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BME 405L

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Preliminary Design Review (PDR) Report for Non-Invasive Blood Glucose Monitor

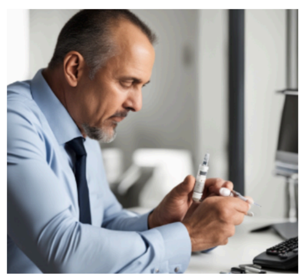
1. Updated Storyboard (Use-Case Scenario)

John, a type 2 diabetic, just had his lunch. He returns to work but feels uneasy.

He decides to drink some water. Even now, he still feels incredibly thirsty.

He then refers to his wrist sensor because he feels like it has something to do with his glucose levels.

His monitor shines blue. He is hyperglycemic!



Because he knows this, he will now take his medication to control his sugar levels, as recommended by his doctor.

Thanks to our sensor, John was able to take appropriate measures. He feels better!

Figure 1: Use-Case Scenario Storyboard

2. Updated Use-Case Scenario:

Diabetes mellitus affects 38.4 million working-age adults in the United States. Of that number, 8.7 million people are undiagnosed [1]. In an effort to make diabetic healthcare more accessible, our team wants to develop a wearable wrist-sensor that detects if a patient is hypoglycemic, normal (euglycemic), or hyperglycemic. This device enables patients to conveniently monitor their blood glucose levels and seek medical assistance when necessary.

Consider the case of John, a type 2 diabetic who is heavily engaged in his work, leaving little time for managing his health. One day, after experiencing excessive thirst, frequent urination, and persistent hunger following a large meal—symptoms indicative of hyperglycemia—he is unaware of his elevated blood glucose. By utilizing his wearable wrist sensor, John checks his glucose level, which reads 180 mg/dL, with a blue light confirming hyperglycemia. As a result, John can promptly take measures to reduce his blood sugar. If his reading had been below 70 mg/dL, the device would display a red light, signaling hypoglycemia. In the normal range of 70-120 mg/dL, the monitor would display a green light.

Stakeholders:

In this use-case scenario, John–the patient and user–is the primary stakeholder. The device is intended for working-age adults (25-54) that want to take more ownership of their health and wellbeing. With a simple check of his wrist monitor, he is able to tell whether his blood glucose level is normal or if action must be taken—increasing the accessibility of real-time blood glucose readings to John and patients alike. Working-age adults were chosen for the target population as they will benefit from this device the most: taking a look at your wrist for blood glucose readings saves a substantial amount of time from having to use other blood glucose readings, such as finger pricking or even using a CGM (as it requires scanning of the CGM sensor to obtain a blood glucose reading), and will save them time in their busy work day. With this new information, John can seek out additional support if needed.

The second stakeholder would be endocrinologists, nutritionists, and other healthcare providers. This medical device would be useful for observing how certain foods can raise John's glucose level. With this type of data, these healthcare providers will be able to use their expertise to create a personalized plan that can exactly suit John's needs.

Then, the third stakeholder would be the caregivers. They can make micro-adjustments as necessary, using the monitor as a guide. For instance, if John is showing hyperglycemic levels that day, the caregiver can cook John a meal better suited to lower his blood glucose.

The fourth stakeholder would be the engineers of the device. The engineers need to ensure their products work, via the engineering design process, so that people like John could live a better life and take better control of this chronic disease.

3. MVP Features (Ranked)

1) A display-system for patient signaling, letting the user know if their current condition is hypoglycemic, normal, or hyperglycemic. Park et al. shows that convenience is a factor for people to make changes in their health [2]. In particular, products that make being healthy more attainable will entice users to improve their wellbeing. A display system that effectively classifies the user's glucose state will enhance convenience, enabling timely and appropriate action when necessary.

2) Portability. As the device is intended to be a wearable, portability must be a key consideration in the MVP. While the exact size may vary, it should at least fit comfortably on the forearm. This aligns with the emphasis on convenience, as highlighted by Park et al. [2]. Furthermore, the device must be lightweight to avoid causing discomfort to the user, which could lead to decreased usage or abandonment.

3) Effortless Usage and Monitoring. The device must accommodate individuals with limited time to monitor their blood glucose, as existing methods require either finger pricking or scanning a CGM and navigating a GUI. This device, therefore, should allow users to check their glucose levels as effortlessly as checking the time on a watch. By offering this level of convenience, users are more likely to incorporate the device into their daily routine, promoting consistent use.

4) Live-time, Continuous Monitoring. The Cleveland Clinic recommends that users keep up-to-date with their glucose levels by actively monitoring throughout the day [3]. Ideally, the monitor should display the user's glucose level whenever they wish to check it. The wearable device should continuously display a specific LED color signal and update within a short time frame. This enables the user to obtain a fast and accurate reading at any time.

4. MVP Specifications (Ranked)

Specifications in order (most to least important)	Functional Requirement	Solutions for Requirements
LED-Display	The device should have a way for users to easily access necessary information right away. It is important that what is presented is clear, unambiguous, and simple. It should also be universally understood in case there is a language barrier.	To achieve universal understanding and quick access, our team will incorporate an LED display. The display will illuminate with one of three colors (red - hypoglycemia, green - normal, blue - hypoglycemia) to alert the users of their current condition.
Live Sampling Time	It is imperative that the device works in real-time. The glucose monitor needs to report the user’s condition within a few minutes at the latest so that the user can take appropriate interventions.	A sampling rate of 24 Hz at three minute intervals each will be used to ensure that the signals are being received in a timely manner.
Portable and Usable Design	The design should revolve around the idea that people can use this device anywhere. It has to be a convenient product so that people using it can actually save time.	Since this device is meant to be worn on the wrist, there needs to be some size constraints. According to Edmond et al., the average forearm length is about 25 cm [5]. Thus, this will be our length constraint.

