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CENTER FOR NUTRITION EDUCATION AND RESEARCH

MCNER Webinar Series

A Review of Digital Innovations for Precision Nutrition

Thursday, February 22, 2024

Moderator:
Lisa Diewald, MS, RDN, LDN
Associate Director
MacDonald Center for Nutrition Education and Research
Villanova University M. Louise Fitzpatrick College of Nursing

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Finding Slides for Today's Webinar

- Slides are posted at villanova.edu/cope
- From right menu→ Webinars
- Go to 2/22/24 webinar presented by Ricardo Gutierrez-Osuna, PhD.

Continuing Education Credit Details

- This Continuing Professional Education (CPE) activity is pending approval by the Commission on Dietetic Registration for 1 CPEU.

- Contact hours are not available for nurses for this webinar.

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Continuing Education Credit Details

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A Review of Digital Innovations for Precision Nutrition

Ricardo Gutierrez-Osuna, PhD.
Professor of Computer Science and Engineering
Texas A&M University

FEEDING THE NEED
DEVELOPING SOLUTIONS

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Disclosures

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A review of digital innovations for precision nutrition

Ricardo Gutierrez-Osuna

COMPUTER SCIENCE
& ENGINEERING
TEXAS A&M UNIVERSITY

Motivation

Diet and exercise are essential components of interventions to diabetes and obesity

– Sensing approaches exist to measure exercise automatically

Motivation

Diet and exercise are essential components of interventions to diabetes and obesity

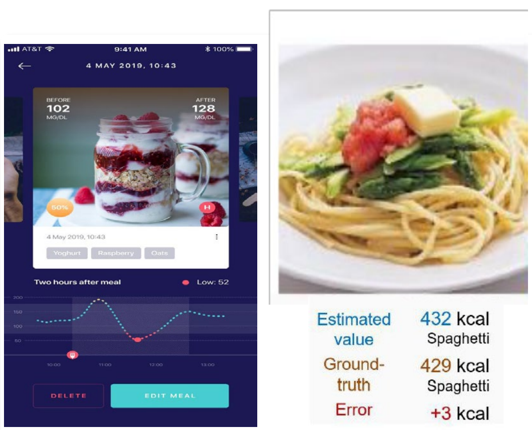
- Sensing approaches exist to measure exercise automatically
- Yet, no automated methods exist to measure diet
- Currently, diet monitoring requires manual entry or recall, which are tedious and error-prone
- Can sensing technology and AI help?

Overview

In this talk, I overview current technology in 3 areas

- Advances in mobile applications for diet logging
- Wearable sensors to detect dietary behaviors
- Personalized nutrition programs

I also present ongoing work at TAMU in this area



Advances in mobile apps

Sensors for diet monitoring

Personalized nutrition

I. Mobile applications for diet logging

Advantages over paper-based diaries

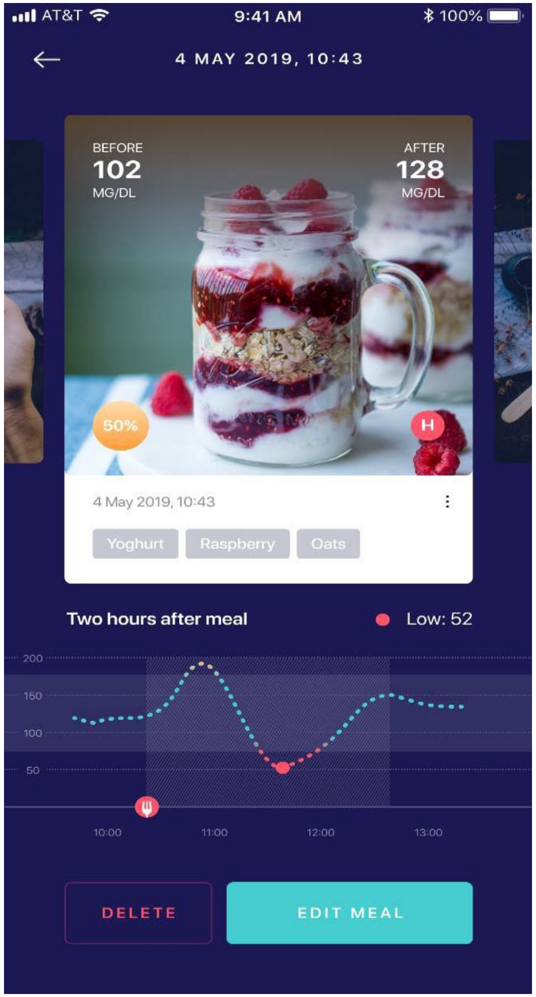
- Ubiquity of smartphones avoids the need to carry physical food diary
- Access to large food databases
  - MyFitnessPal has 11M food items (unverified)
  - Nutritionix has 800k grocery items and 170k restaurant items (verified)
- Ability to scan barcodes of packaged foods
- Can be integrated with external devices
  - Smart scales
  - Fitness trackers
  - Continuous glucose monitors, ketone monitors

Recent advances in mobile apps

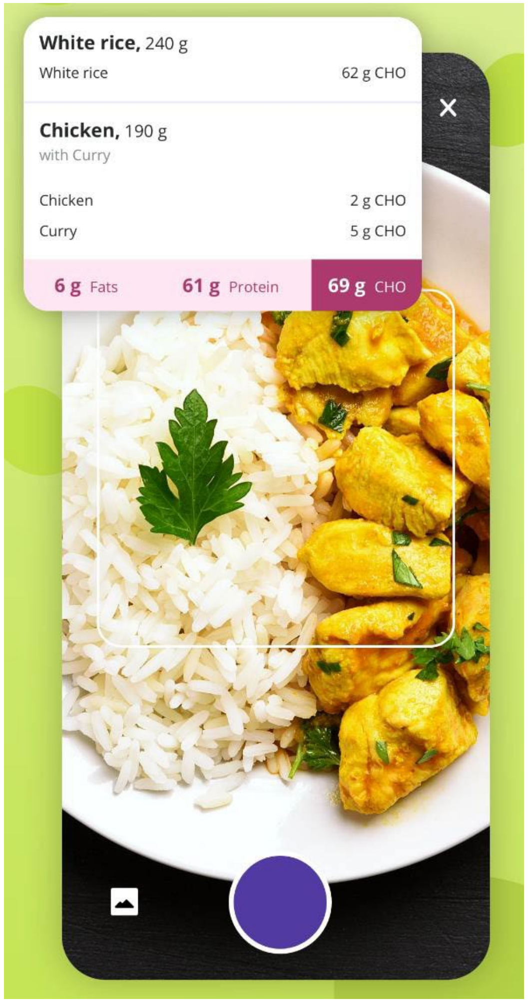
- Photographic food diaries
  - Avoid data hoarding
  - Photos encourage in-the-moment awareness
  - Photos improve memory recall and understanding
- Food recognition from photographs using AI
  - Apps: Lose it!, CalorieMama, Snaq, Undermyfork
  - APIs: bite.ai, FoodAI

