 Hierarchical Task Abstraction

5.1 Hierarchical Task Analysis of Clinician Workflow

We emphasize three important aspects of hierarchical task analysis that can benefit the visualization domain: (1) task hierarchy, (2) task sequence, and (3) task context.

Task hierarchy: The task hierarchy provides insights about the "bigger-picture" of each atomic task—a task that does not contain any subtasks—helping ensure that we always consider higher-level goals. For example, if the atomic task is to examine an event's details, a tooltip perfectly solves the problem. However, if the parent task is to reason about blood glucose levels overall, a tooltip is grossly insufficient.

Task sequence: As tasks often have dependency relationships with each other, there can be a required task sequence. E.g., one has to view data before reasoning about it, and an overview visualization needs to be presented before selecting and examining outliers. Therefore, visualization tools should not simply fulfill discrete tasks without providing for a natural flow between consecutive steps. Integrating task sequence information can help mitigate the user's mental burden and provide a better overall user experience.

Task context: While many abstract tasks are similar (e.g. discover patterns and trends, reason about outliers), visualization tools often are used in a domain-specific context. E.g., we are designing a tool for clinic appointments in which communication between patients and clinicians and patient education are essential. We cannot simply peel off the domain-specific context, abstract to common data visualization tasks, and then design for those tasks. Context is key.

We performed a hierarchical task analysis of a clinician working with a type 1 diabetic patient on data analysis during a clinic visit. Our analysis is based on contextual inquiry [7] interviews with a CDE, a dietitian, and an endocrinologist. We interviewed and observed each clinician over multiple sessions. We later iteratively refined and validated our task analysis from our study with six clinicians (see Section 8). Figure 3 shows a diagram of our hierarchical task analysis.

During a clinic visit, the overall goal for clinicians is to help the patient develop a treatment plan and perform educational interventions (*Task 0*). Clinicians collect and show the patient's available data (*Task 1*). They download and print out reports for each of the patients' medical devices (*Task 1.1*) and ask for any diabetes logbook the patient or their caregivers have recorded (*Task 1.2*). Note that we include *Task 1* in the hierarchical task abstraction diagram despite it not being a visualization task, as it imposes important constraints on what data are available for analysis and whether the data can be integrated in one visualization. This further indicated the design requirement (**DR1**).

After clinicians have the data at hand, they get a general impression of how things are going (*Task 2*). They want to identify broad challenges/goals and degree of severity (e.g., high all the time, frequent lows, noncompliance/mistakes/confusion). They do this by scanning the day-by-day data (*Task 2.1*). Then they are able to get a sense of the "good" days when most of the glucose levels are within range (*Task 2.1.1*) and "bad" days when a lot of high and low readings appear (*Task 2.1.2*). Meanwhile, they may investigate the quality of data (*Task 2.2*). In general, they identify missing, uncertain, or erroneous data (*Task 2.2.1*). If there are issues of data quality—and the data is necessary for crafting the treatment plan or understanding noncompliance with recommendations—the clinician may ask patients to reconstruct what happened using the available data as a guide (*Task 2.2.2*). The clinician will also discount any explainable abnormalities, such as sickness, user/device error, or a holiday meal (*Task 2.2.3*).

Afterward, or iteratively intertwined with *Task 2*, clinicians reason about the patient's blood glucose levels (*Task 3*). Iteration is shown with **blue arrows and bold text**. The reasoning is complex and requires multiple operations to achieve the goal. Clinicians tend to reason in different ways. Clinicians often look for typical "good" days so that they can provide positive reinforcement. Clinicians also need to find the baseline to compare against when they reason about what led to "bad" days. The most common tasks performed by clinicians include examining the details of events (*Task 3.1*), exploring how glucose levels change in response to events (*Task 3.2*), and understanding what happened between meals to investigate the interplay between events (*Task 3.3*). Clinicians also evaluate key variables for sub-day time intervals (*Task 3.4*), such as basal and bolus insulin amounts and carbohydrates eaten between 6 a.m. and 10 a.m. over the past few weeks.

Lastly, clinicians are able to make treatment plans for patients based on their evaluation and reasoning. To fully accomplish *Tasks 4* and *5* requires extensive professional knowledge and experience in working with patients, and is thus not the focus of this work. But our tool addresses the data analysis portion of those tasks and aids clinicians in communicating with patients and jointly reconstructing event sequences. We indicate the interplay of patient education (*Task 4*) with the rest of the process with **orange lines and bold text**.

5.2 Hierarchical Task Abstraction

Based on the hierarchical task analysis, we transform the domain tasks into abstract forms to understand the similarities and differences between domain situations [3, 29]. We apply the framework proposed by Lam et al. [27] to generate the task abstraction to best fit our study since our work is in line with the aims of their framework to connect goals and tasks. Task abstractions are integrated in Figure 3.

6 Design Requirements

We identified design requirements based on the informal qualitative user study with clinicians and abstractions discussed above.

DR1. Composite Visualization of Integrated Data: Clinicians usually need to analyze information from multiple sources (e.g., patients' devices, logbooks) to perform temporal inference. A design that visualizes integrated, multidimensional, interrelated data can be of great value for more efficient and effective clinic appointments.

