Evaluating Effects of Physical Activity and Nutrition on Individualized Postprandial Glucose Response

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Motivation

- Diabetes is a growing chronic illness and the 7th leading cause of death in the United States [1]
- Severe complications make diet monitoring and good glycemic control vital
- Conventional methods fail to account for interpersonal variation → inaccurate and inconvenient

Goal: Automated diet monitoring

Background

Postprandial Responses are Affected by Many Factors

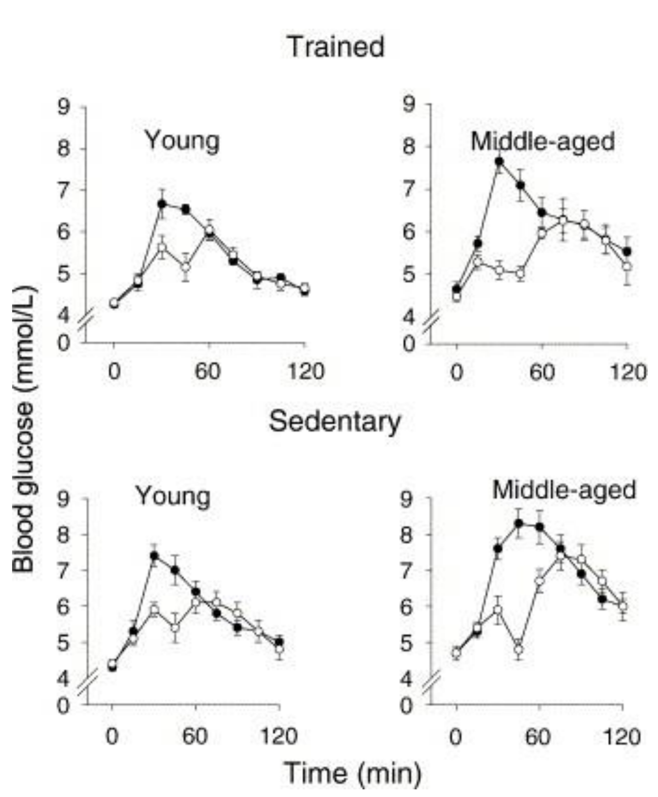


Figure 1: PPGR curves with and without activity

- Macronutrients, activity, individual, and microbiome impact **Postprandial Glucose Response (PPGR)**
- Activity correlated with lowered or blunted peak
- **Metabolic Equivalent of Tasks (METs)** measure energy expenditure

Previous Work Predicting PPGR with Limited Features

- Linear mixed effects with controlled meals found macros + individual to impact PPGR prediction [2]

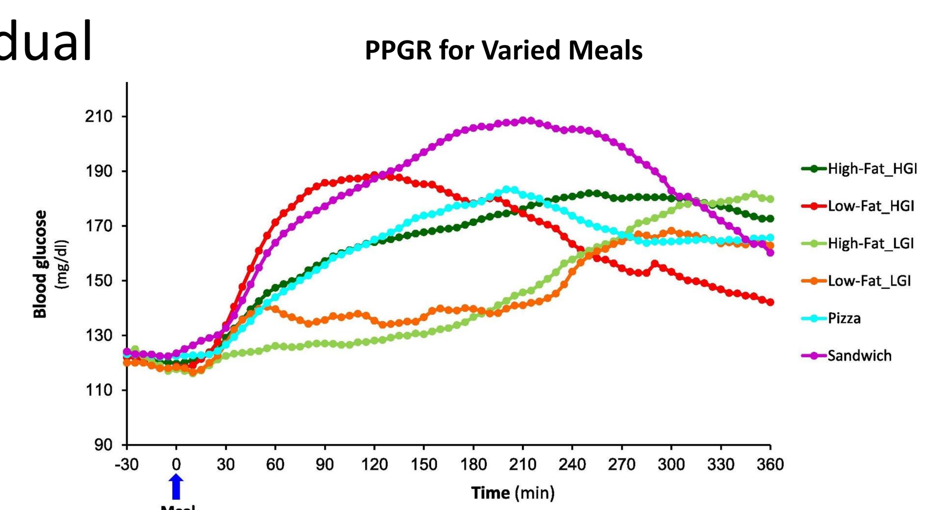


Figure 2: PPGR curves varying with macronutrient contents of meal [2]