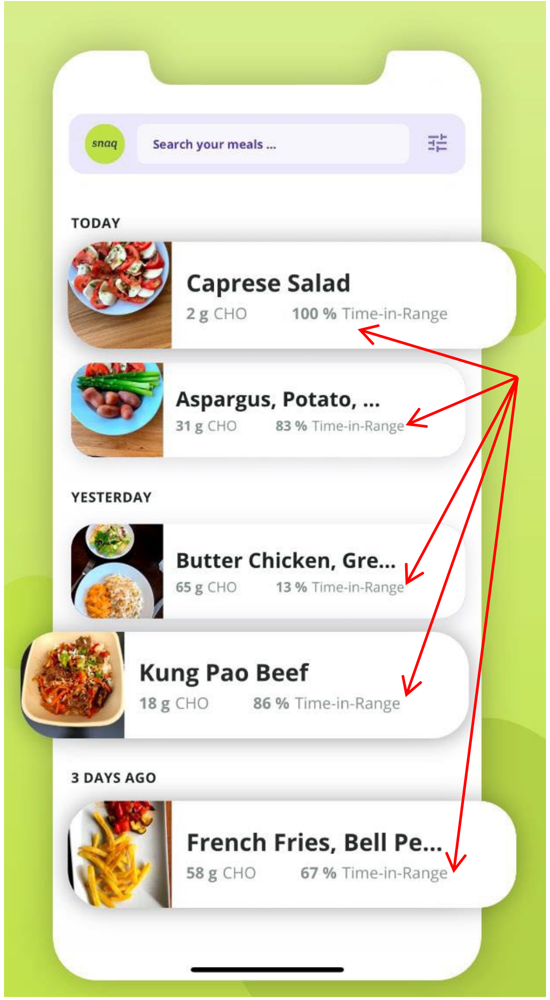
Examples

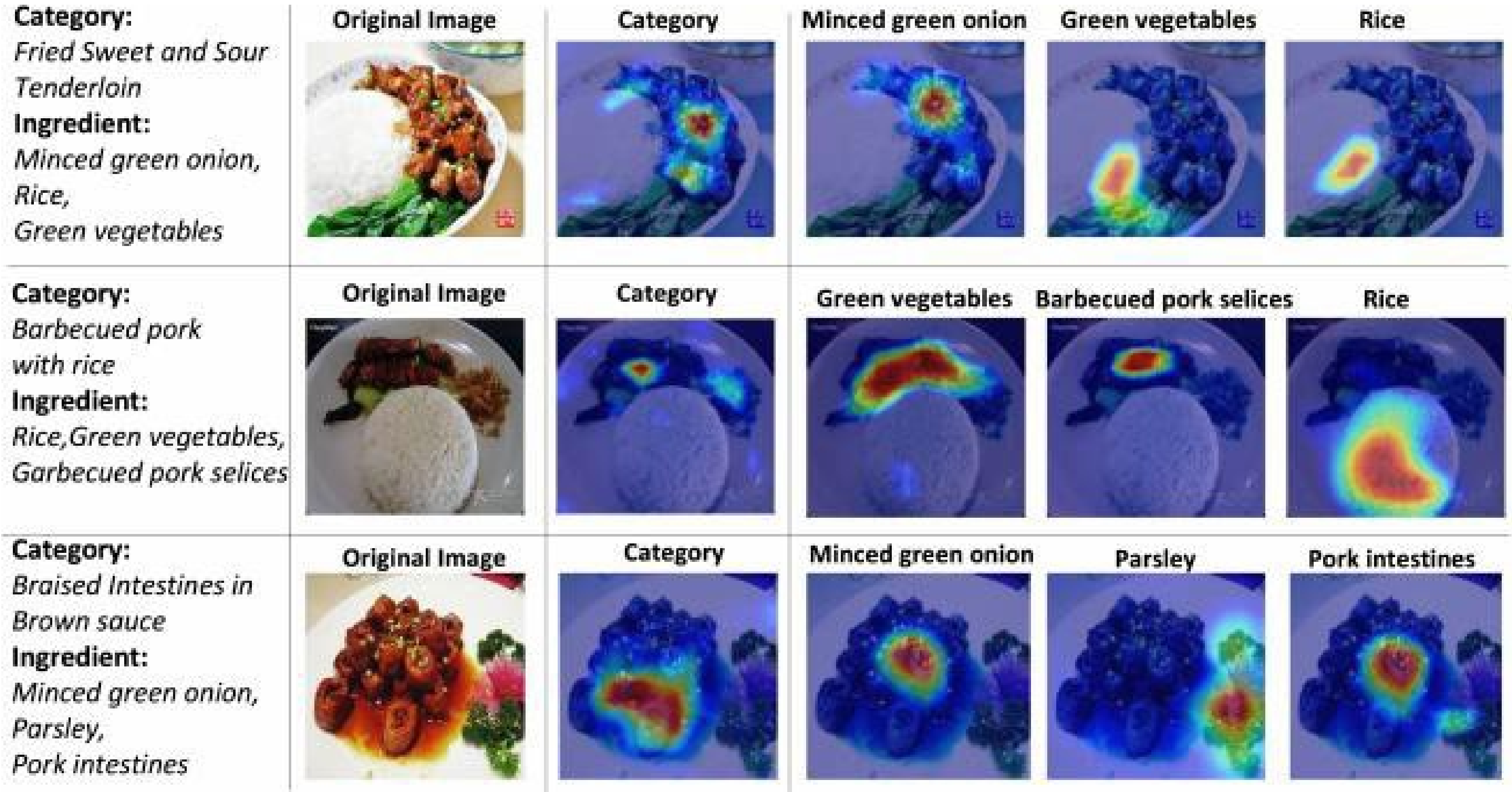
undermyfork



snaq





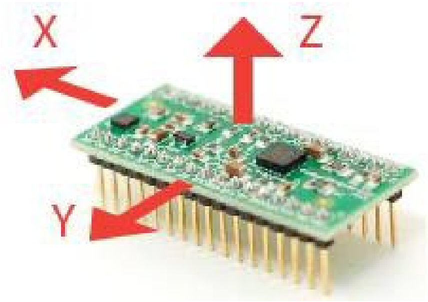


S. Jiang, W. Min, Y. Lyu, and L. Liu. 2020. Few-shot Food Recognition via Multi-view Representation Learning. *ACM Trans. Multimedia Comput. Commun.* Appl. 16, 3, Article 87 (August 2020), 20 pages. https://doi.org/10.1145/3391624