		Additionally, having a battery power supply will allow the users to carry the device everywhere. This would eliminate having the sensor plugged in to work.
Machine Learning	The device's classifications and correlations should be reliable and accurate. When reporting health information, an inaccurate reading could lead to severe consequences.	There needs to be a machine learning algorithm to classify the results of our signals. Prior to this, we must also train the model so that it can accurately predict the incoming information. Without a proper mechanism to categorize the data, the displays will show data that may be inaccurate.
Signal Processing	Considering that the device has the limitation of being portable, there needs to be an optimized method of signal processing to reduce power consumption. While some methods of data acquisition and processing may work, it needs to be as efficient as possible so that the user doesn't have to replace the power supply often.	The PPG signal received will be an RGB wavelength, as outlined by Satter et al.'s protocol [7]. After the signal has been processed, the CatBoost algorithm can process the PPG signal waveforms (of each R,G,B waveform) and output a blood glucose reading. This blood glucose reading will then feed into another system—the LED Signaling Compartment of the MVP—and based on the exact numerical value of the blood glucose reading will shine a corresponding color. We envision the second part of this code to be done on the Arduino IDE using several "IF" logic statements.
Amplifier	It is important that the device	Signal amplification can

	receives a strong signal. With a weak signal, the signal processing stage might take longer, as there is not as much information to work with.	increase the target signal's intensity. This may help our team get a better reading from the PPG sensor's RGB values. As a result, it may help us to classify the information more easily.
Filter	All signals carry noise, which may dampen the signal that the device wants to receive. This may hinder its overall reading and delay the processing time for the patient's glucose level.	Including a Butterworth filter will aid in clearing out the noise of our signal. In particular, it draws out the low and high frequencies of approximately 0.5 Hz and 8 Hz. Hopefully, this will allow for a better signal for our algorithms to read.

5. Indications for Use (IFU) and Intended Use (IU) Descriptions.

Our team referenced the Apple Watch ECG IFU and IU [4] (Note: the Apple Watch is not a Predicate Device).

Indications for use:

The device is indicated for people who are or think they are type 2 diabetic. The wearable device is for people over the age of 18 and under the age of 59, as the definitions of hypoglycemia, normal, and hyperglycemia vary outside of this group [6]. It is also indicated if the user experiences symptoms of hyperglycemia or hypoglycemia. These include, but are not limited to, polyphagia (hyperglycemia), polydipsia (hyperglycemia), polyuria (hyperglycemia), pallor (hypoglycemia), cool/clammy skin (hypoglycemia), weakness (hypoglycemia), etc.

Intended use:

The device is intended as a reference for people to see their glucose levels. It is for informational use only. The user should refer to the color classifications presented to see their glucose levels (red - hypoglycemia, green - normal, blue - hyperglycemia). With the information, the user should seek out healthcare professionals for further interpretations and interventions. It is not recommended for the user to act on their own to change their glucose levels, as this may result in unwanted and dangerous complications.

6. Block Diagram(s)

Project Process Flow Block Diagram

Refer to the Lucidchart Block Diagram by clicking this link: [Here](). Below is a snapshot of the overall block diagram:

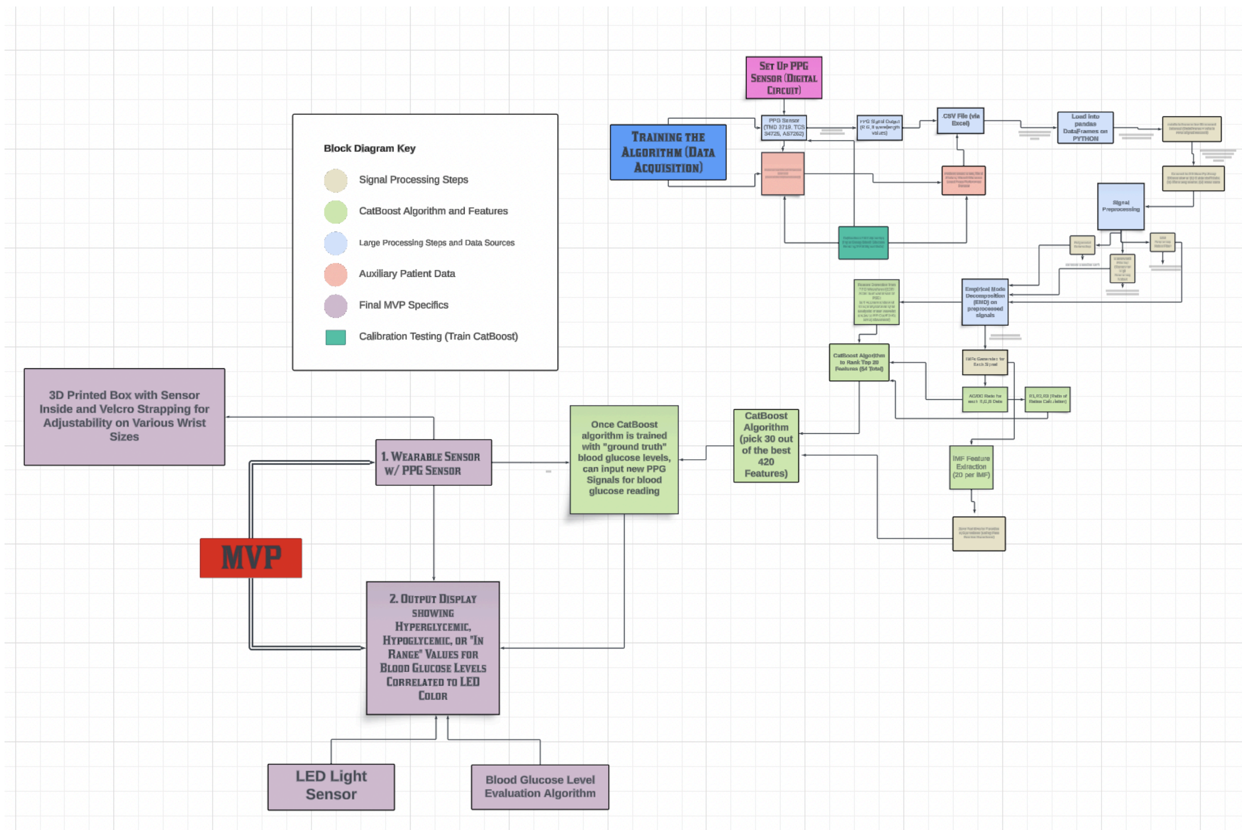


Figure 2: Screenshot of the Block Diagram (Please Click the Link Above to Zoom In For Details)