DR2. Composite Visualization of Folded Temporal Data: Visualizations should support trend identification both for an individual day and across 14 days of integrated data.

DR3. Align and Scale Temporal Data: Clinicians should be able to reason about why a particular abnormal reading took place. They should be able to discover patterns and trends around mealtimes and identify precursor, co-occurring, and aftereffect events.

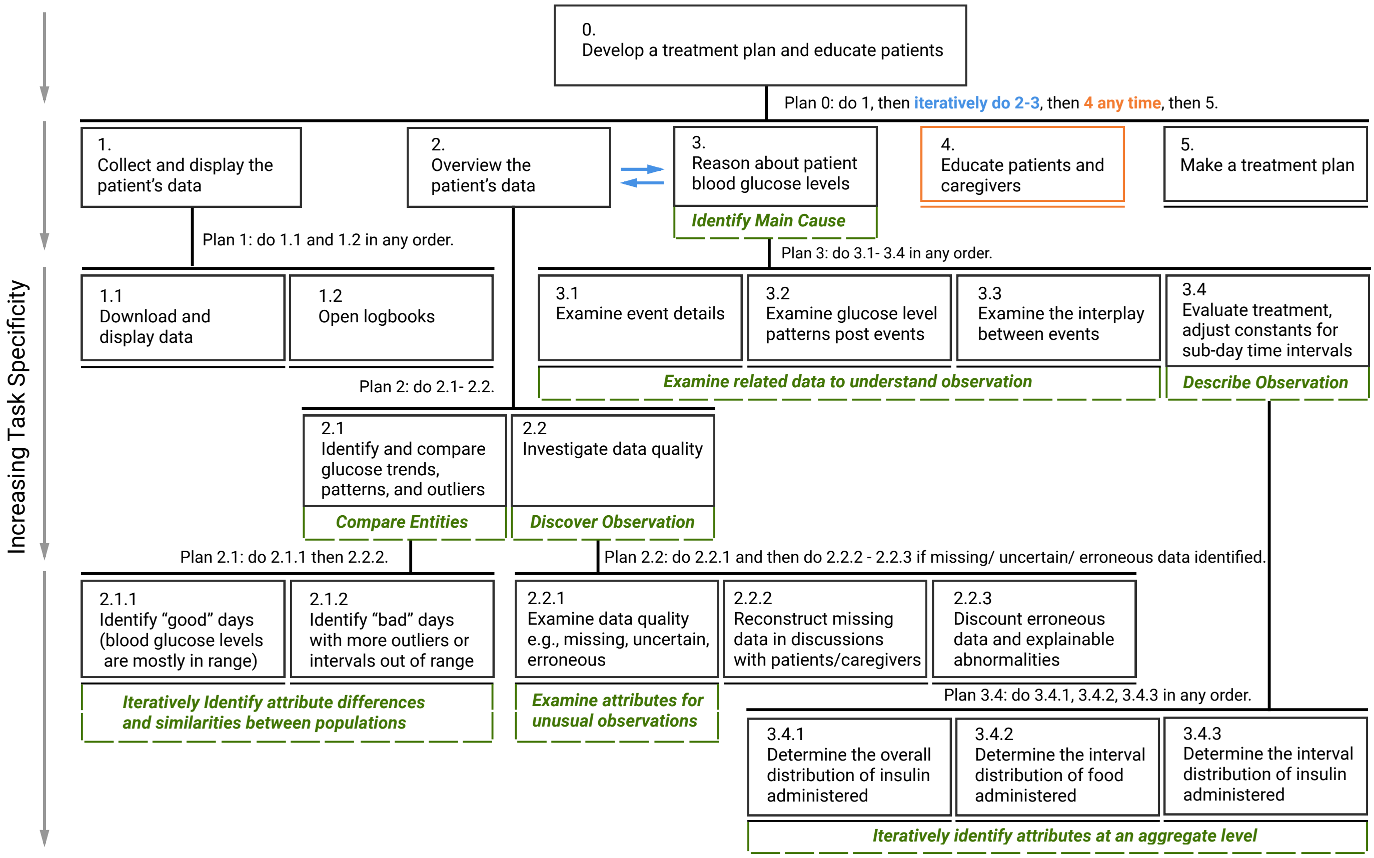

Fig. 3. Hierarchical task abstraction of clinician domain problems and process using box-and-line notation. We follow standard conventions for hierarchical task analysis [38] where tasks are represented by named boxes with a unique ID which also denotes the level of the hierarchy. The hierarchical relationship between a task and subtask is expressed using a vertical line with a horizontal line at the bottom that extends above the subtasks. The text alongside a vertical line provides detail on the sequence of subtasks. If a task has no subtasks, a thick horizontal line is drawn underneath the corresponding box. Task abstractions using [27] are denoted by ***green, bold, & italic text*** surrounded by green dashed lines.