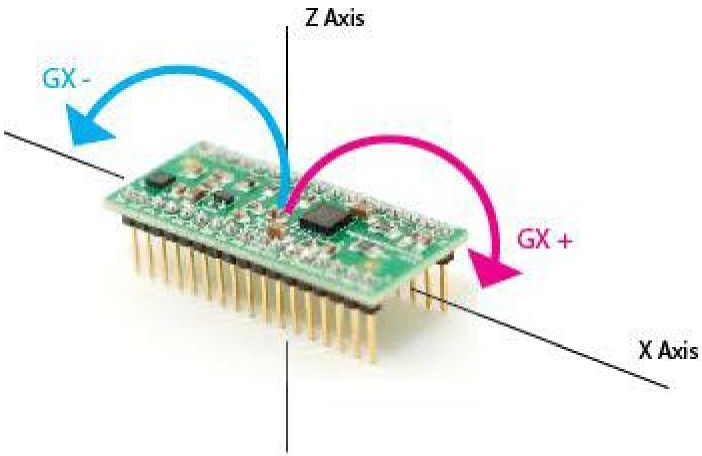
II. Wearable sensors for diet

Physical sensors

- Gesture recognition with inertial sensors
  - 3D accelerometers
  - Gyroscopes



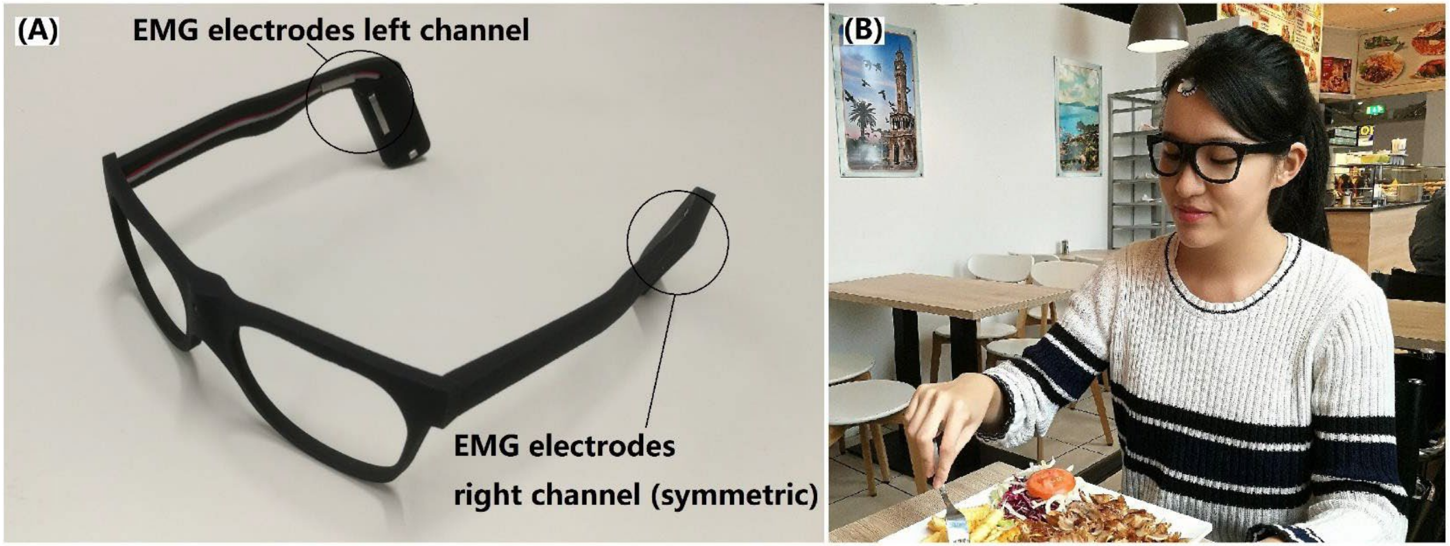
https://mug.ee.auth.gr/intake-cycle-detection/



II. Wearable sensors for diet

Physical sensors

- Gesture recognition with gyro and accelerometers
- Muscle movement and sound with electromyography and microphones



Zhang, R.; Amft, O. Retrieval and Timing Performance of Chewing-Based Eating Event Detection in Wearable Sensors. *Sensors* **2020**, *20*, 557. https://doi.org/10.3390/s20020557

II. Wearable sensors for diet

Physical sensors

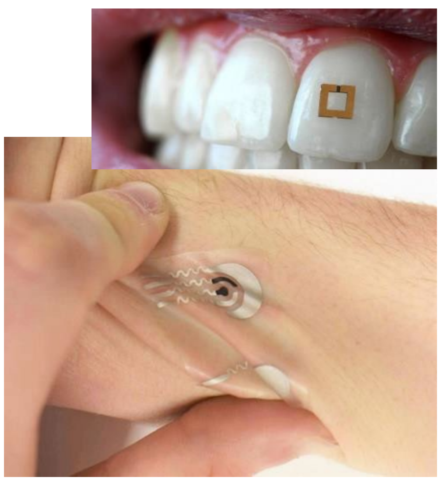
- Gesture recognition with gyro and accelerometers
- Muscle movement and sound with electromyography and microphones
- Smart utensils

https://www.hapilabs.com/

Chemical sensors

- Breathalyzers (ketone meters, metabolic fuel)
- Experimental sensors (sweat, tooth-mounted)
- Continuous glucose/ketone monitors

https://www.ketonix.com/
https://www.lumen.me/



[Tseng et al, 2018]
[Sempionatto et al. 2020]

https://www.freestyle.abbott/
https://www.dexcom.com/
https://www.ascensiadiabetes.com/