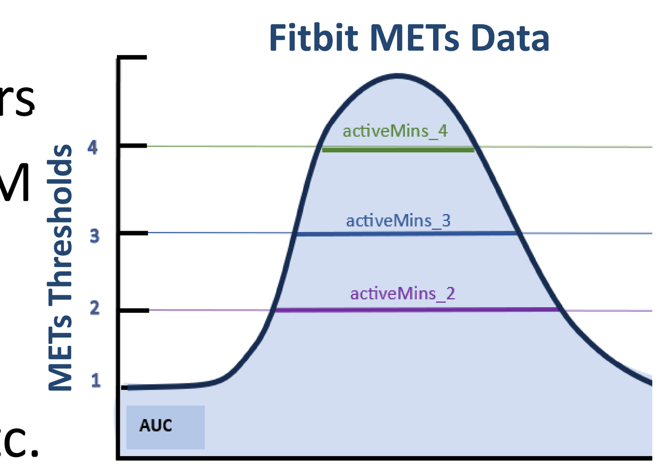
- Random forest, Support Vector Regression, XGBoost, and Elastic-Net used with estimated carbohydrate data and activity → *XGBoost found to perform best [3]*

Methods

Modeling through Gradient Boosting and Linear Mixed Effects

Raw Dataset

- 27 participants, varied dinners
- Blood Glucose – Dexcom CGM
- Activity - Fitbit Sense
- Individual Lab Data
  - Age, HbA1c, triglycerides, etc.



Feature Extraction (3-hour postprandial window)

- **PPGR** – iAUC, AUC, peakheight, time, duration, start
- **METs Activity** – activeMinutes (2,3,4), AUC, average
- **Heart Rate** – start, max, AUC

Model Training

Individual Dataset / Combined Dataset → XGBoost / Linear Mixed Effects (LME)

LME Fixed effects: Macros, lab data, and activity

Random effect: participant ID

Results

- Models evaluated through RMSRE and R^2
- Individual and activity data improved models

Root Mean Squared Relative Error

$$RMSRE = \sqrt{\frac{1}{s}\sum\frac{(y-\hat{y})^2}{y^2}}$$

Predict	No Activity	Activity
Peak height	0.186	0.183
PPGR AUC	0.16	0.15
Carbs	0.44	0.42
Calories	0.43	0.41

Figure 3: RMSRE for XGBoost model

$$R^2 = 1 - \frac{RSS}{TSS}$$

R^2 = coefficient of determination
RSS = sum of squares of residuals
TSS = total sum of squares

LME Model	Breakfast	All Meals
Base (macros)	0.14	0.10
Base (with HbA1c + age)	0.47	0.20
Activity	0.49	0.23
Activity + Triglycerides	0.53	0.40