MVP Block Diagram 1: PPG Sensor

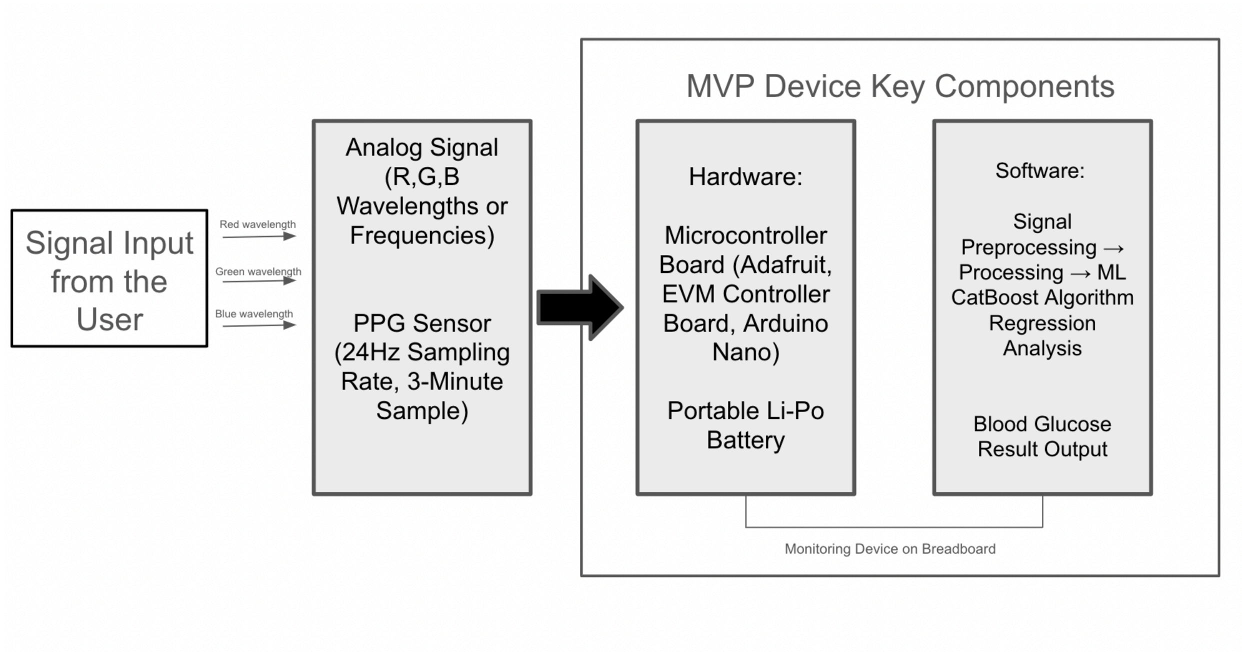


Figure 3: Functional Block Diagram of the PPG Sensor (Analog) → Numerical Blood Glucose Reading (Digital). Note: the signal input is in the waveform (wavelength format) and will change to a digital signal (blood glucose result output) after going through the functional system (hardware + software)

MVP Block Diagram 2: LED Patient Signaling Compartment

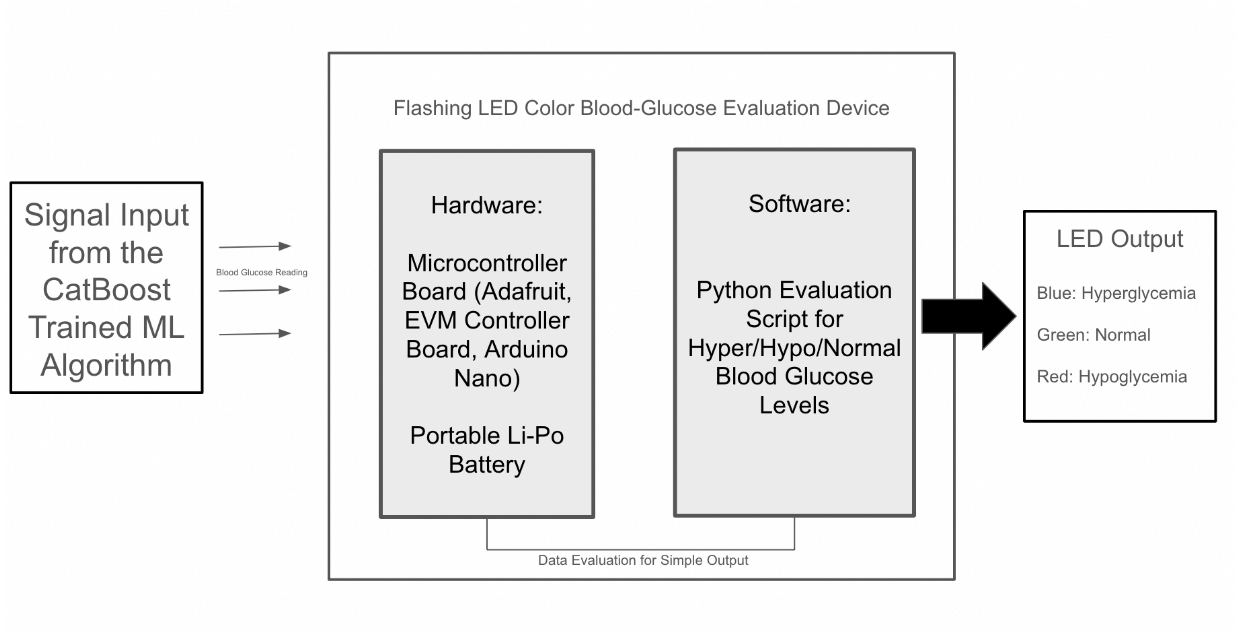


Figure 4: Functional Block Diagram for the LED Signaling Device (Showing Red, Green, or Blue depending on Set Glucose Reading Threshold. Note: the signal input will be a digital signal from the processed signal using the CatBoost ML Algorithm (it will be a blood glucose reading), and after going through this compartment with the hardware and Python script (software) it will output one of three LED colors depending on the patient's exact blood glucose reading.

