# Insights Report

## Biometrics Dashboard

Biometrics Dashboard assess core health markers such as HbA1c, BMI, fasting glucose, triglycerides, and cholesterol ratios to categorize subjects into normal, prediabetic, or diabetic risk zones. These indicators offer a baseline understanding of metabolic health and are central to clinical profiling.

### Insights:

* The dataset comprises of 45 total subjects with age range of 18-69. 35% of the subjects are prediabetic and 31% are diabetic.
* Most participants are female, and a significant portion self-identify as Hispanic/Latino.
* High prevalence of overweight and obese individuals, particularly females, indicate weight-related metabolic strain.
* 44% (20 of 45) fall into the “Desirable” cholesterol range, but 11 are “Borderline High” and 6 are “High”. While the majority are okay, nearly 38% are at potential risk and warrant lipid monitoring or intervention.
* 12 subjects (27%) meet combined triglycerides + HDL criteria for “At Risk.” These individuals qualify for closer cardiometabolic surveillance or dietary change recommendations.
* “Good” microbes taper off with age while “Bad” microbes increase post-midlife. Microbiome shifts with aging could be impacting inflammation, digestion, and overall metabolic health. Probiotic/prebiotic support may be beneficial.
* 14 out of 45 subjects are above the “Normal” triglyceride threshold. This indicates a substantial proportion with dyslipidemia risk. It reinforces need for fat metabolism optimization.

## 2. Subject Health Report Dashboard

The Subject Level Health dashboard provides a detailed overview of each individual's gut microbiome profile, including microbial counts and gut health scores, along with insights into macronutrient intake and glucose spike patterns.

### Insights:

* It gives the key indicators of the selected subject like ID, age, gender, race, average heart rate, cholesterol/HDL ratio, hbA1c, fasting glucose, glycemic status, BMI, BMI category, triglycerides and category.
* The selected subject’s score for each gut health attribute where the scoring is factored as 1: Not optimal, 2: Average and 3: Good. It helps determine gut imbalances linked to glucose metabolism. Example, a low score in butyrate producers or a high pathogen load may correlate with poor glycemic control.
* The selected subject’s most abundant microbial groups in the gut microbiome. This can be useful for identifying microbial imbalances. Example, high presence of Firmicutes, Proteobacteria, or pathogens may indicate a dysbiosis state.
* Total Significant Glucose Spikes (glucose spikes that crossed a significant threshold (30 mg/dl after meal) by Meal Type of selected subject identifies which meal type consistently causes glucose spikes. It can guide personalized meal planning or macro nutrients adjustment. Example, if dinner shows the most spikes, subject might need to reduce carbs or increase fiber at night.
* Largest Drop and Rise in Glucose for each meal type can identify volatile glucose responses. Large drops may indicate hypoglycemia risk. Large rises may signal carb overload or low insulin response.
* Hourly Macronutrient Intake and Post-Meal Glucose can reveal patterns like: High morning carbs leading higher glucose peaks, Late-night fat intake leading delayed glucose spikes. Most importantly, it can inform time-restricted eating, macro balancing, or meal timing adjustments.

## 3. Microbial and Gut Health Dashboard

Microbial and Gut Health Dashboard analyze gut microbiome composition across functional groups such as butyrate producers, potential pathogens, and probiotic strains. These microbial patterns are evaluated in relation to glucose variability and systemic inflammation, providing insight into how gut health may be influencing metabolic responses.

### Insights:

* Microbial balance is a key health driver. Subjects with low good bacteria and high harmful microbes show clear signs of gut dysbiosis often linked to poor metabolic outcomes.
* Low butyrate producers lead higher inflammation. Individuals with reduced butyrate-producing microbes fall into “Not Optimal” inflammatory categories, reinforcing the gut’s role in regulating inflammation.
* Gut endotoxins and insulin resistance are connected. Subjects flagged with "Not Optimal" LPS biosynthesis profiles show nearly double the fasting insulin, suggesting a gut-derived endotoxin burden may worsen insulin sensitivity.
* Cholesterol and gut health are related. Higher counts of butyrate producers are seen in subjects with desirable cholesterol levels, while those with borderline or high cholesterol tend to have depleted beneficial microbes.
* Microbiome imbalance flags metabolic risk. Obese individuals often cluster in the “high harmful, low beneficial” microbe zone linking gut composition with body fat and systemic risk.
* Fasting insulin > 20 µIU/mL often coexists with bad bacteria compared to good bacteria: A quick scan of insulin levels and microbial counts helped spotlight microbially influenced hyperinsulinemia.
* HbA1c-linked insights drive targeted recommendations, HbA1c-based risk status and personalized recommendations are based on Gut health pathways and microbial score. Subjects are stratified into high, medium, and low risk. It enabled subject-specific dietary intervention planning.