DR4. Summary Statistics: Clinicians would like to know the distribution of key variables (e.g., insulin administered, carbohydrate intake) to help them evaluate patient status and performance. The design should provide a summary view of key variable distributions.

7 Visualization Design

IDMVis is an open source browser-based interactive visualization tool[1] built with JavaScript and d3.js [8]. The goal of IDMVis is to assist clinicians in interpreting blood glucose measurements alongside relevant data about diet, exercise, and behavior so as to accurately reason about the fluctuations in blood glucose levels. IDMVis allows clinicians to explore data with patients or their caregiver(s) to support reflection, collaborative data reconstruction, and patient education.

The main interface of IDMVis, as shown in Figure 1, incorporates (A) a 14-day overview, (B) a detail view of a single day, and (C) a summary statistics view. Note that the letter annotations in Figure 1 are not part of the application. We apply Shneiderman's graphical user interface design guideline "Overview first, zoom and filter, then detail-on-demand" [45] as it well fits our design requirements. We iteratively designed IDMVis over 18 months with periodic consultation from the same CDE, dietitian, and endocrinologist we interviewed to create the initial hierarchical task abstraction.

7.1 14-Day Overview

The overview panel occupies the major part of the interface and integrates the CGM data and events from the patient's logbook to support **DR1** and **DR2**. The purpose of the overview is to allow clinicians to quickly and easily identify glucose trends and patterns, as well as provide ways to reason about the glucose trends via sentinel event alignment. By default, the overview presents 14 days of event sequence data as it reflects the clinicians' workflow and convention (see Section 9.2).

To best fulfill **DR1** and **DR2**, we use a composite visualization design. We superimpose discrete visualizations of data from multiple event sequence sources to facilitate temporal inference [6, 22]. To help clinicians identify the trends and patterns across days, we use small multiples to partition data folded by days [29]. We do not show the overview as a continuous timeline because we respect the periodic nature of the data, as the blood glucose level generally shows similar patterns from day to day. We also do not show it by superimposing multiple days, as shown in Figure 2, to avoid clutter and interference from different days [22]. The row arrangement also enables easy comparison among days as small multiples.

Our first design iteration included a scrollable view of the small multiples, each showing both SMBG and CGM data and taking 1/4 of the vertical screen space. We quickly realized when consulting with clinicians that the amount of scrolling up and down the list proved to be a limiting factor. Our next iteration used a simplified time series on a small vertical scale such that two weeks fit on the screen. Therefore, IDMVis is designed to be a single-window application with no scrolling. We saved screen space and reduced information complexity by moving the legend to the *About* page (see the supplemental material).

Each day is presented in a row, with a date label on the left and event sequence following. Each CGM reading is displayed as a dot arranged on a small vertical scale for the row to modestly indicate blood glucose level. The blood glucose level is also shown using color encoding—this is the primary encoding. By default, sea green indicates the normal range of blood glucose (70-180 mg/dL), with purple for above range

[1] Website, live demo, and source code: github.com/VisDunneRight/IDMVis
Demo video: youtu.be/Omc2cNqG7b4

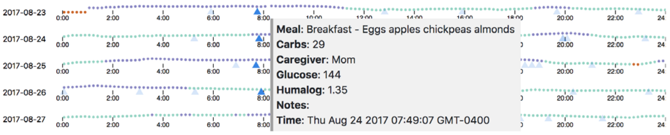

Fig. 4. Hovering over a triangle event mark in the overview shows a tooltip and all events of the same type are highlighted while others fade.

(over 180 mg/dL), and orange ● for below range (below 70 mg/dL). The colors are chosen such that extreme events pop out due to variation in lightness. The color scheme is color-blind friendly—we checked the colors through Coblis, a color blindness simulator [14]. Clinicians may wish to customize their colors and blood glucose thresholds for a patient. As a rendering and human performance optimization, multiple rapid events from a CGM are coalesced into one for every five minutes. Since blood glucose is a smooth changing variable, no significant information is omitted and the detail view of each day does not omit data points. This strategy has also been described as "Coalescing Repeating Point Events into One" by Du et al. [17].

Each event from the patient's logbook is displayed as a blue triangle ▲ [57] with the top vertex indicating the exact event timing. A mouseover tooltip for each event displays data from the patient's logbook (*Task 3.1*). Additionally, on mouseover all events of the same type (Breakfast, Lunch, and Dinner, etc.) are highlighted as all other events are faded out ▲ (see Figure 4).

The 14-day overview mainly supports *Task 2.1*. When the visualization is presented, clinicians can scan to understand how things are doing and can immediately identify broad challenges/goals and degree of severity throughout the day. Many clinicians first look at the morning data, so might hover on a breakfast event and can immediately see all the breakfast events highlighted and understand when the patient ate (or skipped) breakfast. If they check the CGM data immediately before breakfast or the glucose level data in the tooltips, they should be able to identify well-controlled mornings. This partially supports *Task 3*. However, without more advanced features and coordinated views, clinicians may not easily complete those tasks. Therefore, we introduce several features for facilitating temporal inference.