7. Test Plan Outline

In order to create a MVP, testing is not just performed in the end-stage development process: rather, it is a continuous process in the overarching design system. Thus, our test plan will be split up into two—one in the beginning of the design process, for calibration, and one at the end, for end-user testing.

In order for the PPG sensor wearable device to function as intended, we will need to integrate some calibration tests before the device is ready for use. For instance, in order to be able to train the ML Algorithm (we will be using the CatBoost ML Algorithm Regressor) to predict blood glucose results based on PPG signals, we need to gather data points. These data points will be collected by taking several blood glucose readings using the reference blood glucose monitor and the PPG signal simultaneously. The PPG signal will be taken for 3 minutes at a sampling rate of 24Hz (see block diagram of PPG Sensor above). We plan to test multiple times a day (before/after food) in order to generate different blood glucose reading results to calibrate the sensor effectively. We desire to gather at least 30 data points for maximal correlation accuracy between the PPG signal and the blood glucose readings. In the case that this data is unobtainable for any reason, we can consider using online data through ML databases such as Kaggle or Open ML for any blood glucose readings, and refer to the literature to determine whether there is a positive or negative correlation between PPG signal wavelengths (for R,G and B) and blood glucose readings. It should be recognized that given the timeline and constraints for this class, less realistic data may be required to be chosen and utilized for training the algorithm. Having said that, the MVP should be able to estimate a blood glucose reading based on a PPG signal to show that the idea and project in theory works, and might be applicable for more advanced applications should it show promising results.

Additionally, if it is decided to implement the LED Patient Signaling Compartment, we will have to undergo calibration testing that will take the output from the PPG Sensor Device (the estimated digital blood glucose readings) and will input that into a generated Python script to a microcontroller board connected to a 3-count LED circuit. Based on the inputted blood glucose reading into the script, the program should be tested to make sure that a flashing red LED indicates a hypoglycemic blood glucose reading, a blue LED indicates a hyperglycemic blood glucose reading, and a flashing green LED indicates a normal blood glucose reading. In the case that there is issues connecting the ML algorithm (first part of the MVP) to the LED patient-signaling compartment (second part of the MVP), we can program the script using random blood glucose readings and refer to the literature on what is considered hyperglycemic, hypoglycemic, and normal for diabetics in the 18-59 age range [6].

For end-user testing, a workable test plan might require volunteers from the BME 405 class to prove that the MVP is correctly able to estimate blood glucose readings from the wearable PPG device. We would ask students in BME 405 to volunteer to get their finger pricked for blood glucose (using the reference blood glucose sensor) and measure the PPG signal simultaneously. From this, we can have the developed and trained CatBoost ML Algorithm to estimate a blood glucose reading and match it to the actual blood glucose reading to determine the percent accuracy and show that the MVP is successful. While this may be a possible solution, it should be noted that due to the class constraints and whether taking volunteers will be allowed/feasible, we may need to mimic phantom end-user testing. This phantom will use online datasets of diabetes that are publicly accessible, and real-time data from a relative of a group member who logs their blood glucose level using the CGM Freestyle Libre App for the last two weeks.

Throughout the design process, we should ensure that the different components of the MVP work, and testing/verification should take place. For instance, in order to ensure that the ML Algorithm works, artificial random data should be implemented once the CatBoost ML Algorithm is trained to verify it works. Furthermore, the LED Patient Signaling Compartment should be tested by inputting artificial random blood glucose readings to determine if the correct LED lights up depending on the hyper/hypo/normal glucose reading inputted. Finally, we move to end-user testing to determine if the whole MVP works in conjunction with each other.

In a perfect environment for this project, we would be able to conduct realistic clinical patient end-user testing. However given the time constraints and the inability for students in this class to obtain actual patients for end-user testing, a realistic clinical patient trial can be outlined but unfortunately not implemented. Nevertheless, following is the realistic clinical test plan, for both calibration and end-user confidence testing. We would take patients in our defined age range (18-59) who go to work just like John in our use-case scenario and ask them to wear the wearable wrist sensor where we would record their PPG signal wavelength for three minutes. At the same time, another group member would use their other hand to finger-prick them using the reference blood glucose sensor and record this data. Then, the ML algorithm would output a blood glucose level (in mg/dL) and we would determine the percent accuracy of the PPG sensor compared to the actual blood glucose level. This would be ideal as the algorithm would be able to take this real diabetic patient data and use it to improve the accuracy of its blood glucose reading predictions.

Hardware:

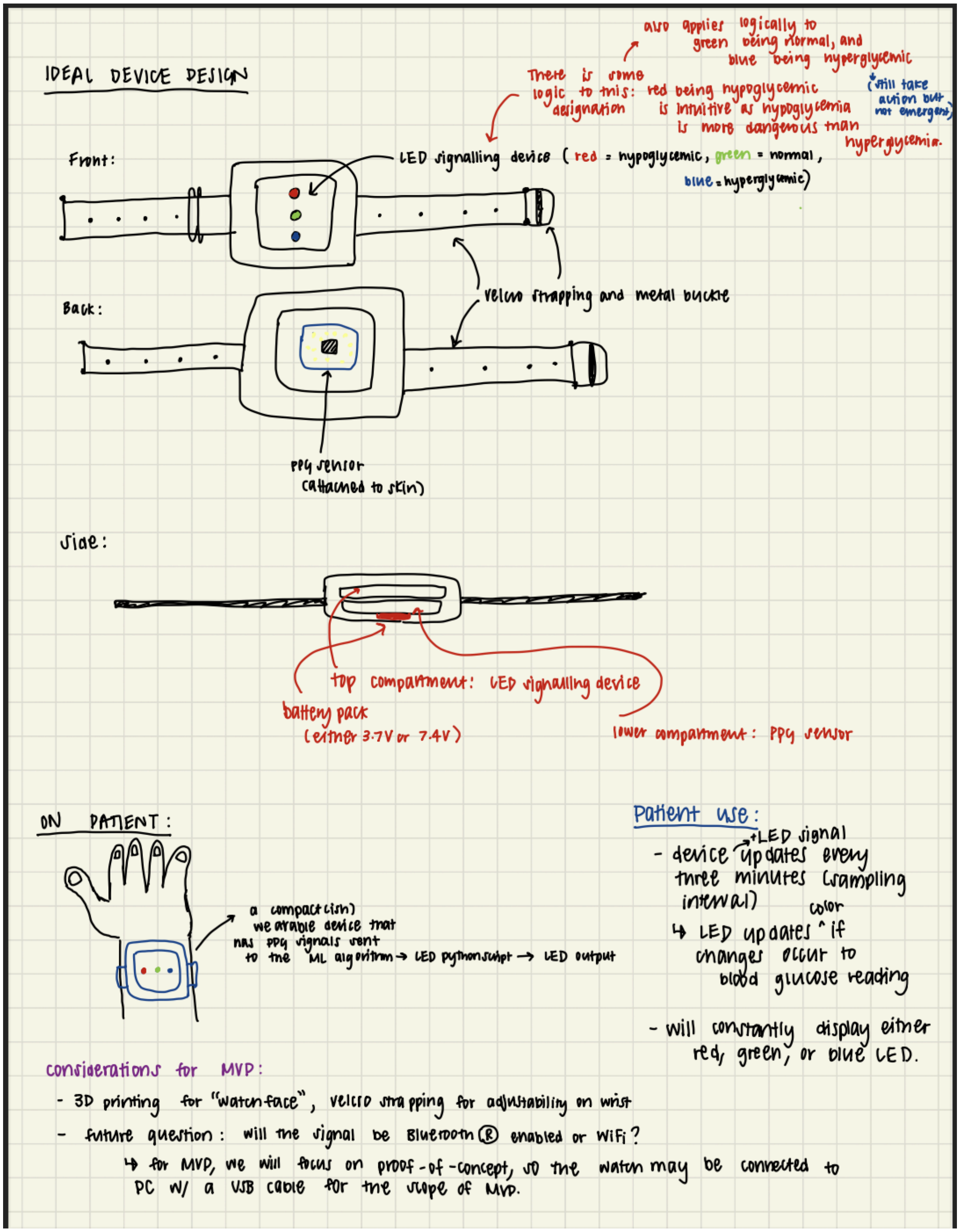


Figure 5: Rough Hardware Design of MVP and Key Considerations

Sensor Options:

In the project, we are currently exploring three different sensors to acquire the PPG signals. The sensors are all sensors that collect R,G, and B wavelength/frequency data which will be the main signal input for the CatBoost ML algorithm when it comes time to design the software and signal processing components of this project.

TMD-3719 EVM: [Link to User Guide]

1.1 Kit Contents

Figure 1:
Evaluation Kit Contents

No.	Item	Description
1	TMD3719 Daughter Card	PCB with TMD3719 sensor installed
2	EVM Controller Board	Used to communicate USB to I2C
3	USB Cable (A to Mini-B)	Connects EVM controller to PC
4	Flash Drive	Include application installer and documents

Figure 6: TMD 3719 EVM kit contents.

This sensor is included in our BOM and is a kit which includes its own daughter card and the controller board. This kit will connect to an online software designed just for this sensor which is able to deliver red, green, and blue wavelengths to the software and record data in real-time. The device software is a GUI that only works on a PC thus we plan to use the PC in the laboratory to install and be able to utilize the software. The TMD 3719 sensor will record three wavelengths (R,G,B) and it will show up on the GUI. We will take a 3-minute measurement of the signals for each subject and then use the waveforms for training of the CatBoost algorithm. The EVM controller board will provide power and it will be an I2C connection with the daughter board through a seven-pin connector. The EVM is connected to the PC using the included USB cable. Based on the literature regarding PPG Signals to Glucose Readings, and because they had utilized this same sensor, this seems like the most practical choice for the MVP.