III. Personalized nutrition

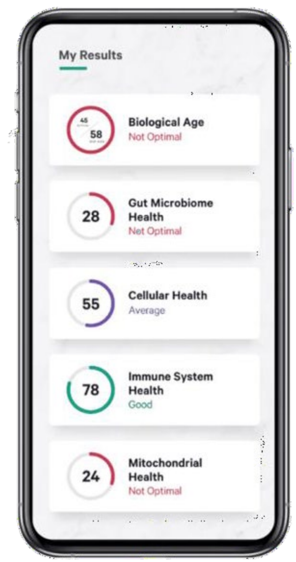
Based on gut microbiome

- DayTwo
- Viome

Based on CGMs

- NutriSense
- Levels
- Cignos

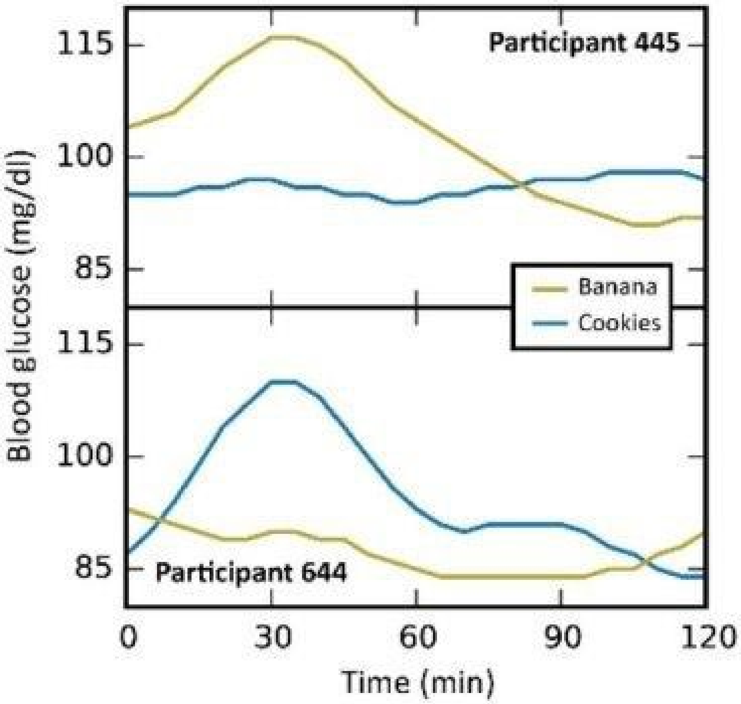
https://www.daytwo.com/

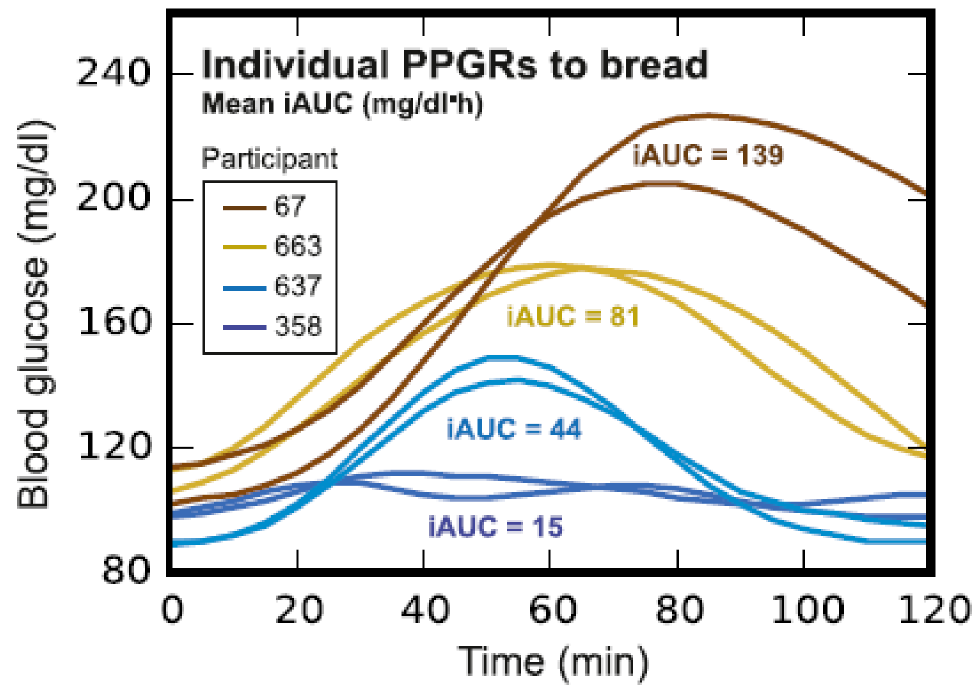


https://www.viome.com/

https://www.nutrisense.io/

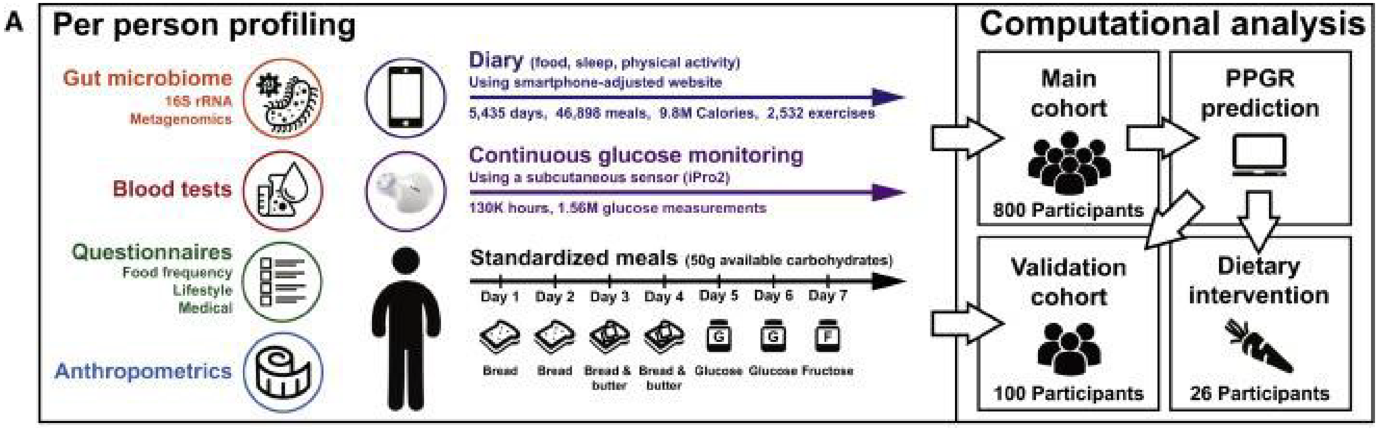
DayTwo [Zeevi et al. 2015]



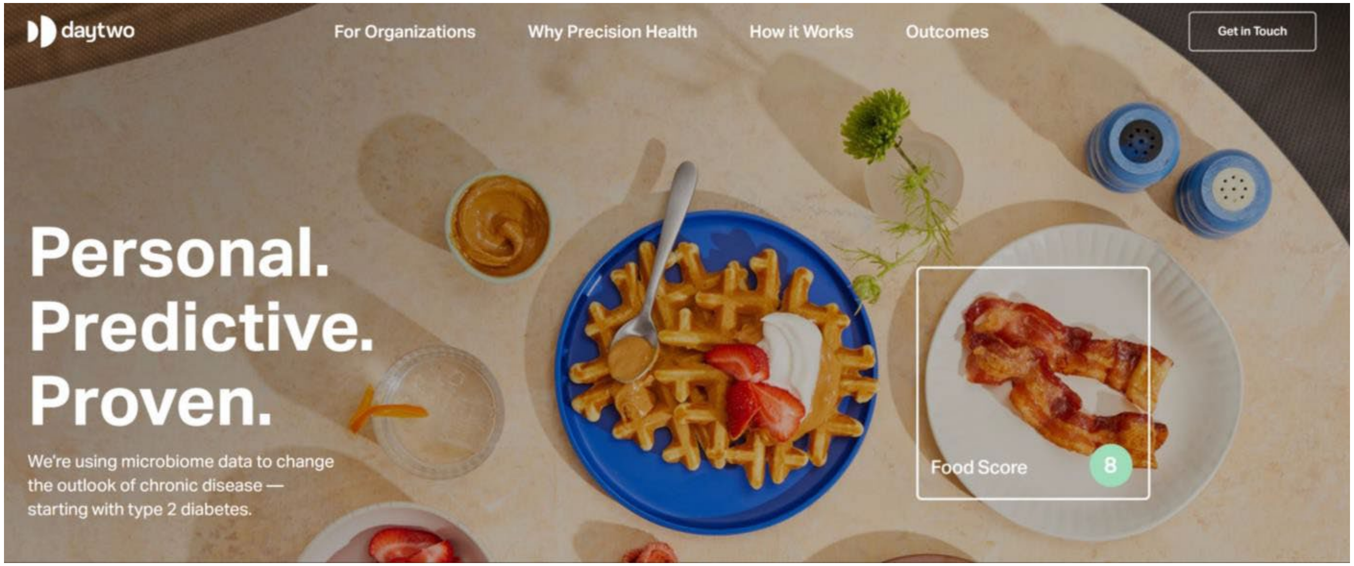


Zeevi D, Korem T et al. Personalized Nutrition by Prediction of Glycemic Responses.
Cell, 163(5):1079-1094, 2015 doi: 10.1016/j.cell.2015.11.001.

DayTwo [Zeevi et al. 2015]