7.2 Alignment

In the overview alone, it would be challenging for a clinician to reason about individual event types and what events generally precede and follow them. For example, to examine how blood glucose levels change in the next three hours after breakfast, the clinician would have to search for breakfasts across days to evaluate them independently. Comparisons within days require understanding the timing differences of the events.

To address this problem and support **DR3**, IDMVis can align sentinel events of interest vertically and color them green ▲ to directly compare preceding and following events. We introduce four types of alignment:

Single-event alignment vertically aligns the first instance of a chosen sentinel event type in each day, as in LifeLines2 [57]. Alignment can help examine how blood glucose levels respond to an event (*Task 3.2*). It can help with comparison of the blood glucose patterns in the same situation (rather than the exact same time) of each day. For example, a patient may eat lunch at vastly different times on different days, or skip it entirely. Aligning sequences by lunch helps clinicians understand patterns across days. As shown in Figure 5, we can see the post-meal blood glucose levels tend to be high in the afternoon (purple circles ●). However, time scales are now individual for each day.

Dual-event alignment aims to further reveal the sequence of events surrounding and between **two** sentinel events. Aligning two events imposes a unique challenge in that the time interval between two events across days may not be the same. If we force two events to be located at certain positions on the time axis, the time scale may be distorted. To explore how various distortion techniques may impact the user experience, we provide three time scaling schemes for dual-event alignment. As shown in Figure 6, each day's timeline is ticked every two hours to be interpretable without too much clutter. In dual-event alignment, we place the first sentinel event at 30% from the left of the row and the

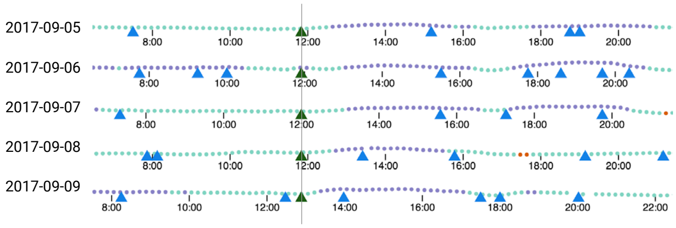

Fig. 5. Single-event alignment by lunch allows exploration of temporal patterns across days and analysis of following trends. This patient has a pattern of high blood glucose after lunch shown by purple circles ● ● ●.

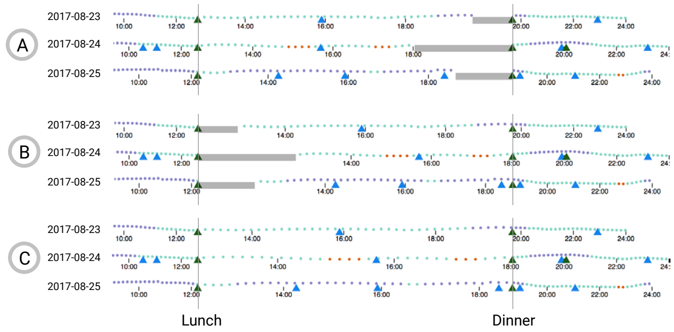

Fig. 6. Showing dual-event alignment by lunch and dinner using (A) left-justified, (B) right-justified, and (C) stretch time scaling.

second at 70%. This provides us with plenty of room to visualize the interval between events (*Task 3.3*) using our time scaling techniques.

Left-justified time scaling is shown in Figure 6 (A). In this method, we determine the longest time interval between the two sentinel events among the 14 days. The associated day's timeline is stretched to fill the 40% of the row remaining between the events. Note that this time scale will likely differ from the scale for the outer 60% of the row. Next, we use the same time scale for each day's interval, beginning at the first sentinel event to show the event sequence following it. As all these intervals are equal or shorter in length than the original one, we have unused space to the right of the interval which we fill with a gray bar up to the second sentinel event. This prevents any confusion about whether there was missing data during that period. By examining the gray bars, a clinician can see which day has the shortest interval (longest bar) and the distribution of the interval lengths.

Right-justified time scaling, shown in Figure 6 (B), is done just as in left-justified scaling—except that shorter intervals between the two sentinel events end at the second event instead of beginning at the first. This helps to display the event sequence preceding the second event.

Stretch time scaling, shown in Figure 6 (C), is a straightforward approach where the intervals between the two sentinel events are stretched to fill the available space. This means that the intervals have completely different time scales, unlike with the left- and right-justified approaches where the intervals all have the same scale. However, a modest indicator of this variation is shown by variation in spacing of the CGM dots which occur every five minutes. Stretch time scaling can be useful when the duration is not the emphasis but event sequence is, thus we give as much space as possible to showing the sequence.

7.3 Detail View

Clicking on a day of interest, the detail view will pop up at the bottom of the screen, as shown in Figure 1 (B). The detail view shows more information for the selected day to support **DR1**, including the CGM and SMBG readings, basal insulin rate, and bolus insulin administration. CGM readings are shown as colored dots as in the overview but have a much larger vertical axis to display the trend more effectively using position as the primary encoding. Each event log entry is represented as a triangle positioned and colored by SMBG readings: orange ▲ for low, sea green ▲ for normal, purple ▲ for high, and gray ▲ for none.