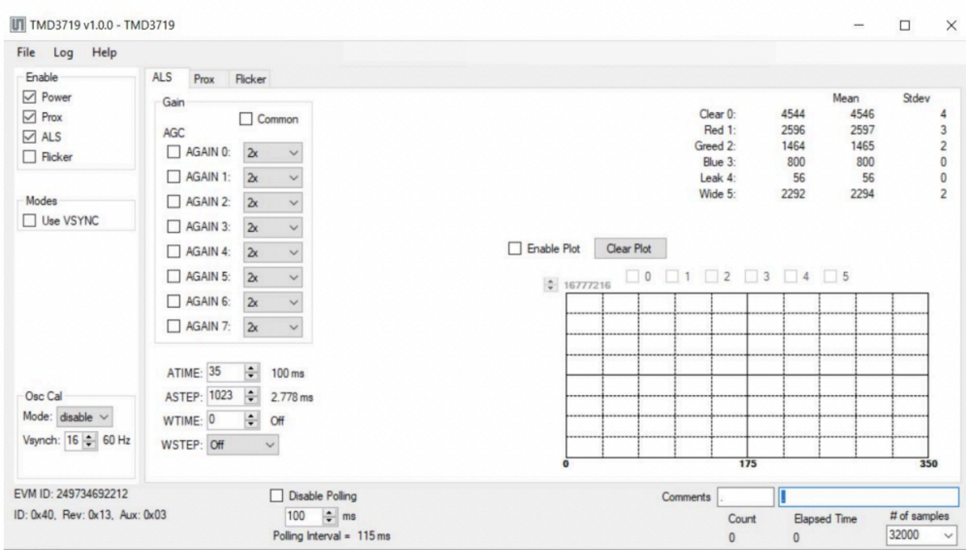


Figure 7: Main Window of the GUI

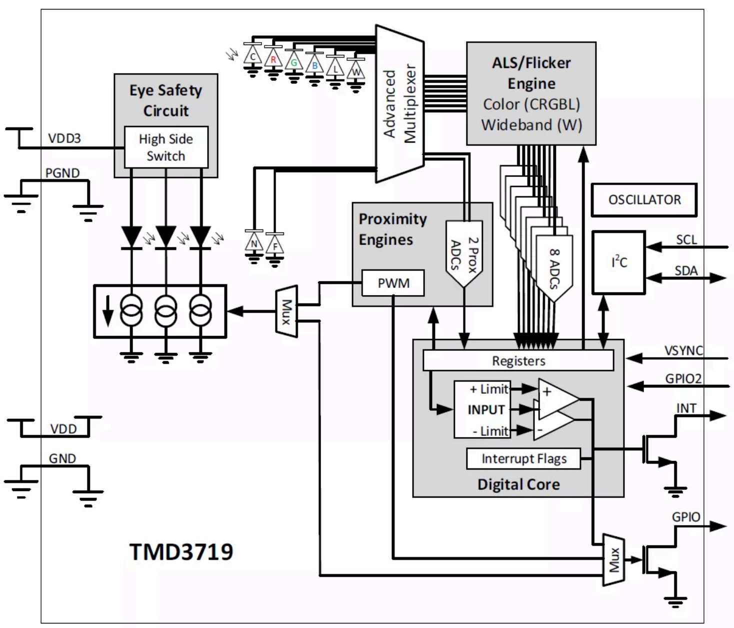


Figure 8: Block Diagram of the Sensor (included in the User Guide)

TCS34725 RGB Color Sensor: Link to User Guide

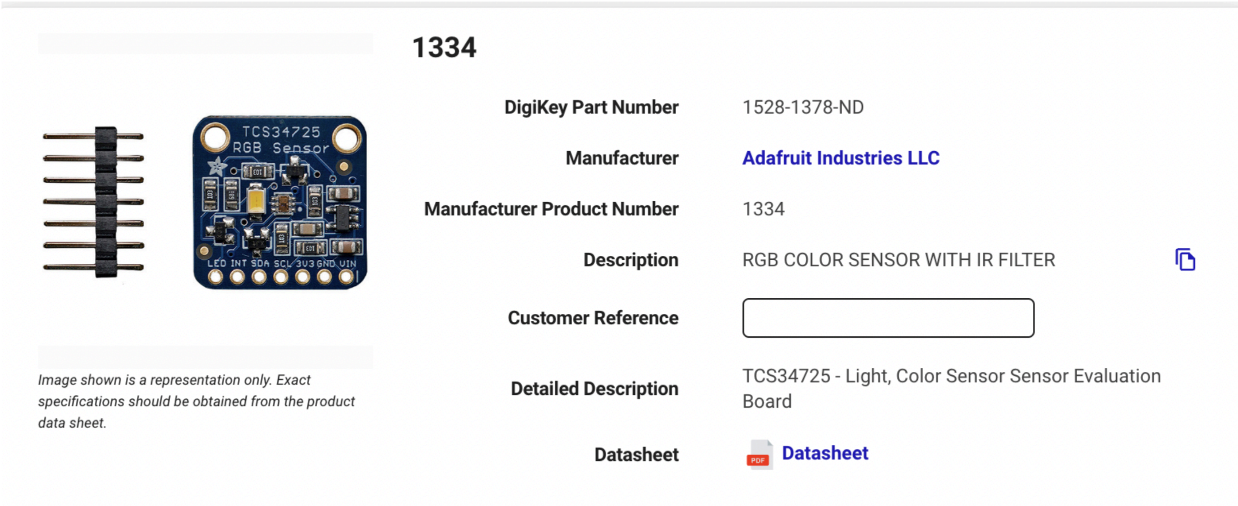


Figure 9: TCS34725 RGB Color Sensor Information

In the case that we are unable to obtain the above sensor, we will use the TCS34725 RGB color sensor to replace the above TMD sensor. The TCS Sensor has been previously tested in the laboratory and it uses the Particle Photon 2, which we have included in the BOM. We will be able to use an IoT to collect the waveform data and proceed with the Signal Processing as highlighted in the steps above. The TCS34725 RGB color sensor is an Analog sensor and is an I2C compatible interface, which we will use to communicate with VS code if this sensor is used. It senses Red, Green, Blue, and Clear light sensing with an IR blocking filter. Additionally, it contains four analog-to-digital converters (ADCs) in the sensor itself. It works best behind dark glass, which will be useful when refining the hardware design with the MVP as we will be able to add a protective glass layer that makes it easier and safer to use and collect data for patients.