## 4. Meal and Macronutrient Impact Dashboard

Meal and Macronutrient Impact dashboard analyze how carbs, fat, fiber, and protein correlate with glucose variability. It evaluates how macronutrient ratios, meal types (breakfast, lunch, dinner, snack), and timing affect the subject’s glucose patterns, supporting food personalization.

### Insights:

* Higher fat intake links with higher BMI. Some lean outliers tolerate high fat well. Moderate fat and high BMI suggest other factors (e.g., carbs, inactivity).
* Macronutrient Patterns of Meal types show dinner as most energy-dense and balanced. Breakfast is high in carbs; snacks are low in all macros. Eating more earlier can avoid night-time spikes.
* Carbs vs. Glucose by Meal Type shows dinner with wide glucose variability may be due to late eating and fat load.
* Fiber intake and Glucose spike are inversely related. Higher fiber intake trends with lower glucose. Fiber helps reduce glucose spikes.
* Meal Composition of High-carb, low-fat meals cause biggest spikes. Pairing carbs with fat/protein helps reduce spike magnitude.
* Calories by HbA1c & BMI revealed Obese and T2D groups eat more, with wider intake spread. But some T2D subjects tends to eat less so quality and timing matter too.
* No clear link between calories and glucose. T2D subjects show high glucose at all intake levels.

## 5. Glucose Response Trend Dashboard

Glucose Response Trend Dashboard explore post-meal glucose spikes, identify significant rises and drops, and analyze glucose behavior across different hours of the day. By linking these trends with macronutrient intake and microbiome profiles, we generate dynamic insights into glucose sensitivity, metabolic flexibility, and circadian glucose patterns

### Insights:

* Glucose peaks are highest between 12–8 PM, showing the impact of meal timing. Some subject’s spikes are greater 200 mg/dL, others stay below 140 mg/dl, highlighting personalized responses.
* High Cholesterol/HDL ratio leads to Insulin Risk. Subjects with insulin resistance often have cholesterol/HDL ratios greater than 4.0. Lower Ratios have Safer Profile as Those with ratios less than 3.5 typically fall in the normal insulin range.
* Breakfast Causes Most Spikes. Highest number of significant spikes occur after breakfast, possibly due to fasting or carb load. Lunch & Dinner Also Matter as they show many spikes too, pointing to a need for balanced meals across the day.
* More Activity leads to Lower Glucose. Highly active subjects burn more calories and show better glucose control. Whereas Low Activity leads to Higher Glucose. Sedentary individuals show elevated and erratic glucose trends.
* Different combinations of metabolic risk factors classify individuals into chronic disease risk categories. Subjects with all four markers elevated triglycerides, low HDL, high glucose, and high insulin are labeled as Cardiac Arrest Risk, indicating the most severe profile. Those with only high glucose fall under Prediabetes / Diabetes Risk, while combinations like low HDL and high glucose result in Dyslipidemia Risk. Severe Metabolic Syndrome Risk reflects elevated glucose, insulin, and at least one lipid marker. Individuals marked Not at Risk have all biomarkers within normal limits.

Together, these analytical layers deliver a holistic view of each subject’s health, enabling data-driven recommendations for personalized nutrition and lifestyle interventions. These dashboards transform raw health data into actionable insights for each subject, empowering clinicians, researchers, and users to make informed, individualized health decisions.

# Challenges:

1. **Challenge**: Handling the Missing Data of photo path in the table CGMacros.

**Solution**: We automated the script by pulling the list of photo filename in the csv format and then proceeded with extraction from the filenames and inserted the missing photo paths.

1. **Challenge**: Reducing the volume of the CG Macros data from minute timeseries to hour.

**Solution**: We converted the minutes to start of the hour and took the average of all numerical data for the particular hour. This helped in reducing the volume but keeping the key information about each hour for the subjects.

1. **Challenge**: Handling almost 2000 microbes for each subject.

**Solution**: We grouped each microbe in the categories based on the functionality. We summed up the presence of microbe for each patient according to the microbe group. For the insight, we further segregated the groups into good, bad and neutral bacteria.

1. **Challenge**: Showcasing the insights of each subject all together.

**Solution**: We decided to go with bookmark navigation to visualize the insight on individual subject level. This enhanced the detailed overview of each individual's gut microbiome profile, including microbial counts and gut health scores, along with insights into macronutrient intake and glucose spike patterns.

1. **Challenge**: Reduction of the similar charts and insights with different macronutrients with glucose levels.

**Solution**: We created parameter for each macronutrient to be compared to the glucose levels and used the parameter to switch to the macronutrients and see the relation with glucose levels.

In this project, we didn’t just visualize data we listened to what it had to say.  
 From biometrics to microbes, from meals to movement, we wove together stories that show the hidden forces shaping metabolic health. Each dashboard revealed a new lens, but also a challenge. Whether it’s incomplete logging, missing context, or the complexity of human biology, real-world data is messy. But in that mess lies meaning. As analysts, our job is not just to show charts, but to translate them into actions. And even if we had minutes of data, we converted each minute into an hour of insight.

Thank you for reading.