# Longitudinal Insights for People Living with Type I Diabetes

Authors: Kayenat Peera and Heidy Majdi

Advisor Signature: ______________

Words: 4751

Number of Figures: 5

Number of Tables: 1

Number of Equations: 0

Number of Supplements: 2

Number of References: 9

# Longitudinal Insights for People Living with Type I Diabetes

**Kayenat Peera[a] , Heidy Majdi[b]**

[a] University of Virginia Department of Biomedical Engineering, Undergraduate
[b] University of Virginia Department of Biomedical Engineering, Undergraduate

**Abstract**

Type 1 diabetes (T1D) is a chronic autoimmune condition where the immune system attacks and destroys insulin-producing beta cells in the pancreas. Demanding strict management of blood glucose and insulin levels, people living with T1D rely on continuous glucose monitors (CGMs) and insulin pumps which generate vast amounts of data related to blood glucose levels, insulin dosing, and lifestyle factors. Tidepool, a nonprofit committed to improving the lives of people with diabetes, currently has a functioning data platform that is used by clinicians and people living with diabetes and aggregates data from various diabetes devices and displays it through interactive dashboards, helping users and healthcare providers visualize trends in diabetes management. However, due to extensive amounts of data and literature in the diabetes space, insights within patient data can be difficult to find. To help clinicians and people living with diabetes understand their data more easily within, we're working with Tidepool on this project to enhance the their platform by developing two major features: (1) Time of Day and Time of Week graphs that highlight times during the day or week where the patient needs to be vigilant, and (2) a "five-minute summary" feature that synthesizes the patient's monthly history to deliver actionable insights and personalized suggestions for improvement. These additions are designed to empower patients to proactively manage their condition and assist providers in delivering more informed care. Future work includes approval from diabetes data experts on the algorithm used to create the graphs, enhancing graphs to be able to detect a time of week to be vigilant over a wider range of patterns, and real patient feedback collected for the five-minute summary to prioritize trends that would be most beneficial to patients.

Keywords: Tidepool, Type I diabetes, diabetes data visualizations, continuous glucose monitors, digital health platforms

## Introduction

Type 1 Diabetes (T1D) is a chronic autoimmune disease where the immune system attacks and destroys insulin-producing beta cells in the pancreas, leading to critical deficiency of insulin. Without insulin, the body is unable to regulate blood glucose levels effectively, resulting in hyperglycemia or hypoglycemia in blood sugar, which can lead to serious complications such as neuropathy, retinopathy, cardiovascular disease, and kidney failure if not managed effectively[1]. Type I diabetes requires lifelong management involving frequent blood glucose monitoring, carbohydrate counting, and insulin administration. For many patients, this daily burden significantly impacts quality of life and requires vigilant attention to both biological and behavioral factors[2].

With several technologies existing today for the management of T1D, continuous glucose monitors (CGMs) and insulin pumps are commonly utilized by patients. CGMs are modern devices that are inserted under the skin and continuously collect blood glucose readings in real time through a sensor. As they provide steady reading, CGM's can offer insights into glucose trends throughout the day and night[3]. Insulin pumps are programmable devices that deliver insulin in small, controlled amounts either continuously or in larger doses at mealtimes[4]. While these technologies allow for more precise glucose management and have become essential tools in modern diabetes care, they aren't enough on their own for optimal management. Managing T1D goes beyond the advances in insulin delivery and glucose monitoring due to the challenges of interpreting the data these devices collect. To address this, organizations like Tidepool provide tools that organize and simplify data, making it more accessible for patients, caregivers, and healthcare providers[5].

Tidepool is a nonprofit organization that offers an open-source platform designed to consolidate and visualize diabetes device data. The platform integrates information from CGMs, insulin pumps, and blood glucose meters into a web-based interface that allows patients and providers to track trends, log behavioral data, and manage treatment more effectively. Tidepool's user-friendly interface allows patients and healthcare providers to view trends in glucose levels, insulin usage, and lifestyle factors. The platform supports a wide range of technologies and manufacturers in hopes to pave the way to optimal diabetes management, for both patients and clinicians[5]. Tidepool's strength lies in its ability to centralize diabetes data into intuitive dashboards that reflect users' glucose levels, insulin dosing, and other key metrics. However, while the Tidepool platform effectively consolidates data from various devices, it can be enhanced to introduce advanced analytics and features to support both short-term and long-term diabetes management and address current gaps in diabetes data interpretation and usability.