Horizontal blue lines — are arranged vertically to show relative basal insulin rates but not the precise values, as the change throughout the day is more important to know than the exact rate. Vertical red lines display bolus insulin provided by an insulin pump upload or logbook. The height of each line again indicates the relative amount of insulin provided but not the exact quantity. As within the 14-day overview, the visualizations of CGM readings and event logs are superimposed to allow for easy comparison and interpretation across multiple data sources as the user can focus on the same visual space [22].

7.4 Summary Statistics Panel

To fulfill **DR4** and support *Tasks 3.4 and 5*, we designed a summary statistics panel. Our initial design used a 14-day percentile chart but early interviews revealed that this was insufficient for capturing variation in non-periodic event types. Subsequent iterations using summary statistics (median, standard deviation), histograms, and box plots for each event type were deemed insufficient to display variation in samples of a population. We settled on quartile-labeled violin plots as they improve over box plots by showing the probability density of the distribution [21]. It is challenging to align median and quartile labels on multiple violin plots as median and quartile points vary. To enable comparison we fix label positions and draw leader lines to points on the plot. Figure 1 (C) presents the final 14-day summary statistics panel showing the overall distribution of insulin and carbohydrate intake by event type. The violin plots on the top represent the distribution of basal and bolus insulin. The five plots in the middle display the distribution of insulin for specific events: breakfast, lunch, dinner, sugar to treat, and bedtime. The five bottom plots correspond to the distribution of carbohydrate intake for those events. We can see that dinners are the largest meals and the most varied, carbohydrate-wise. Hence, we may want to be careful when adjusting the dinner insulin-to-carbohydrate ratio as a small change could have large and diverse effects.

7.5 Data Integration

IDMVis visualizes a dataset integrating multiple sources. We integrate CGM data from Tidepool [54] and Nightscout [51] APIs, insulin pump data from the Tidepool API, and a Google Sheet electronic logbook. Our integration service pulls from these sources periodically into a central database. Note that this system is set up for a single patient – further deployment would require modification. Techniques for data collection more broadly including behavior tracking and comprehensive food logging are not in the scope of this work.

8 Summative Evaluation

We performed a summative evaluation to understand more deeply the workflow and decision-making process of clinicians and how well IDMVis can facilitate this process.

8.1 Participants

We recruited six clinicians including three CDEs who are also registered nurses (RNs); two dietitians; and one who is a CDE, RN, and dietitian. One CDE/RN and one dietitian who were involved in the contextual inquiry interviews also participated in the evaluation study. We recruited the subjects in an urban city in the Northeast U.S. All participants regularly perform intensive diabetes management with patients with type 1 diabetes. Demographics are presented in Table 2. The mean time they have practiced as a CDE or a dietitian is 17.2 years with a standard deviation of 11.7. All the participants are female—in line with national survey results reporting that 91% of CDEs are female [60]. The gender bias in fact reflects gender inequality issues for registered nurses (90% female) [30] and dietitians (90% female) [12]. Each participant was compensated with a $99.99 USD gift card.

8.2 Apparatus

The dataset used in the evaluation study was from a patient recently diagnosed with type 1 diabetes (1 year, 4 months). We de-identified and integrated a variety of data from a CGM, an insulin pump, and an electronic diabetes logbook. The logbook consisted of timestamped SMBG readings, meal carbohydrate count and contents, exercise and symptom notes, and insulin quantity delivered via injection or pump.

Table 2. Demographic information for clinicians

ID	Provider's Role	Years of Experience	Education Level
P1	CDE, RN	20	Masters
P2	Dietitian	39	Masters
P3	CDE, RN	5	Masters
P4	Dietitian	13	Bachelors
P5	CDE, RN and Dietitian	12	Masters
P6	CDE, RN	14	Masters

Following conventions of existing tools for clinicians (e.g., Dexcom CLARITY [15], Glooko [19], and Tandem t:connect [49]), we used a different color scale for IDMVis in the evaluation study than we present above: green for normal range of blood glucose (70-180 mg/dL), yellow for above range (over 180 mg/dL), and red for below range (below 70 mg/dL). All of our participants were female who are less likely to suffer from red-green color blindness and none reported any color blindness. We also developed an electronic color-coded day-by-meal table to represent the standard clinical presentation.

8.3 Methodology

We met participants at their clinics and upon consent, asked them to fill out a validated pre-study demographic survey. The study includes three parts: (1) a data exploration using the day-by-meal table, (2) a tutorial for IDMVis, (3) and an exploratory data exploration using IDMVis.

The order of showing the day-by-meal table and IDMVis was counter-balanced but a tutorial always preceded IDMVis. The tutorial used a set of comparable but disjoint data from the rest of the experiment. For the exploratory parts, we counter-balanced the presentation of two other disjoint but comparable datasets. I.e., half the participants used dataset A then B and half used the reverse. During the study, participants were encouraged to analyze the data as if they were working with a patient and to "think-aloud" [47], that is, to explain whatever they are looking at, thinking, doing, and feeling at each moment. The goal was to learn clinician reactions, expectations, and decision-making processes for developing and adjusting treatment plans for patients and how IDMVis can facilitate it. We audio recorded and screen recorded this session. This session lasted about 40 minutes.