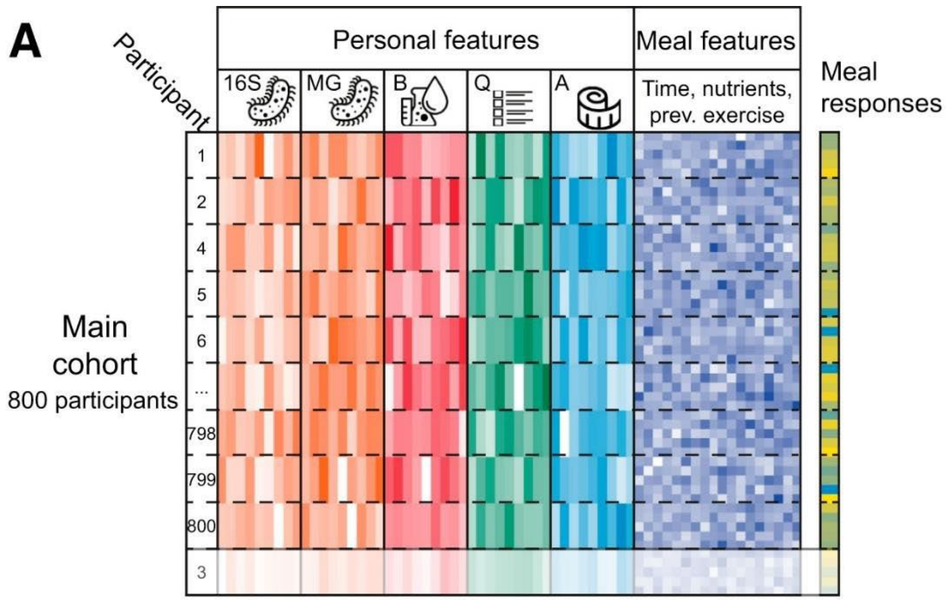


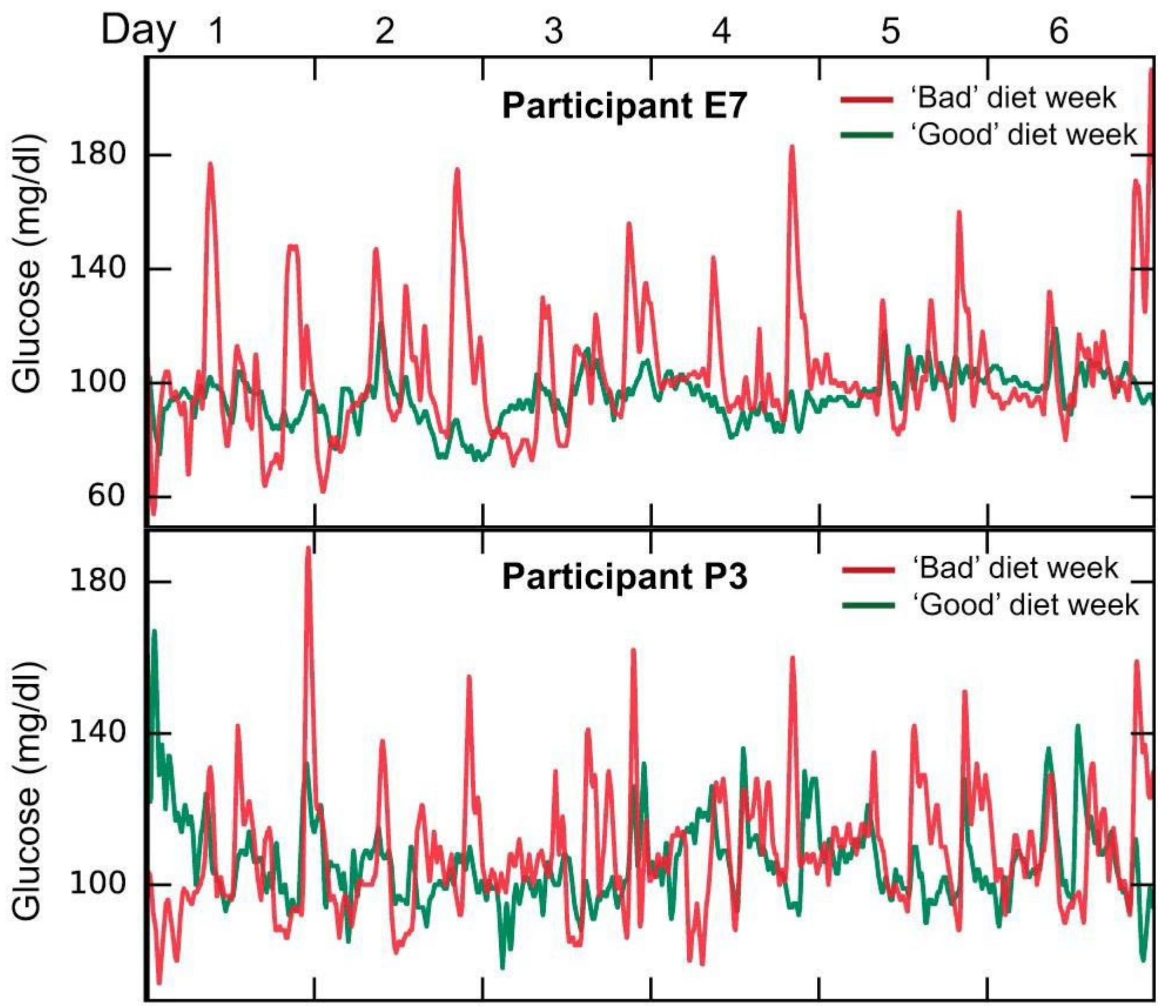
Zeevi D, Korem T et al. Personalized Nutrition by Prediction of Glycemic Responses. Cell, 163(5):1079-1094, 2015 doi: 10.1016/j.cell.2015.11.001.



https://www.daytwo.com/

The Zeevi et al. (2015) study





Day 1 2 3 4 5 6
Participant E7
'Bad' diet week
'Good' diet week
Glucose (mg/dl)
180
140
100
60
Participant P3
'Bad' diet week
'Good' diet week
Glucose (mg/dl)
180
140
100

Ongoing work at Texas A&M University

- The goal of Zeevi et al. (2015) study was to develop a <u>forward</u> metabolic model
  - Given food macronutrients (and phenotype* variables), predict the postprandial glucose response (PPGR)
- My work with colleagues at TAMU aims to develop <u>inverse</u> metabolic models
  - Given the PPGR to a meal (and phenotype), predict the meal's macronutrient composition

* HbA1c, BMI, gut microbiome…

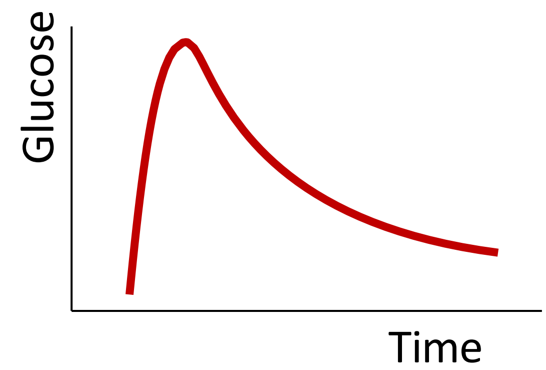
Forward model

Machine learning model

Fat

Carbs

Protein



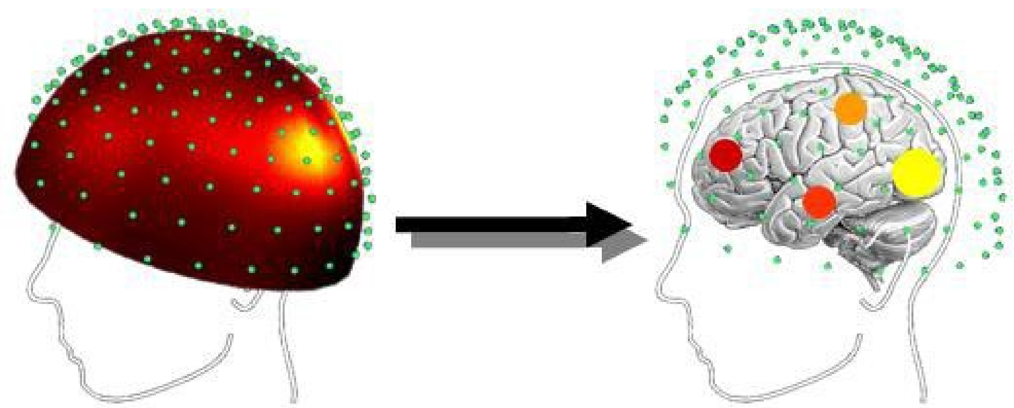
Machine learning model

Inverse model

Inverse problems

Inverse problems deal with calculating the causal factors that led to a series of observations

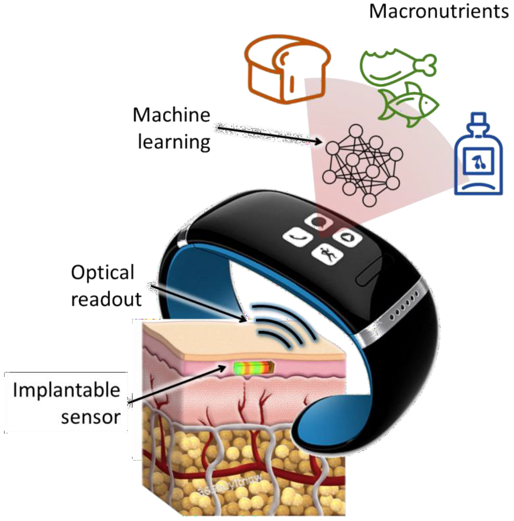
- Localizing brain activity from surface measurements (EEG)
- Localizing a sound from dispersed microphones
- Reconstructing speech acoustics from facial movements
- Solving crime from evidence…