With the existing Tidepool platform and information coming in from these crucial diabetes devices, there is an abundance of data and insights that Tidepool users must parse through which can cause the user to feel overwhelmed by the amount of information that is available. Because of these concerns, for our Capstone project, we wanted to focus on consolidating this information into messaging and visualizations that were easier for users to understand. The goal of our Capstone project was to enhance the existing Tidepool to provide insights that were nuanced, actionable, and personalized for each individual user. With this in mind, we separated our project into two main specific aims. The first specific aim focused on developing an algorithm that detects and displays variations in data from patient's diabetes devices on both daily and weekly scales and indicates times during the day or week that the patient should be vigilant. Potential reasons for why the high or low occurred at that time of day or week would be shared with the patient, alongside opportunities for improvement. The second specific aim was centered around developing a five-minute summary feature that synthesizes the patient's health history from the previous month and presents the results and suggestions for the patient in a clear and easy-to-understand format for patients and providers. Beyond our original specific aims, we wanted to consolidate the visualizations and suggestions that we would provide the patient into a demo-version of a future-state Tidepool application that centered the work that we completed during our Capstone. While our Capstone was a more design-focused project instead of experiment-focused, we hypothesized that the features that we built out over the course of this year would increase user satisfaction in the Tidepool platform. We also hypothesized that the Time of Day and Time of Week features that we developed would help improve the users' blood glucose levels to stay in range during the indicated time of day or week, showing that the algorithm that we designed was successful.

## Deliverables and Results

### *Time of Day and Time of Week Graphs*

For the Time of Day and Time of Week graphs, we wanted to create visualizations that allowed the user to see their blood glucose data over a day's timescale in a manner that was visually-pleasing, as well as easy to understand. Specifically, we wanted the patient to be able to see how their blood glucose levels fluctuated on a daily and weekly basis and capture the variation in their blood glucose data. Using these specifications, we decided on creating a visualization that was similar to an ambulatory glucose profile (AGP) graph, which is very commonly used and accepted in the diabetes community[6]. In our visualization, we highlighted the user's median blood glucose levels across a day's timescale as a centerline in the graph. This centerline displayed the medians of five-minute intervals across the span of the day to allow for the most accurate data measurement at that point in time and would change color based on the value of median. The color of the median line aligned with Tidepool's blood glucose level buckets and color standards, with in-range blood glucose values (70-180 mg/dL) as green, above range (>180 mg/dL) values as purple, and below range (<70 mg/dL) values in red. We then indicated the variation in the data by displaying the blood glucose readings that fell between the 25th and 75th percentiles in the data in dark gray and the readings that fell between the 5th and 95th percentiles in the data in light gray, alongside a secondary y-axis that shows where the data within these different percentile ranges lie.

For the Time of Day graph (Figure 1), we indicated the hour that the patient should be vigilant using a vertical, translucent-gold highlight on the graph. The user would then be able to hover over the gold highlight to find more details about whether they were more commonly experiencing highs or lows during that time.

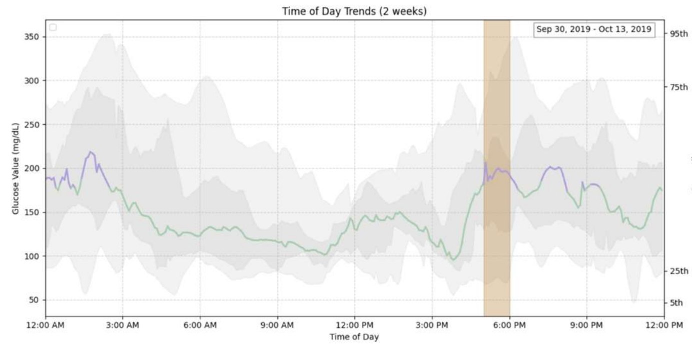



**Figure 1:** Time of Day graph for a Tidepool user. Data was collected from the last two weeks of data that was available (Sept. 30, 2019 – Oct. 13, 2019). The algorithm indicated that this user was commonly experiencing highs from 5 PM to 6 PM. In the future-state application, the user would be able to see a list of factors and once a factor was clicked on, the definition and opportunity for improvement.

For the Time of Week graph (Figure 2), we chose to focus on creating analyses for two different times of the week, weekdays and weekends, as studies conducted on people with diabetes and patients themselves have observed very distinct types of patterns in their blood glucose trends between the weekdays and weekends[7]. To visualize both the weekdays and weekends, we created a graph that displayed the data over a day's timescale, to allow the user to view and understand the graph with more ease and then highlighted a three-hour block on the graph that showed the time of week where the user should be vigilant. When hovering over the gold-highlighted section on the Time of Week graphs, the user would be able to find out more information about whether they were experiencing highs or lows and the specific day of the week and time that they should be vigilant for.