We then conducted a semi-structured interview about their reactions to the tool and their decision-making process for treatment adjustment. We audio recorded the session. Each session lasted about 20 minutes. The entire study session lasted approximately one hour.

8.4 Analysis

We digitized the survey and transcribed all the audio recordings. We conducted an inductive qualitative analysis [52] of the transcribed text. The first author performed the open coding and met regularly with the third author to discuss and refine the themes.

9 Results

Overall, we found that IDMVis well reflected the workflows of clinicians. The overall feedback from clinicians was positive in terms of how well IDMVis can facilitate their decision-making process, data reconstruction, and patient education. Clinicians also wanted to recommend IDMVis to other clinicians and use it in their daily work. In this section, we discuss the qualitative analysis results and emerging themes following the typical workflow of a clinic visit.

9.1 Visualizing Integrated Data

We first reflect on the clinicians' experience with their current tools and workflow. The first task that a clinician would perform during patient visits is to collect and show the data to patients. They download and print out the reports generated from the software applications that connect to the patient's monitoring devices. The choice of software applications may vary depending on the devices used by the patient and the specific manufacturer, which results in multiple sets of reports.

Clinicians also need to look at the patient's diabetes logbook. They look for key patterns (e.g., normal, low, and high blood glucose levels;

missing data) by scanning dozens of pages of reports. P1 explicitly expressed her frustration with current tools in terms of data complexity and how IDMVis can help her: "*When I have a 30-page CGM download, and then I have a pump download, and then I have a meter download, and then I have an old-fashioned log book written in pen and ink, I will go to the log book every time... They'll write down here's when gym was. Here's when he was low. This is what we did. They take notes. So what [IDMVis] does for me is this gives me a place where the notes are incorporated.*" One of the biggest improvement that IDMVis brought to the clinicians was the integrated data and the effective set of coordinated visualizations of it. Clinicians were able to read, compare and reason about the data much easier, as we will discuss shortly.

Although visualizing the integrated data received positive feedback, P4 was concerned about the user input burden. Since managing diabetes itself requires a lot of work, P4 mentioned the new technology should be designed "*as easy as possible*" and minimize user input.

9.2 Identifying Trends, Patterns, and Outliers

A recurring theme was the ability to identify a patient's overall trends and patterns (*Task 2.1*).

Overview supports identification of glucose trends and patterns: Most clinicians (P1, P2, P4, P5) expressed that they benefited from the 14-day overview as this feature helped them understand the big picture, while still allowing them to explore event details. P3 emphasized the value of using the overview with color encodings to understand general trends over the past two weeks.

We found that our choice of time window (14 days) reflected current practices. All the clinicians mentioned that they usually looked at the last two weeks of data leading up to a clinical visit. Within two weeks, patients can often still recall "*what happened on a certain day*".

However, our encoding choice limited some exploration. Clinicians wanted to differentiate between meals and other types of events (e.g., sickness, exercise) rather than showing all events as identical triangles.

Violin plots increase the understanding of variability: Four clinicians (P2, P3, P5, P6) explicitly mentioned the plots were useful to help them understand the variability of insulin and carbohydrates administered. Both P2 and P6 indicated they would compare the basal and bolus violin plots and check against the standard ratio between the two types. P2 explained: "*When I look at a basal-to-bolus rate, we're always looking for bolus to be slightly higher than basal, unless their diet is very high in protein. Then, you're gonna see the bolus and the basal closer together. So, I would use it for that.*"

Some clinicians (P1, P2, P6) also mentioned the second group of violin plots allowed them to discover the variability in carbohydrates eaten across meals. P6 described the value of these plots for making treatment decisions: "*... these (violin plots) are very helpful. The averages which is good to know if he was always having a huge breakfast, his numbers are good but if he's always having and then going low at lunch, you could kind of compare those... That's a good visualization to kind of see where his ranges are.*"

Collectively, these findings showed that the violin plots enabled clinicians to understand the basal-to-bolus ratio and identify the variability of insulin and carbohydrates. However, we noted that some clinicians (P1, P2, P3, P5) expressed unfamiliarity of the violin plots. P2 said she was uncertain of the usefulness of the violin plots, as opposed to simply presenting the median and quartiles. She found the small multiple insulin-by-meal violin plots to be unnecessary for her purposes.

Superimposed visualization helps identify issues of data quality: The superimposed visualizations of the detail view helped clinicians identify issues of data quality such as missing or conflicting data. The absence of data for an interval usually made clinicians concerned and served as a starting point for patient education. All the clinicians said they would interrogate their patient regarding the missing values. P1 discovered missing data using the detail view: "*So sugar-to-treat [blood glucose] should have gone up from here, not down. It went down. Kept going down, kept going down. Sugar to treat should be here, before this curve comes back up. That's my concern. It's missing something here.*" P1 also expressed that she would ask the patient to recall what happened then and what event was missing from the logbook.