Figure 4: R^2 values for LME models predicting peakheight

Discussion

Feature Importance for gradient boosting and LME models

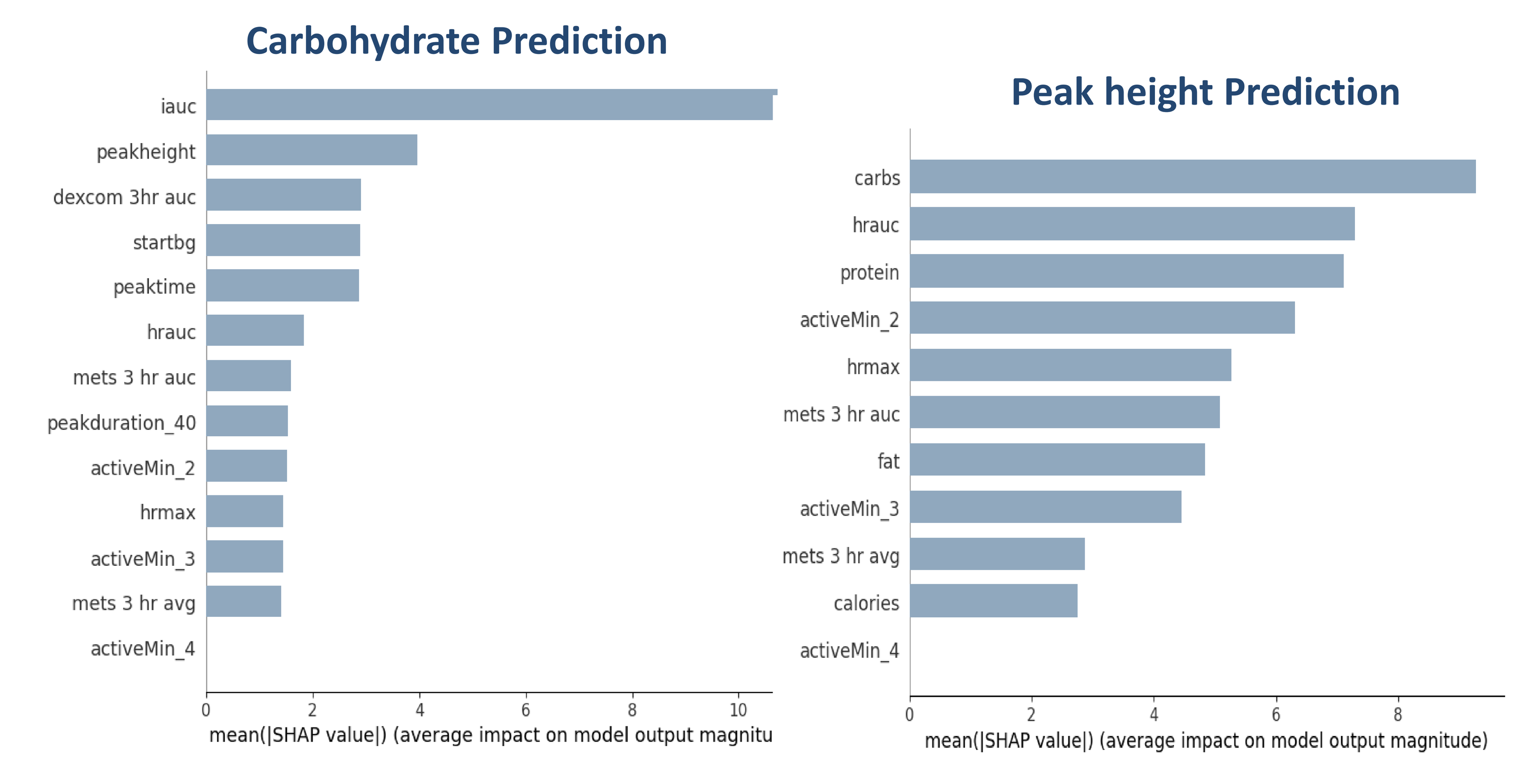


Figure 5: Combined SHAP Explainer results showing which features had largest impact on model

Fixed Effect	HbA1c	Carbs	Protein	activeMin2	hrauc
t-value	3.778	3.607	-4.997	-2.056	2.707

Figure 6: Significant t-values in LME model predicting peakheight

Conclusions

- Factors like HbA1c, triglycerides, activeMinutes, and heart rate impacted PPGR predictions
- Further tuning with activity data and more individual data may be promising for accurate predictions

Next Steps

- **Feature engineering:** integrate heart rate variation, more METs, lab tests, and microbiome
- **Time Frames:** different windows and dinner group
- Larger dataset and predict other features with LME

Acknowledgements and References

Thank you to Dr. Mortazavi, Sicong Huang, Ryan King, the STMI lab, and the Precise Advanced Technologies and Health Systems for Underserved Populations (PATHS-UP) REU for all your help!

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