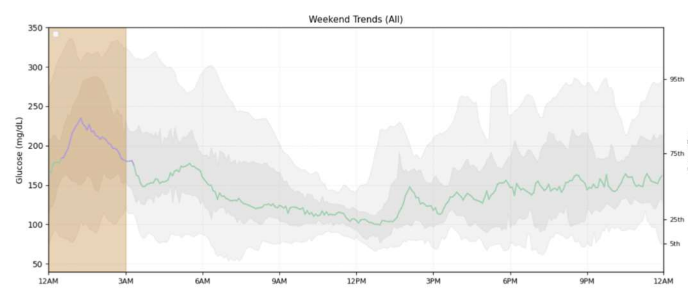



**Figure 2**: Time of Week graph for a Tidepool user analyzed for weekend trends. Data was analyzed using all of the user's available data. The algorithm indicated that this user was commonly experiencing highs from 12 AM – 3 AM on Saturdays. In the future-state application, the user would be able to see a list of factors and once a factor was clicked on, the definition and opportunity for improvement.

Furthermore, we allowed users to be able to select the amount of time over which the Time of Day or Time of Week analyses were conducted so that they could get the information that was the most relevant to them. Specifically, we allowed users to select between '2 week', '4 week', or 'All' timescales, with the default option showing the analysis for all the blood glucose data that was present, for both Time of Day and Time of Week graphs. This way, the user would be able to view and reflect on their blood glucose data over a variety of different time lengths and days of the week. Underneath the Time of Day and Time of Week graphs, we created response prompts that would guide the user to think about a series of behavioral or biological factors that could contribute to the high or low occurring at the indicated time of day or week. When the user clicks on a particular factor, they would be able to read a definition of that factor and then click on a feature that says ‘Opportunities for Improvement’ that provides a suggestion for how they can improve upon this factor, if it is relevant to them. Beneath the information regarding the list of factors and opportunities for improvement, is a space for reflection, where the user can type in their thoughts on the suggestions provided above. Once the user saves their reflection, they would be able to view their reflections on the ‘Reflections’ page in the demo-application that we created.

### *Response Prompt Flow*

As mentioned previously, underneath the Time of Day and Time of Week graphs, we curated a series of behavioral and biological factors that could contribute to the high or low blood glucose levels at the indicated time, alongside an opportunity for improvement for each of the individual factors that are provided to the user. To compile the factors for each possible timing, we first conducted extensive background research to compile a list of different biological and behavioral factors that affect blood glucose levels, as well as definitions for each factor. From there, we conducted further research to find how these factors affected blood glucose levels during certain times of the day, then bucketing them into three-hour time blocks starting from 12 AM-3 AM and continuing throughout the day. Factors frequently repeat themselves across adjacent time blocks. The Time of Day analysis would indicate a specific hour during the day where the user had the greatest number of high or low events, so based on the three-hour bucket that this hour of the day fell into, the demo application that we built would show the associated factors for that three-hour block. For the Time of Week analysis, the analysis would find one of the eight three-hour blocks on a specific day of the week or weekend that the user is experiencing the greatest number of high or low events and the demo would then show the factors associated with that three-hour block.

To develop the ‘Opportunity for Improvement’ associated with each factor, we conducted further research into how diabetes experts recommended on improving that factor and used that information to design prompts that would gently guide the user through improving upon that factor. We also received feedback from our advisor and a certified diabetes care and education specialist (CDCES) at Tidepool to review both the factor definitions and opportunities for improvement to ensure that we are guiding users in a constructive way and align with Tidepool’s mission. Compiling all of this information together, we created a “standard response prompt” with the following wording:

*In the past [selected amount of time], your glucose levels were most likely to be [high/low] between __ and __ [on [day of week, if applicable]]. Here are a few factors that often cause this pattern:*

The algorithm that detects the time of day or week would fill in the relevant information into this response prompt and the factors associated with that hour or three-hour block would automatically compile underneath.

While conducting our research, we found that there was a vast variety of trends that diabetes experts have analyzed and found within blood glucose data that are associated with very specific biological or behavioral factors that we wouldn’t be able to capture in the algorithm that we created for the Time of Day and Time of Week graphs. To supplement Tidepool and guide future development, we created a flowchart of these different trends and associated factors (Figure S1).