Clinicians were also able to identify issues of conflicting data. Four clinicians (P1, P2, P4, P5) raised questions regarding data conflict and discussed how they suspected the data was inaccurate. All clinicians noticed that CGM readings sometimes failed to match the SMBG readings. These issues stood out as their expectation was that CGM and SMBG should be closely aligned. Clinicians seemed more likely to trust the SMBG values (when done properly) as they tend to be more accurate. P5 explicitly described her decision-making process: "*It's tricky because they're not matching ... but if I'm making a decision which data am I using.... you would know what their calibration habits are and whether we trust the device. But if I'm using the colors purely visually, then it just might skew it a little bit. I would tend to rely a little bit more on the meter (SMBG) than the CGM particularly ...*"

Overall, we found that the superimposed visualization in the detail view helped clinicians identify data quality issue because these visualizations allowed users to conduct temporal inference analyses easily across data sources.

9.3 The Reasoning Behind Treatment Decisions

Detail view enables collaborative reconstruction of patient records: The superimposed detail view also helped clinicians reconstruct patient records. To understand troubling event sequences in the face of missing data, clinicians need to question the patients regarding what happened on a particular day (e.g., unlogged insulin, food, exercise, sickness). P6 was trying to rebuild the event sequence using the detail view: "*... He felt low, shaky at this time. So they gave him some carbs, and then meal nothing 'cause he was a little higher. P.E. check... Post-P.E. check. And then he's fine. And then drops really low maybe 'cause he had a gym that day, and then comes high 'cause they maybe over treated him ...*" One clinician (P1) mentioned that the ability to reconstruct patient's records pointed to "*opportunities to discuss with the family what's actually happening*" and to understand "*what's behind the numbers*". These findings indicate that the superimposed detail view helped clinicians gain an in-depth understanding of a patient's past experience and reconstruct patient records. Being able to retell a patient's experience can further help them identify causes of troubling event sequences and educate patients.

Sentinel event alignment allows exploration of event sequence relationships: Clinicians interacted with the alignment features in different ways. Most clinicians (P1, P2, P4, P6) looked for meal consistency using single-event alignment. Dietitians used the single-event alignment primarily for developing meal plans for patients. One dietitian (P4) explained how she would use alignment: "*If we're working on a goal for a lower glycemic index breakfast, then I can show that much more easily [in] a program like this versus if they have variability in their day in terms of when they're eating...*"

We observed clinicians using the three variants of dual-event alignment differently. Four clinicians (P2, P3, P4, P6) interacted with the left-alignment feature more frequently than the other two. P4 said the dual-event alignment was the most helpful feature and "the easiest to understand". One clinician (P5) strongly preferred the stretched-alignment and felt it was more straightforward, while P1 did not express any preference among these alignment options.

The primary uses of dual-event alignment by clinicians was to examine the variability of eating patterns. For example, P6 explained: "*I like being able to see how you could separate and see between the length, the time between meals... You can't tell them to eat three times a day at the same time. So it's just sort of helpful to sort of see the variability... It would help you plan for it in the fact that you might reduce his basal based on the fact that he's an erratic eater.*" In addition to being able to see meal variability, P6 also mentioned how she used dual-event alignment to differentiate between days with different patterns by identifying the sequence of events. She pointed out the differences between weekdays and weekends: "*...because the gaps weren't so big. He was sort of eating frequently, he was sort of snacking... I presume with school it's a very set schedule, they have a snack. And they sometimes have a very early lunch, very regulated. But the weekends... he's eating more on demand... So that's Saturday, Sunday, then here's a Monday.*"

Most clinicians believed sentinel event alignment was very helpful, in particular, P4 advocated the dual-event alignment and said "*what was easiest to understand or to see is the ability to align the (two) events even if the timings aren't consistent. It just helps consolidate the data or at least visually place that data in a line for you to be able to make those adjustments.*" But we also observed one participant (P1) who thought single-event alignment was more "*appealing*" and easy to understand, compared with the dual-event alignment.

10 Discussion

10.1 Reflection on Hierarchical Task Abstraction

When designing data visualization tools, it is crucial to choose visual and interaction designs that solve the real-world problems of our target users. Task abstraction is widely used to support this process by characterizing user tasks as domain- and interface-agnostic abstract tasks for which design best practices are known [28]. During the design of IDMVis, we found that task abstraction alone was insufficient for capturing the larger goals and context of our users' tasks.

To address this, we developed hierarchical task abstraction. We propose hierarchical task abstraction as a three-step process: (1) understand the problems and data of domain users; (2) perform hierarchical task analysis to understand user tasks, goals, and the relationships among the tasks as part of a larger analysis process; and (3) abstract the user domain tasks. We recommend that designers additionally perform a data type abstraction [28]. The task abstraction framework used in step (3) can be generic or domain-specific [35]—we recommend designers identify a suitable framework for their domain and data types. Hierarchical task abstraction can leverage existing task abstraction frameworks in combination with a systematic analysis of user tasks, goals, and processes.