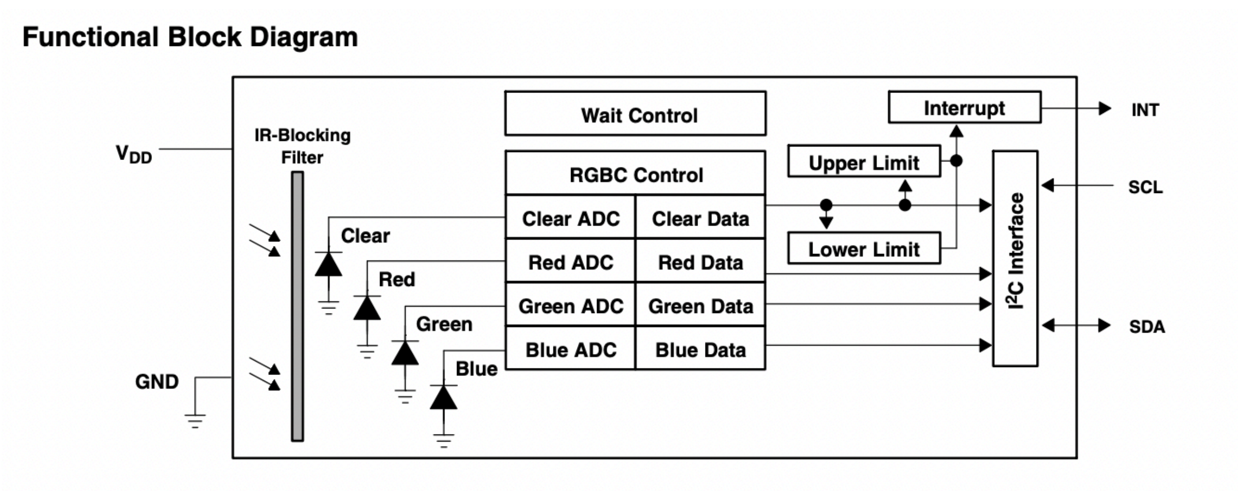
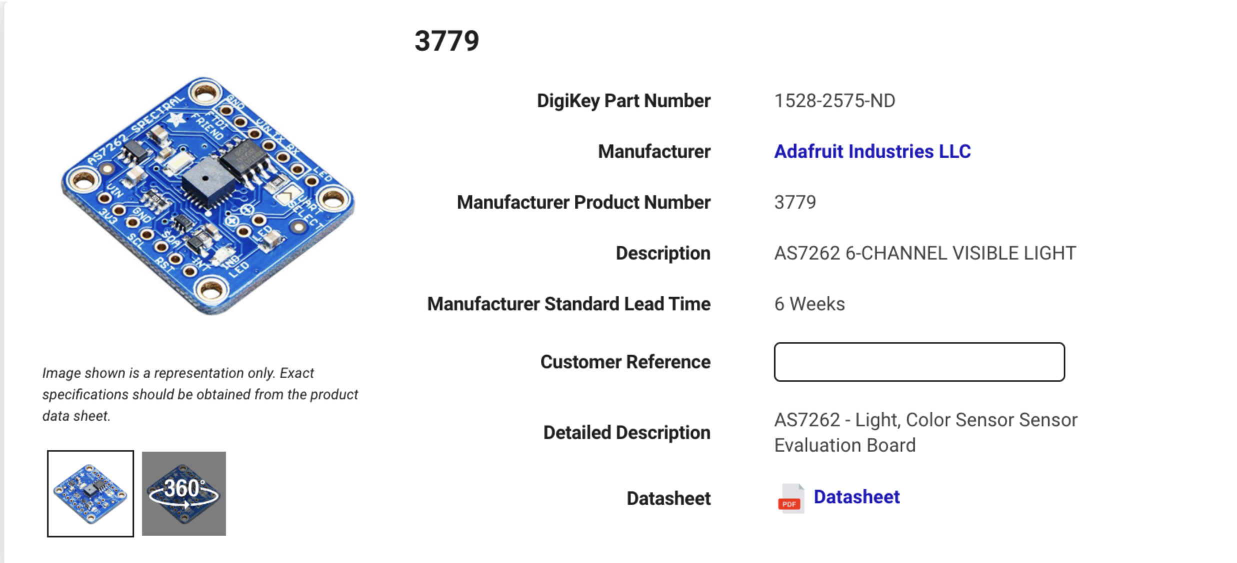


Figure 10: TCS34725 RGB Color Sensor Functional Block Diagram

Adafruit AS 7262:



3779

Image shown is a representation only. Exact specifications should be obtained from the product data sheet.

DigiKey Part Number	1528-2575-ND
Manufacturer	Adafruit Industries LLC
Manufacturer Product Number	3779
Description	AS7262 6-CHANNEL VISIBLE LIGHT
Manufacturer Standard Lead Time	6 Weeks
Customer Reference	
Detailed Description	AS7262 - Light, Color Sensor Sensor Evaluation Board
Datasheet	Datasheet

Figure 11: Adafruit AS 7262 Information

This is our third option for the PPG sensor, and will be used if the above two sensors are unavailable (or if this sensor turns out to be more practical for our use-case scenario. This sensor has 6 integrated visible light sensing channels with 6 different colors. It uses an I2C interface for and has established software libraries on CircuitPython/Arduino for easy data collection. We can use the Adafruit Metro microcontroller for this sensor, and as a result the Adafruit Metro microcontroller is included in the BOM below. We will use Python to interpret the signals for this sensor, and filter the code to only accept R,G, and B wavelengths/frequency for further signal processing.

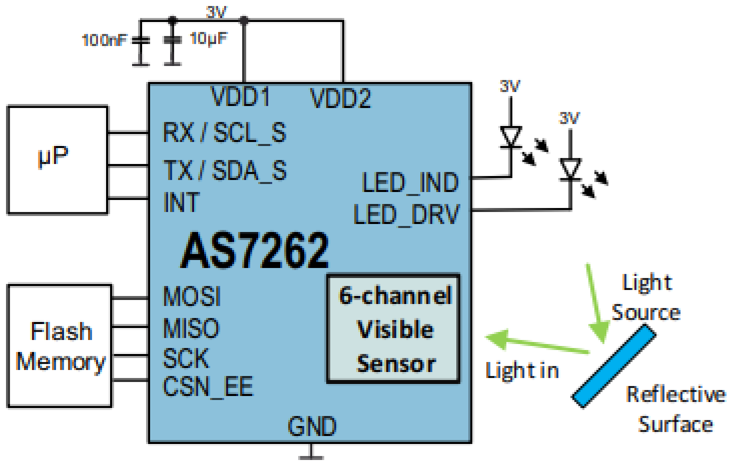


Figure 12: Adafruit AS 7262 Functional Block Diagram

Signals Collected/Outputted:

- PPG Waveform (R,G,B) signals
    - The initial PPG signals are analog, which need to be converted to digital. This signal is then processed through the remainder of the system.
- LED Signal (R,G,B)
    - LED signals are received from the CatBoost algorithm, which are outputted in one of three color modalities (red, green, blue).