### *Five-Minute Summary Visualization*

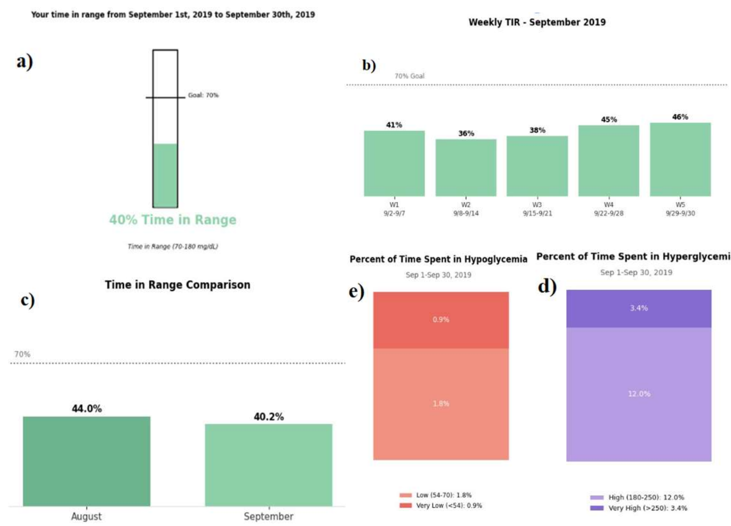



**Figure 3.** Five Minute Summary Feature graphs. a) Time in Range thermometer, b) Week by Week Breakdown of Time in Range, c) Time in Range comparison graph, d) Time Spent in Hyperglycemia, e) Time Spent in Hypoglycemia

For the five-minute summary feature (Figure 3), we wanted to create a series of graphs and visualizations that would help the user learn and reflect on the previous month’s health history. Specifically, we wanted to focus on a metric called “Time in Range”, which is the percentage of time that a patient’s blood glucose levels are in range (70-180 mg/dL). This metric is especially important when considering goal-setting for the patient, since it is a key metric that people with diabetes use to measure the success of treatments or lifestyle changes[8]. Furthermore, in the demo-application that we created, we included text boxes as spaces for reflection that the user could use to write down their thoughts after seeing the five-minute summary visualizations.

The first graph that we created for the five-minute feature is a Time in Range thermometer (Figure 3a), showing the amount of time that the user spent in range as a green bar that fills up a thermometer, with the top of the thermometer representing 100% of time in range. The user can also set a goal time in range for themselves to fit their personal health goals, that they would be able to adjust in the future state of the Tidepool application. This visualization also shows the dates over which the time in range is measured across at the top of the graph. We created this graph so that the patient can compare their time in range to the goal that they set for themselves.

The next graph that we created was a week-by-week breakdown of the percent of time spent in range (Figure 3b). This visualization breaks up the weeks of the month into different bars, with the dates of each week written on the x-axis of the graph underneath each of the bars. The percentage of time spent in range for each week is written along the top of each bar in the graph. There is also a dotted line running horizontally across the graph that represents the goal time in range value that the user has set for themselves. We created this feature so that users can compare their weeks from the previous month so that they can reflect on any variations

in their blood glucose levels across the weeks. We hope to prompt the user to think about any habits, activities, or events that happened during particular weeks that could be the cause of any fluctuations in the time in range for that week, which could help guide their actions to manage their diabetes condition moving forward.
The third graph that we created was a Time in Range Comparison graph (Figure 3c) that compares the time in range from the previous month to the month before that. In this visualization, we displayed two different bars in a bar chart to compare the two times in range, once again including the percentage of time spent in range on top of both bars in the graph. We also included a dotted goal line with the user's goal time in range displayed horizontally across the graph. This feature was created so that users can compare the previous month to the one before, allowing them to reflect again on the past two months to think back on any behavioral or lifestyle changes that may have occurred that could cause a distinct change in time in range (if relevant).
The last two visualizations that we created for the five-minute summary feature were a Time Spent in Hyperglycemia (Figure 3d) and a Time Spent in Hypoglycemia (Figure 3e) features. These bar graphs show the amount of time that the user spent either above (hyperglycemia) or below (hypoglycemia) range. These visualizations segment the bar by 'High' (180-250 mg/dL) and 'Very High' (>250 mg/dL) for the Time Spent in Hyperglycemia graph and 'Low' (54-70 mg/dL) and 'Very Low' (<54 mg/dL) for the Time Spent in Hypoglycemia graph. The dates for which the analysis was conducted are indicated at the top of the graph and percent time spent in each blood glucose level segmentation is indicated within the bars in the graph itself. This feature was included so that the user could get a broader understanding of how their blood glucose levels were spread out across time spent in range compared to in hyper- or hypoglycemia. By understanding the amount of time that they spent in hyperglycemia and hypoglycemia, the user may get a better idea of what they need to focus on improving to create the greatest positive impact on their diabetes condition.