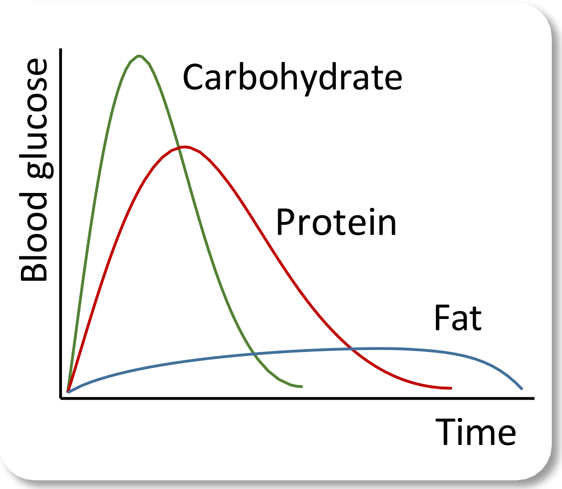
How to build inverse metabolic models

In the long term, by developing sensors for other nutritional biomarkers

- Amino acids (for protein)
- Triglycerides (for fat)
- Glucose + Insulin (for carbs)



In the short term, by exploiting information in the PPGR



Laboratory study (proof of concept)

Fifteen subjects consumed nine liquid meals with different amounts of macronutrients

- Participants consumed meals in a fasted state
- Participants rested for 8 hours in a clinic
- Study days were 2-3 days apart
- Participants wore a Freestyle Libre CGM

Meal	CHO (g)	Protein (g)	Fat (ml)
C1P1F1	52	15	13
C1P2F2	52	30	26
C2P2F1	95	30	13
C2P1F2	95	15	26
C2P2F2	95	30	26
C2P2F3	95	30	52
C2P3F2	95	60	26
C3P2F2	180	30	26
C3P3F3	180	60	52

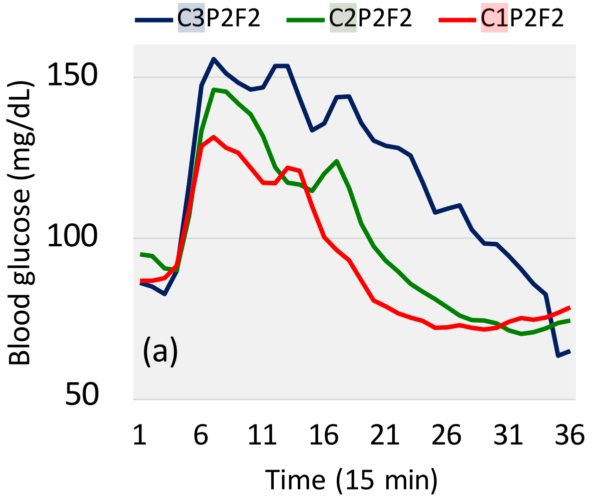
Experimental data (2)

At regular intervals, we drew blood samples to measure four types of biomarkers

- Glucose (CGM, LC, finger stick)
- Amino acids (24 AAs + combos)
- Triglycerides
- Insulin

#	Name	Abbreviation
1	Aspartate	ASP
2	Glutamate	GLU
3	HydroxyProline	hPRO
4	Asparagine	ASN
5	Glutamine	GLN
6	Citrulline	CIT
7	Serine	SER
8	Glycine	GLY
9	Arginine	ARG
10	Threonine	THR
11	tauMethylHistidine	tauMEH
12	Alanine	ALA
13	Taurine	TAU
14	Proline	PRO
15	Valine	VAL
16	Methionine	MET
17	Isoleucine	ILE
18	Leucine	LEU
19	Tryptophan	TRP
20	Phenylalanine	PHE
21	Ornithine	ORN
22	Histidine	HIS
23	Lysine	LYS
24	Tyrosine	TYR
25	Branched Chain Amino Acids[1]	BCAA
26	Essential Amino Acids[2]	EAA
27	Non-Essential Amino Acids[3]	NEAA
28	Sum Amino Acids[4]	SUMAA
29	Liquid Chromatography (LC) insulin	LC-insulin
30	LC triglycerides	LC-TG
31	LC glucose (venous blood)	LC-glucose
32	Finger stick glucose (venous blood)	Stick-glucose
33	CGM glucose (interstitial fluid)	CGM-glucose