Software Components:

- Initial Database Building – Microsoft Excel
    - The gathered data from the PPG sensor will be contained in a .CSV file for storage.
- Pandas Data Frames on Python
    - Pandas DataFrame is a 2D structure that has rows and columns. There will be a conversion of the .CSV file to Pandas Data Frames, then to a 3D NumPy Array is necessary for the signal processing portion. The three criteria for the NumPy array will include 1) subject/trials, 2) time segments, 3) RGB data.
- EMD/IMF (Python)
    - Empirical Mode Decomposition is a process that decomposes datasets into components of Intrinsic Mode Functions. The purpose is to analyze all these signals before ultimately sending them off to the CatBoost ML algorithm.
- CatBoost ML Algorithm (Python)
    - An example of the ML Algorithm code is below:

```
# Import necessary libraries
from catboost import CatBoostRegressor, Pool
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, r2_score

# Load dataset
data = pd.read_csv('ppg_features.csv') (Here can maybe use Karishmas's dad's data as well)

# Split features and target (Assuming 'glucose' is the target variable)
X = data.drop(columns=['glucose'])
y = data['glucose']

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Initialize CatBoostRegressor
model = CatBoostRegressor(
    iterations=1000,       # Number of boosting iterations
    learning_rate=0.01,    # Learning rate for gradient boosting
    depth=6,               # Depth of trees
    loss_function='RMSE', # Loss function to minimize, RMSE in this case
    verbose=100            # Verbosity of output during training
)

# Train the model
model.fit(X_train, y_train, eval_set=(X_test, y_test), early_stopping_rounds=50)

# Predict on test data
y_pred = model.predict(X_test)

# Evaluate the model
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

print(f'Mean Squared Error: {mse}')
print(f'R² Score: {r2}')

# Feature Importance
importances = model.get_feature_importance()
feature_names = X.columns
for feature, importance in zip(feature_names, importances):
    print(f'Feature: {feature}, Importance: {importance}')
```

- ○ Once the CatBoost algorithm is trained, we can now implement the PPG signals for it to classify into the three groups of blood sugar levels.

- <u>Arduino for LED Signaling Compartment</u>
  - ○ Arduino will encompass IF statements that will trigger a light to display based on the signal received (red - hypoglycemia, green - normal, blue - hypoglycemia).

8. Bill of Materials (BOM)

Link: [Click Here]()

<u>Screenshot of BOM:</u>

Group #8	Link URL	Product Name	Unit Count	Price of Each Item	Line Price	Part #	Item Description	Date entered Here	Da
	this is the most important column	double checks B				double checks C	checks B	Team enters this	BM
Hardware Components for Sensor and Signal Ouput, and LED Patient Signalling Device									
option 1	https://www.digikey.com/en/products/de	TMD 3719 RGB Sensor - Evalu	1	$225.36	$225.36	4991-EVALUATIO	Evaluation Kit Module fo	09/26/24	
option 2	https://www.amazon.com/HiLetgo-TCS-	TCS34725 RGB Light Color Se	1	$6.99	$6.99	Model #: 3-01-126	TCS-34725 TCS34725 F	09/26/24	
option 3	https://www.adafruit.com/product/3779#	Adafruit AS7262 6-Channel Vis	1	$19.95	$19.95	Product ID: 3779	The 6 channels on the A	09/26/24	
	https://www.digikey.com/en/products/de	3533 (Graphic Display TFT RG	1	$7.95	$7.95	1528-2327-ND	Graphic LCD Display Mo	09/26/24	
option 3	https://www.digikey.com/en/products/de	2488 (Adafruit METRO board)	1	$17.50	$17.50	1528-1214-ND	ATmega328 METRO	09/26/24	
option 2	https://www.amazon.com/Adafruit-Feath	Adafruit Feather RP2040 Ada 4	1	$16.74	$16.74	Model #: 4017	RP2040 32-bit Cortex M	09/26/24	
	https://www.amazon.com/EL-CP-003-B	ELEGOO 3pcs Breadboard 830	1	$8.99	$8.99	UPC: 7465916123	630 tie-point IC-circuit ar	09/26/24	
	https://www.digikey.com/en/products/de	1311 (Silicon Wire for Breadbo	1	$15.95	$15.95	1528-1743-ND	Hook Up Wire, 22 AWG I	09/26/24	
Backup Microcontroller	https://www.amazon.com/ATmega328F	ATmega328P (Arduino Nano)	1	$11.99	$11.99	ASIN:B0CM3C3FC	Mini Nano V3.0 ATmega	09/26/24	
	https://www.digikey.com/en/products/de	PRT-13851	2	$5.50	$11.00	1568-1493-ND	3.7V Battery (Li-Po)	09/26/24	
	https://www.digikey.com/en/products/de	L74A26-2-1-2W	1	$17.87	$17.87	3145-L74A26-2-1-	BATTERY PACK LI-ION	09/26/24	
	https://www.sparkfun.com/products/105	LED - RGB Clear Common Cat	3	$2.25	$6.75	COM-00105	These 5mm units have fo	09/26/24	
Reference Blood Glucose Sensor									
	https://www.amazon.com/Medhome-Dia	Blood Glucose Monitor Kit	1	$21.99	$21.99	ASIN:B0D7PMVRF	100 30G Lancets, Diabe	09/26/24	
Wearable Device Considerations with Integrated Patient Signaling Device									
	https://www.amazon.com/ELEGOO-Fila	PLA+ 3D Printer Filament (Blac	1	$14.99	$14.99	US-EL-3D-PH01, A	ELEGOO Rapid PLA Plu	26-Sep	
	From the Lab (Talked to Dr. Mai and Tr	Velcro Strap	1	NA	NA				
	https://www.amazon.com/White-Sheets	White EVA Foam Sheets	1	$6.99	$6.99	ASIN: B0BD63R4T	White EVA Foam Sheets	26-Sep	
	https://www.amazon.com/BOJACK-Elec	BOJACK Capacitor Kit (0.1 uF -	1	$16.99	$16.99	B07PBQXQNQ	Capacitors for filter	9/27/24	
	https://www.amazon.com/BOJACK-Valu	BOJACK Resistor Kit	1	$9.99	$9.99	B08FD1XVL6	Resistors for filter	9/27/24	
	https://www.amazon.com/DZRCOXI-Pro	PCB	1	$17.99	$17.99	B099PBZBV9	PCB for final circuit	27-Sep	
	https://www.amazon.com/BOJACK-UA7	BOAJCK Op-amp	1	$8.99	$8.99	B08DHQRP56	Amplifier to increase sig	27-Sep	
	https://store.particle.io/products/photon-	Photon 2	1	$17.95	$17.95	RTL8721DM	Backup board for main circuit		
						RTL8721DRTL8721DM M			
	** will also include wires and resistors/capacitor and other circuit components used during lab								

Figure 13: Bill of Materials Snapshot

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