### *Demo-Application of Tidepool's Future State Platform*

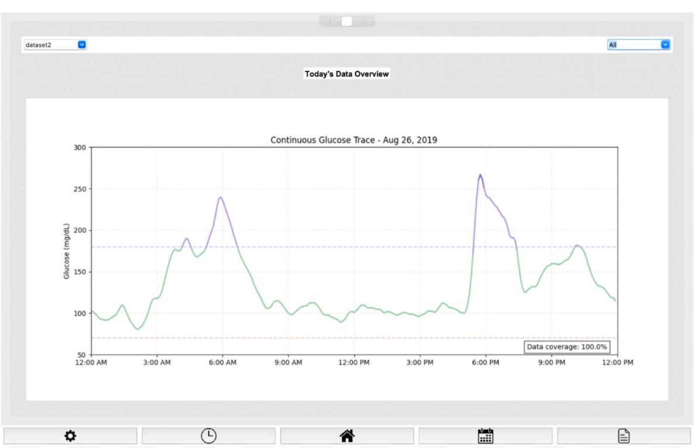



**Figure 4**: Screen capture of the demo-application. Currently showing the landing page, but when the user clicks through the buttons at the bottom of the capture, they will be able to see the different features and visualizations that were created over the course of

Lastly, as part of our deliverables we created a demonstration of what the future-state Tidepool mobile application might look like (Figure 4), centered around the graphs and visualizations that we created during this Capstone project. The demo-application consists of five tabs that the user can click through using the different icons on the bottom of the screen. Starting from the left side of the screen, the tabs include Settings & Profile, Time of Day & Time of Week Graphs, Landing Page, Five-Minute Monthly Summary, and lastly a Reflections page.
The Settings & Profile tab is meant for the patient to update any personal information, like their height and weight, and update any goal features in the future-state application (for example, the time in range goal). This page would also include settings that allowed the user to adjust the way they received notifications from Tidepool, alongside any other technical features that the app would need to incorporate. The Time of Day & Time of Week Graph tab shows the associated graphs and would include the response prompts and spaces for reflection underneath each graph. The Landing Page graph shows the patient's current blood glucose trace for the day (in our application, the graph shows the last day that the data is available for) and a message center with any notifications. The Five-Minute Monthly Summary feature shows the associated five-minute monthly summary graphs and includes the spaces for reflection underneath the visualizations present. Lastly, the Reflections page will include the reflections that the user has made, almost in a journal entry format, as well as a space to create a reflection in that tab. In a future state, the Reflections page could include an AI-generated summary of all the reflections that were made and a calendar feature that saves all of the reflections made on a specific day on the calendar.

## Discussion

### *Design Constraints and Alternatives*

As we developed the project last semester, we came up with a list of design constraints that we thought would help us measure the success of the work completed during our project (Figure S2), including the quantification of measuring the impact of the algorithm on patient's decision making and user review of the platform. However, coming into this semester and further understanding the limitations of this project, we realized that a lot of the design constraints that we set for ourselves would not be possible to use to measure the success of this project. Because of this, we decided on several new design constraints that we would use to help us measure the success of the project. First, we wanted to ensure that code that we used for our analysis would work on any of the Tidepool datasets from the Big Data Donation project that we pulled from. When testing our code, we found that it was compatible with 6 out of 10 datasets that we tested, which was lower than what we had desired. Looking to the future, we would need to update the part of the code that takes in information from the data samples to be more flexible with different datasets and data types.
Second, we wanted to ensure that the analysis and results that we were producing were as accurate as possible and to be sure of this, we wanted to make sure that there was enough data in the dataset to produce an accurate analysis of the time of day or week where the patient should be vigilant. To be sure of this, we made sure to check to see if at least 70% of the data was present for each of the analyses that were conducted. We found that with several datasets and timescales, especially with the 2-week timescale particularly for the Time of Week graphs, there wasn't enough data to reach the 70% benchmark. Moving forward, it may

be better to either use more recent patient data, since more advanced CGMs may collect data points more consistently, or to increase the minimum timescale offered for the Time of Week analysis to 4 weeks. Specifically, we could change the timescale increments for the Time of Week analysis to ‘4 weeks’, ‘8 weeks’, and ‘All’ so that there is an ample amount of data available for analysis.
Lastly, we wanted to make sure that the response prompts were comprehensive of the different behavioral and biological factors that are associated with causing fluctuations in blood glucose levels. As mentioned previously, we conducted extensive research to gather as much information as possible about all the associated factors. While there is no quantitative way to measure the success with which we considered these different factors, we did receive approval from our advisor and a CDCES on both the flow of information for the response prompts alongside the compiled list of factors itself. Once again, we would need another third-party expert on this material that could further confirm to the best of their ability whether we have a fully developed list of factors affecting blood glucose levels, sorted into the right time blockings in the future.