Once constructed, the hierarchical task and data type abstractions should inform visual encoding and interaction design. These abstractions can be complemented by a separate cognitive work analysis [55] in a larger system design framework. Encodings and designs should be validated against these abstractions. Hierarchical task abstraction can also serve as a starting point for creating realistic human subjects studies where domain user context, goals, tasks, and processes are preserved to the degree possible in an artificial environment. This paper serves as an example for future researchers of how to conduct hierarchical task abstraction in service of a design study. We also believe visualization practitioners can benefit by integrating hierarchical task abstraction into their design process.

To illustrate the application of hierarchical task analysis to the design process, consider *Task 3.2*. *Task 3.2* denotes that a clinician needs to "examine glucose level patterns post events". The abstract visualization task for *Tasks 3.1–3.3* is "examine related data to understand observation". Our first design prototype addressed this abstract task having event triangle mouseovers trigger a zoom-in window showing the post-event glucose levels for that day. However, when validating our design against the hierarchical task analysis we realized that it does not address the parent *Task 3* to "reason about patient blood glucose levels" since the clinician needs to understand more than the effect of a single event on a single day. In fact, the iterative interplay between *Tasks 2 & 3* necessitates designing for both and their associated abstract tasks simultaneously. Thus was born **DR2**—Composite Visualization of Folded Temporal Data—and **DR3**—Align and Scale Temporal Data—both of which guided subsequent designs.

10.2 Design Guidelines for Type 1 Diabetes Visualization

Clinician feedback on IDMVis was positive and they were effectively able to use the visualizations. This is at least in part because we took clinician workflow and education goals into consideration via our hierarchical task abstraction. We recommend that future researchers and practitioners designing tools to assist diabetes clinicians leverage and expand upon our hierarchical task abstraction and our associated four design requirements.

Several additional design features would aid diabetes clinicians. Our participants wanted a way to differentiate types of events such as meals. Potential channels to use for encoding the type of event marks include categorical colors and shapes. Labels may also be used in sparser views such as our detail panel. We also noticed clinicians spend a significant amount of time examining event details by using tooltips. To support viewing multiple event details, designs could include a coordinated tabular view, callouts with well-organized leader lines, labels, and direct day-to-day comparison views.

We also learned in our interviews that clinical visits are often in large part focused on educating a patient and their caregiver(s) how to perform data analyses themselves. The gold standard is for the patient/ caregiver(s) to adjust the treatment plan independently so as to better achieve target blood glucose goals. IDMVis can potentially be adapted for patient use as patients may have similar data analysis needs. However, we designed IDMVis for clinicians with high levels of education and training—thus we assumed basic knowledge of statistics and data analysis. However, the health literacy and numeracy of patients/ caregiver(s) varies widely and affects type 1 diabetes outcomes [32, 34]. Therefore, when adapting clinician tools for patient use, designers should take health literacy and numeracy into consideration.

10.3 Lessons Learned for Data Visualization

Our participants appreciated and were able to effectively use superimposed distinct visualizations of multivariate data in the overview and detail panels. This provides further support for the value superimposed distinct views can provide [6]. Superimposed visualizations of both categorical and continuous quantitative data may also prove useful for treating other chronic diseases that require intensive self-monitoring and treatment adjustment, e.g. congestive heart failure. It could also prove beneficial for adjusting the training plan for professional athletes.

Our study also shows that diabetes clinicians were able to easily use and understand single-event alignment for comparing relative time. This confirms guidelines from prior work which evaluated alignment in clinician tools using expert review by four Computer Scientists [20] and interviewing an RN, physician, and two nursing faculty [57]. Dual-event alignment adds complexity to the system and requires careful design consideration. Our participants disagreed on their preferred time scaling: left-justified, right-justified, or stretch. Left-justified was the most used but designers may want to consider providing all three.

10.4 Limitations and Future Work

Our hierarchical task abstraction only covers tasks relevant to data analysis, and does not include a substantial part of clinician work. E.g., the Certified Diabetes Educator exam content [31], Appendix III, is quite varied. This abstraction should not be used as a model for clinician visits overall. By only running six clinician participants, we may be overgeneralizing our results. Ideally we would have had at least ten participants, but it is challenging to recruit these professionals. Our study used two datasets we prepared instead of using the clinicians' own patient data. This protects patient privacy at some cost to validity.

A controlled study is necessary to more directly compare no alignment, single-event alignment, and the three variants of dual-event alignment. Additionally, future research could consider ways to more directly compare events preceding and following sentinel events.

11 Conclusion

We conducted a design study in the domain of type 1 diabetes clinician decision support. We propose *hierarchical task abstraction* to bridge domain problems and visualization design by combining hierarchical task analysis and task abstraction. Using this approach we categorized the process clinicians use when making intensive diabetes management treatment decisions and identified design requirements. We contribute the design of IDMVis—an interactive temporal event sequence visualization tool—which introduces novel techniques for temporal folding, aligning data by dual sentinel events, and scaling the intermediate timeline. Our evaluation found that our approach well matches the workflows of clinicians, helps them identify trends and patterns, and facilitates reasoning behind nuanced treatment decisions.

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