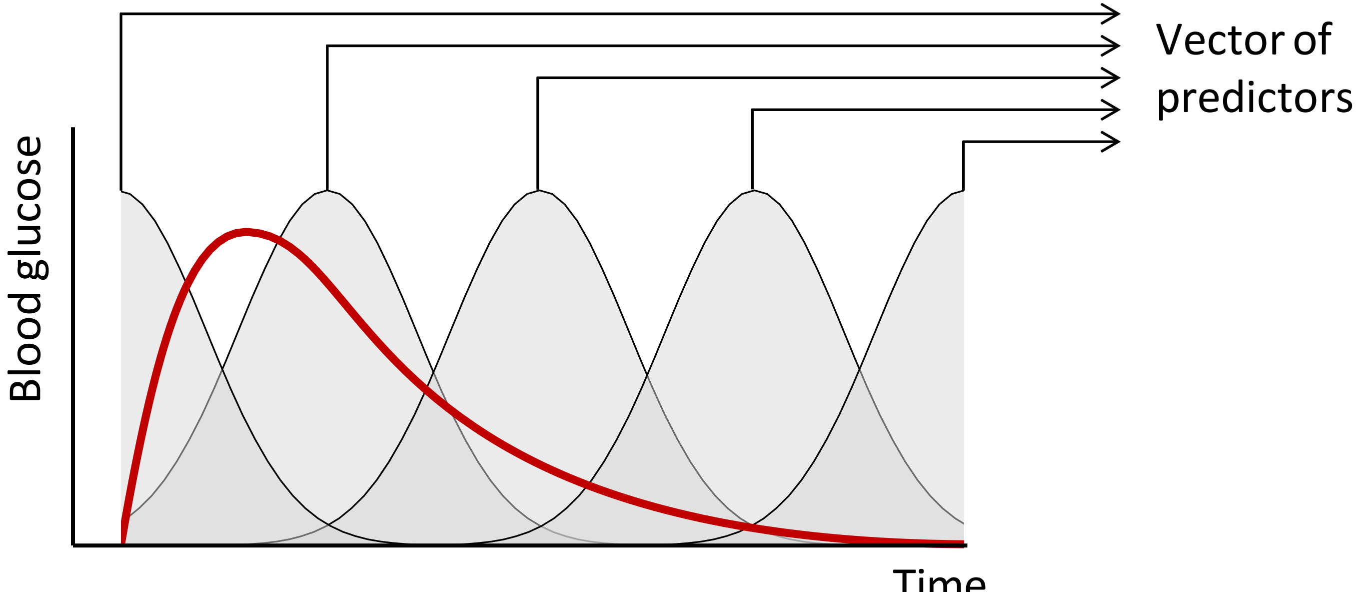
Visual inspection of CGM responses



Data preparation

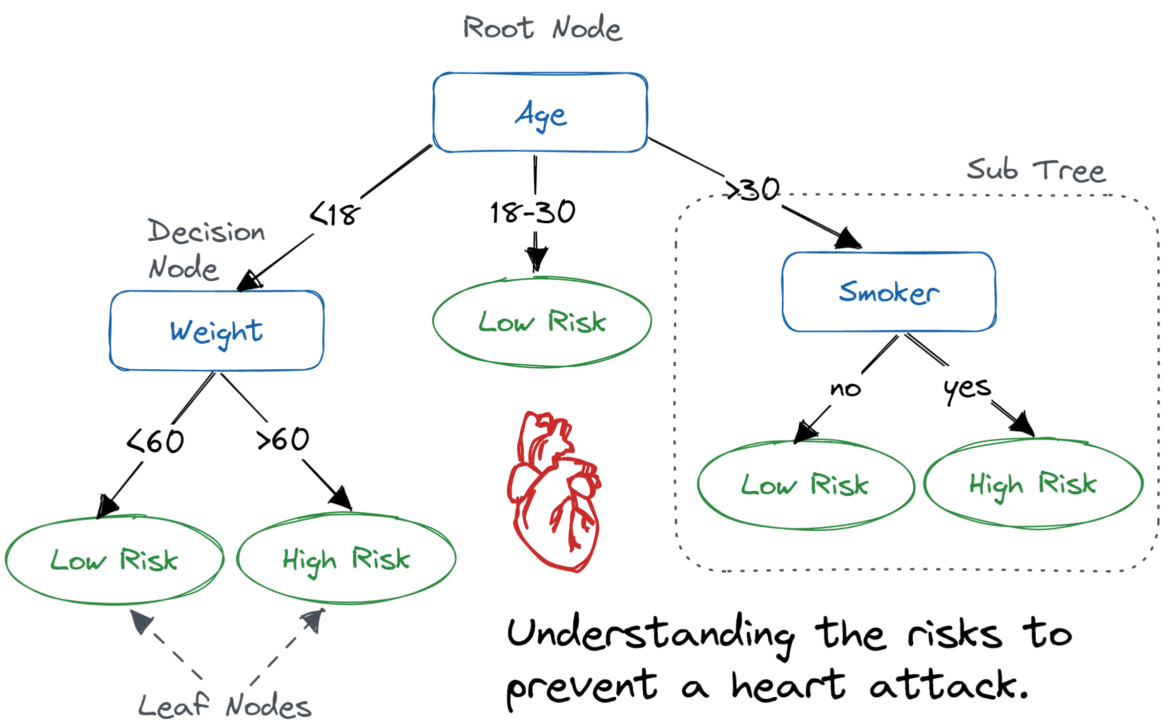
For each post-prandial glucose response (PPGR), we

- Subtract the baseline at mealtime
- Compute area-under-the-curve (AUC) at various times
- Perform z-score normalization to remove individual diffs

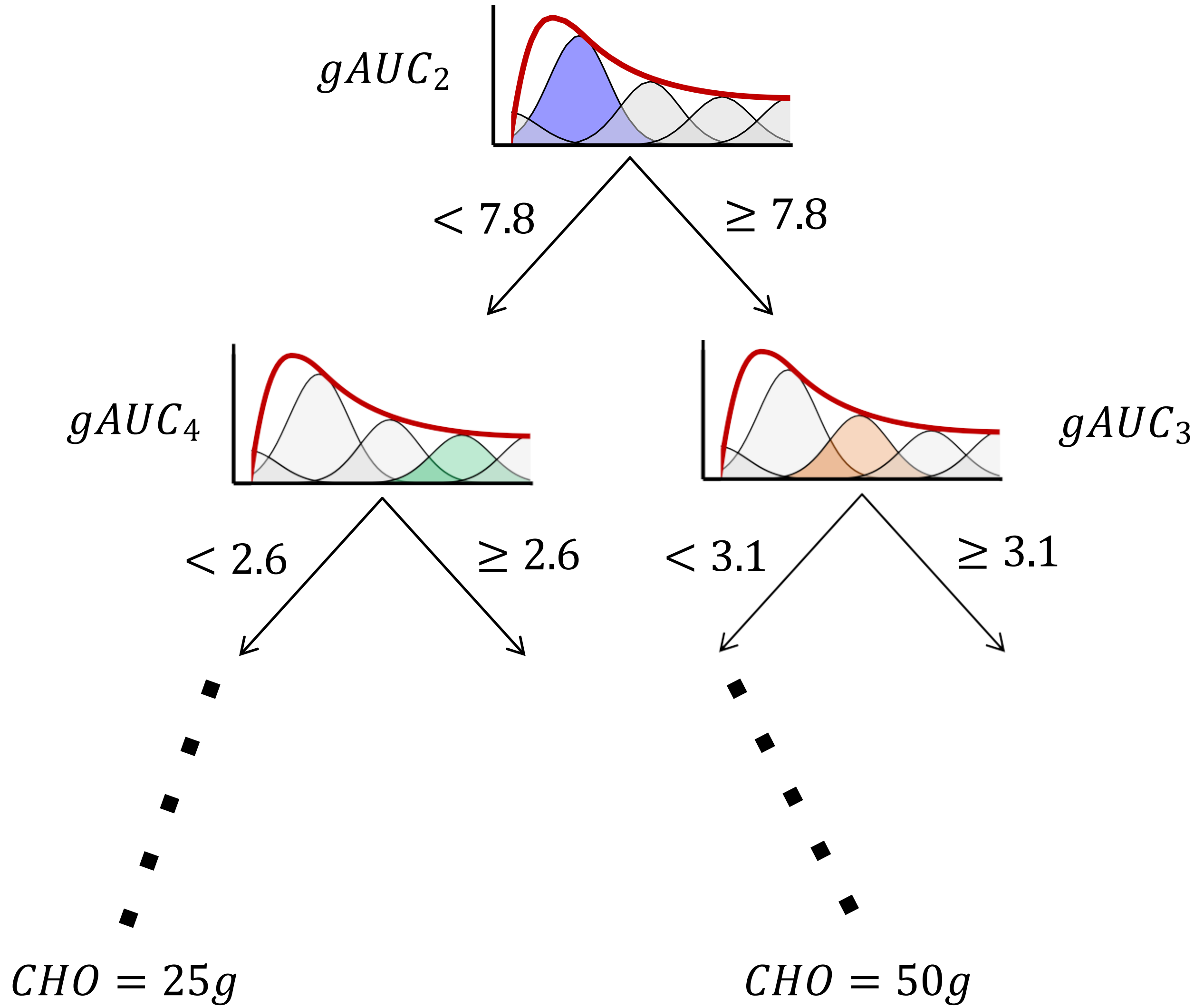


Prediction model

For prediction, we use an AI technique based on decision trees



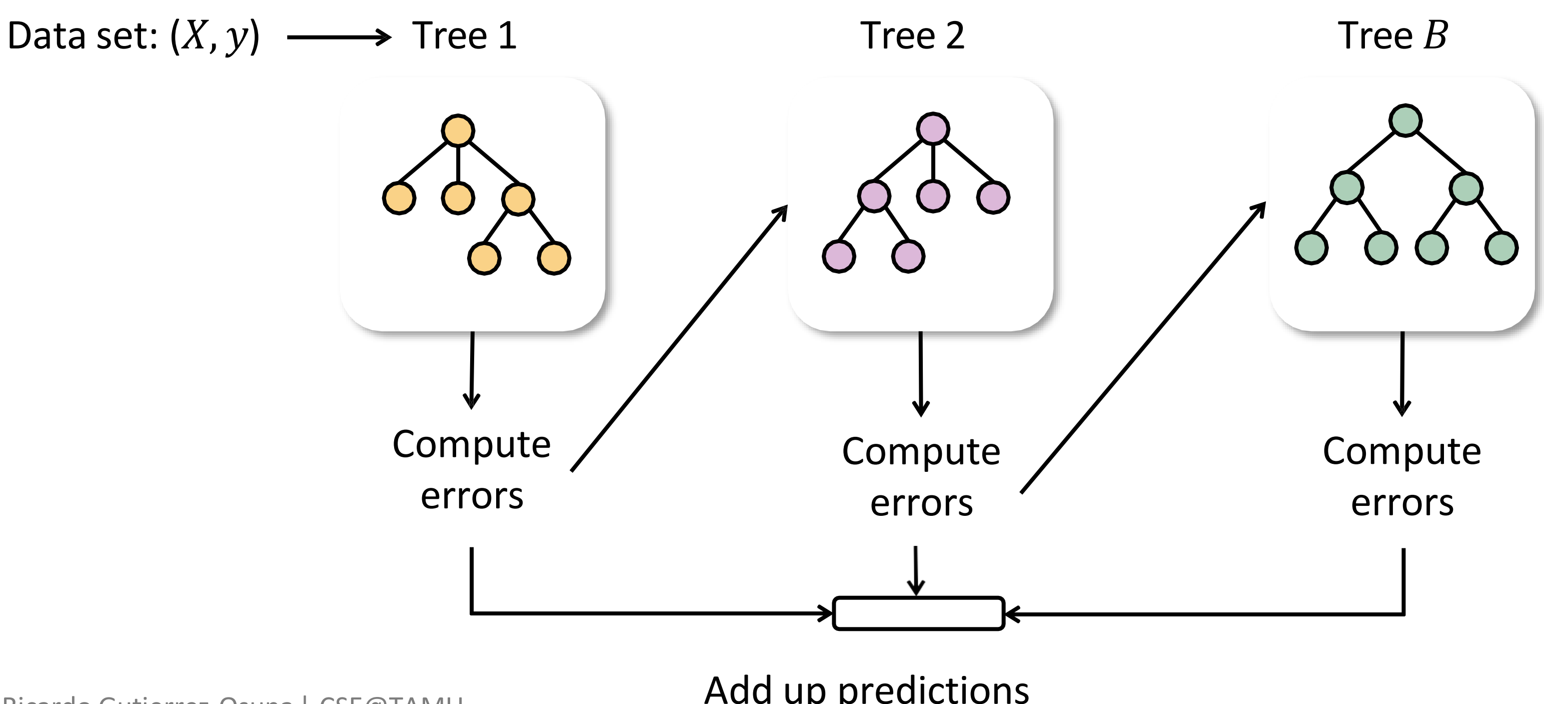
https://www.datacamp.com/tutorial/decision-tree-classification-python