### *Limitations and Future Work*

While the proposed application and developed algorithms have great potential to enhance Tidepool’s diabetes data platform, there are a few limitations that we encountered that highlight the importance of further development and testing. First, we had a limited amount of computational space which affected the speed and accuracy of the analysis that it was possible for us to conduct. The lack of computational resources was particularly an issue when trying to display our graphs and visualizations on the demo-application, as our personal computers didn’t have the power to provide real-time updates to the graphs that were displayed on the application mock-up we created. To circumvent this, the graphs in the mock-up mobile application have been temporarily stored as images that render onto the screen.
In the future-state of this project, the computational power should be off-loaded to Tidepool’s servers. Another limitation that we ran into was our lack of knowledge regarding diabetes data analysis, especially when designing the algorithm that was used to detect the time of day or week that the patient should be vigilant. While we conducted background research and sought out assistance from folks at Tidepool, this doesn’t completely mitigate our lack of expertise on this subject.
There are also many ways that the work completed during this project could be expanded upon and improved. Going back to our original hypotheses that would allow us to reflect on the success of the features that we developed, we weren’t able to test the success of the algorithm and how satisfied users would be with both the Time of Day/Week graphs and Five-Minute Summary Feature that we developed. However, in the future state of this initiative, I believe that it would be very beneficial to Tidepool to have a group of beta-testers use and test out the new features that we have developed to see if it helps them improve their blood glucose levels. Furthermore, I think that it would be beneficial to hear about what information and visualizations the users would like to see in the five-minute summary feature to ensure that they are getting the most out of this aspect of the future-state Tidepool platform.
Next, it would be beneficial to receive insight from diabetes experts on the algorithm that we created to detect the time of day and week that the patient should be vigilant. While we conducted substantial background research and worked alongside several stakeholders within Tidepool to inform the way that the algorithm was constructed, the algorithm design itself hasn’t been officially scientifically validated, nor has a diabetes data expert been involved in the process of creating this algorithm. Before releasing for testing, it would be important to validate our algorithm with an expert third-party in this field or conducting an official study measuring the impact of the algorithm on Tidepool users. Additionally, the current algorithm for the Time of Week graph is limited to detecting trends that exist for weekdays and weekends, however in the future, the algorithm should account for more trends spanning across different combinations of days of the week.
We would also like to see how users use and respond to the factors, response prompts, and opportunities for improvement, as well as the reflection text boxes underneath all of this. While we believe that these features would be beneficial to most Tidepool users, we think it is important to receive their feedback to ensure that these features are as useful and constructive to them as possible.
Lastly, our current demo-application that we have built is meant to function more as a mock-up for what a future-state mobile application version of Tidepool that centers the two features that we have built out during Capstone might look like. I think that if Tidepool chooses to carry forward our work, the mobile application that is built will look very different from the preliminary application that we have built for our project.

## Materials and Methods

### *Data Source and Tech Stack*

For our analysis, we used data from Tidepool’s Big Data Donation project, which pulled from donated user data that has been anonymized and includes over 300 data samples from different Tidepool users[9]. For our tech stack, we used PyCharm as our IDE and Python as the programming language, alongside the pandas, matplotlib, and numpy packages for data analysis and graph generation and the tkinter package to generate the demo-application. To share and collaborate the code, we used GitHub. You can find our github repository at this link:
https://github.com/kayenatpeera/TidepoolBMECapstone.git

### *Time of Day and Week Algorithm Design*

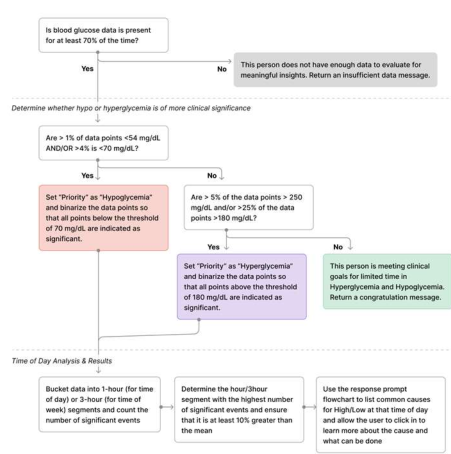



**Figure 5:** Flowchart outlining the process flow for the algorithm used to detect the time of day and week when the user should be vigilant.

To determine the time of day or week that the patient should be vigilant for, we needed to create an algorithm that would be able to detect the most relevant time (Figure 5). We went through several rounds of iteration, considering if it would be best to find the hour or three-hour block where either the median or mean was the highest and lowest and indicating those times to the patient. However, we thought that it may be better to determine the time of day and week where the user was having the highest number of high or low blood glucose events, since the mean is a summary statistic that wouldn't bring much meaning to the user and the median blood glucose values were already accounted for by the design of the time of day and week graphs themselves.

Now, to determine the time block where the user was having the most high or low blood glucose events, we first had to check to see if at least 70% of the data was present in the sample. We noticed that the data in the samples that we received were collected every five minutes, so using the data samples and the amount of time that the analysis was supposed to be conducted over (2 weeks, 4 weeks, or all of the data), we would determine the ideal number of data points for that time range and then calculate the number of data points that was actually present in the data. If this value was greater than or equal to 70% of the number of ideal data points for the sample, then the rest of the time of day and week analysis would be able to be carried out. If not, then we would signify to the user that they need to input more data to conduct the rest of the analysis.
The next step was to determine whether highs or lows were more clinically relevant for that patient. To do this, we would first check if lows were more clinically significant for the patient by check to see if >1% of the data was <54 mg/dL or if >4% of the data was <70 mg/dL. If neither of these statements were true, then the algorithm would check if highs were more clinically relevant by determining if >5% of the data points were >250 mg/dL or if >25% of the data fell between 180 mg/dL and 250 mg/dL. If neither lows or highs were significant, then the user would be notified that there was no time of day or week that they needed to be vigilant for and that they were managing their blood glucose levels well. If either lows or highs were clinically significant, then the blood glucose data would become binarized so that data points that were low (<70 mg/dL) or high (>180 mg/dL), depending on whether highs or lows were clinically relevant, would be deemed as significant (marked with a 1), and all other data points would be deemed as insignificant (marked with a 0). For example, if the highs were clinically significant for the user, then all data points above 180 mg/dL would be considered significant and marked with a 1.
From there, the binarized column was bucketed by the hour for the Time of Day analysis or bucketed into three-hour blocks for each weekday or weekend for the Time of Week analysis. The number of high or low events were counted for each bucket and the bucket with the greatest number of high or low data points was determined. To ensure that there was a significant difference between the largest bucket and the rest of the data, we made sure to ensure that the number of significant data points in the largest bucket is at least 10% greater than the average number of events across all of the buckets. If not, then there would be no significant time of day or week indicated to the user. If so, the algorithm would then return that hour or three-hour time block and day of the week in the associated graph and use the response prompt flow to offer suggestions as to why the high or low might be occurring.

***Acknowledgments***

Thank you to our advisor Sharon Lee and the other contributors from the Tidepool team – Kelli May and Cameron Summers! Also, a big thank you to Professor Allen, Mario, and the rest of the teaching team for a great semester and year!

## End Matter

*Author Contributions and Notes*

**Author A:** wrote the code for the Time of Day and Time of Week graphs and algorithm; wrote the code for the 5-minute summary graphs; designed response prompts and response prompt workflow; materials & methods, discussion, deliverables and results, and some of the introduction for this paper; created poster for BME Capstone Showcase

**Author B:** worked on response prompts and response prompt workflow; created poster for BME Capstone Showcase; worked on abstract, introduction, references, materials & methods, discussion for this paper; created supplementary figures; formatted paper and figures; worked on 5-minute summary code; conducted extensive research into the diabetes space for the project; handled administrative tasks for the project; accessible design practices to ensure features are usable for a wide range of individuals.

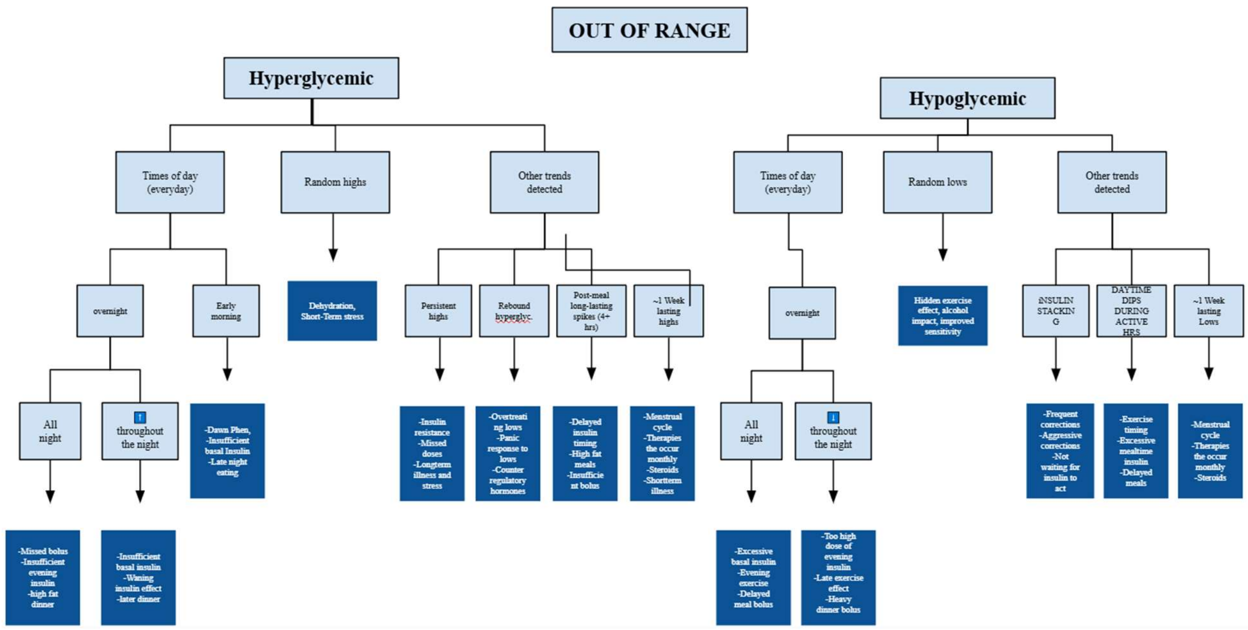
## References

1. American Diabetes Association. (n.d). Type 1 Diabetes. https://www.diabetes.org/diabetes/type-1
2. Atkinson, M. A., Eisenbarth, G. S., & Michels, A. W. (2014). Type 1 diabetes. The Lancet, 383(9911), 69–82. https://doi.org/10.1016/S0140-6736(13)60591-7
3. Heinemann, L., Freckmann, G., Ehrmann, D., Faber-Heinemann, G., Guerra, S., Waldenmaier, D., & Hermanns, N. (2018). Real-time continuous glucose monitoring in adults with type 1 diabetes and impaired hypoglycaemia awareness or severe hypoglycaemia treated with multiple daily insulin injections (HypoDE): a multicentre, randomised controlled trial. Lancet (London, England), 391(10128), 1367–1377. https://doi.org/10.1016/S0140-6736(18)30297-6
4. Yao, P. Y., Ahsun, S., Anastasopoulou, C., & Tadi, P. (2023, August 28). Insulin pump. StatPearls - NCBI. https://www.ncbi.nlm.nih.gov/books/NBK555961/
5. Tidepool Home. (n.d.). https://www.tidepool.org/
6. Czupryniak, L., Dzida, G., Fichna, P., Jarosz-Chobot, P., Gumprecht, J., Klupa, T., Mysliwiec, M., Szadkowska, A., Bomba-Opon, D., Czajkowski, K., Malecki, M. T., & Zozulinska-Ziolkiewicz, D. A. (2022). Ambulatory Glucose Profile (AGP) Report in Daily Care of Patients with Diabetes: Practical Tips and Recommendations. *Diabetes therapy : research, treatment and education of diabetes and related disorders*, *13*(4), 811–821. https://doi.org/10.1007/s13300-022-01229-9
7. Clemmensen, K. K. B., Koster, A., Nielen, Y. T. H., Dagnelie, P. C., Stehouwer, C. D. A., Bosma, H., Wesselius, A., Færch, K., & Eussen, S. J. P. M. (2022). Role of Weekday Variation on Glucose, Insulin, and Triglyceride: A Cross-Sectional Analysis From the

Maastricht Study. *The Journal of clinical endocrinology and metabolism*, *107*(8), e3145–e3151. https://doi.org/10.1210/clinem/dgac286

8. Wright, E. E., Jr, Morgan, K., Fu, D. K., Wilkins, N., & Guffey, W. J. (2020). Time in Range: How to Measure It, How to Report It, and Its Practical Application in Clinical Decision-Making. *Clinical diabetes : a publication of the American Diabetes Association*, *38*(5), 439–448. https://doi.org/10.2337/cd20-0042
9. *Big Data Donation Project | Tidepool.* (n.d). https://www.tidepool.org/bigdata

## Supplementary Figures




**Supplemental Figure 1**: Logic Flowchart for Glucose Patterns. This flowchart walks through a more nuanced set of trends associated with very specific biological factors that could be incorporated into a future-state Time of Day/Week algorithm.

| Design Constraint/Metric | Unit of Measure | Marginal (Acceptable) | Ideal Value |
|---|---|---|---|
| User review of the platform | Percentage of satisfaction from user reviews | 70% | 100% |
| Accuracy of the predicted spikes | Time difference (in hours) between predicted time to be vigilant and spike in patient's biometrics | <2.5 hours | ~ 1 hour |
| Impact on patient's decision-making | Amount of times a patient uses the summary to make a health-related decision (collected using patient feedback surveys) | 1x a month | 4x a month |
| Amount of patient data available in the Tidepool platform | Amount of data (in months) available for analysis | <5 months | >6 months |
| Impact of improving upon the identified health factor on the patient's health standing | Percentage difference in average blood glucose levels | <1% | 5% |
| Time between updates to the Tidepool platform | Minutes | 30 minutes | < 10 minutes |
| Accuracy of detecting fluctuating factors | Difference between predicted fluctuations and actual fluctuations of the patient's health factor | > 20 % | <5 % |

**Supplemental Figure 2:** Original design constraint list created last semester for our Capstone Proposal submitted at the end of the fall semester.