$gAUC_2$
< 7.8
≥ 7.8
$gAUC_4$
$gAUC_3$
< 2.6
≥ 2.6
< 3.1
≥ 3.1
$CHO = 25g$
$CHO = 50g$

Prediction model

For prediction, we use an AI technique based on decision trees

– The particular technique is known as XGBoost
– XGBoost builds an ensemble of trees in an iterative fashion

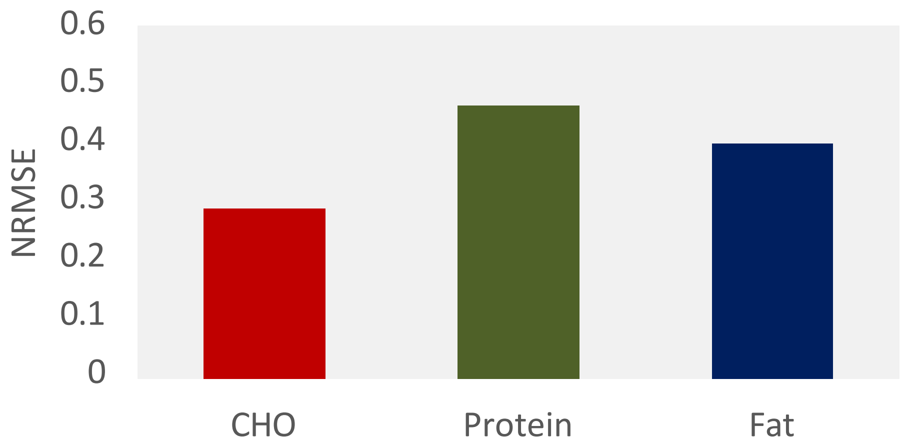


Prediction results from CGM

We report prediction accuracy in terms of the Normalized Root Mean Square Error (NRMSE)

- NRMSE is the percent error relative to ground truth
- Assume a participant consumed a meal containing 50 grams of carbs, and the model predicted 40 grams

$$NRMSE = \frac{50 - 40}{50} = 20\%$$



Prediction results from CGM

Prediction errors based on CGMs alone are too large to be of practical use

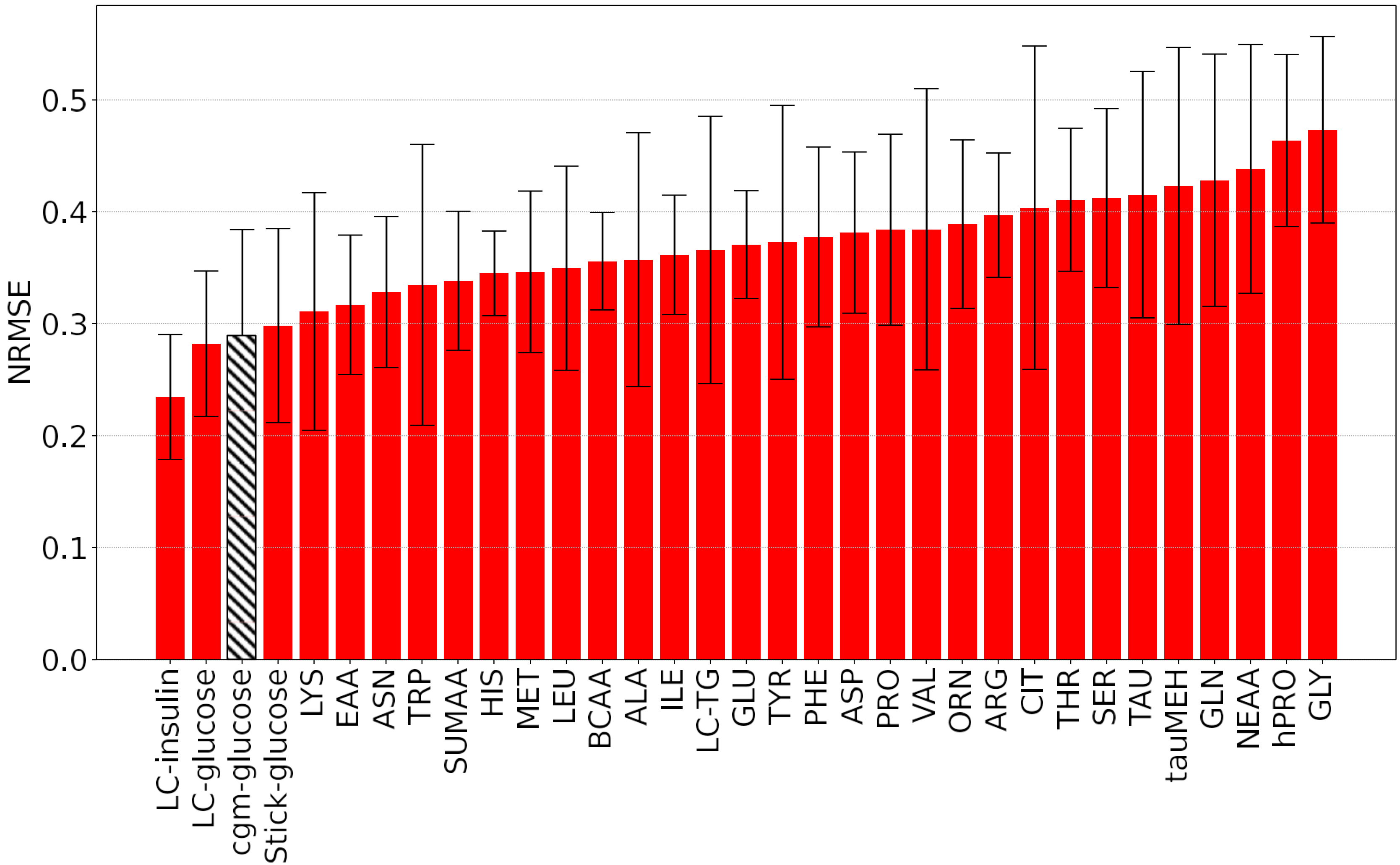
In a second step, we investigated additional biomarkers that might help reduce errors

- Individual biomarkers (e.g., Leucine)
- Combinations of biomarkers (e.g., Leucine + Glucose)

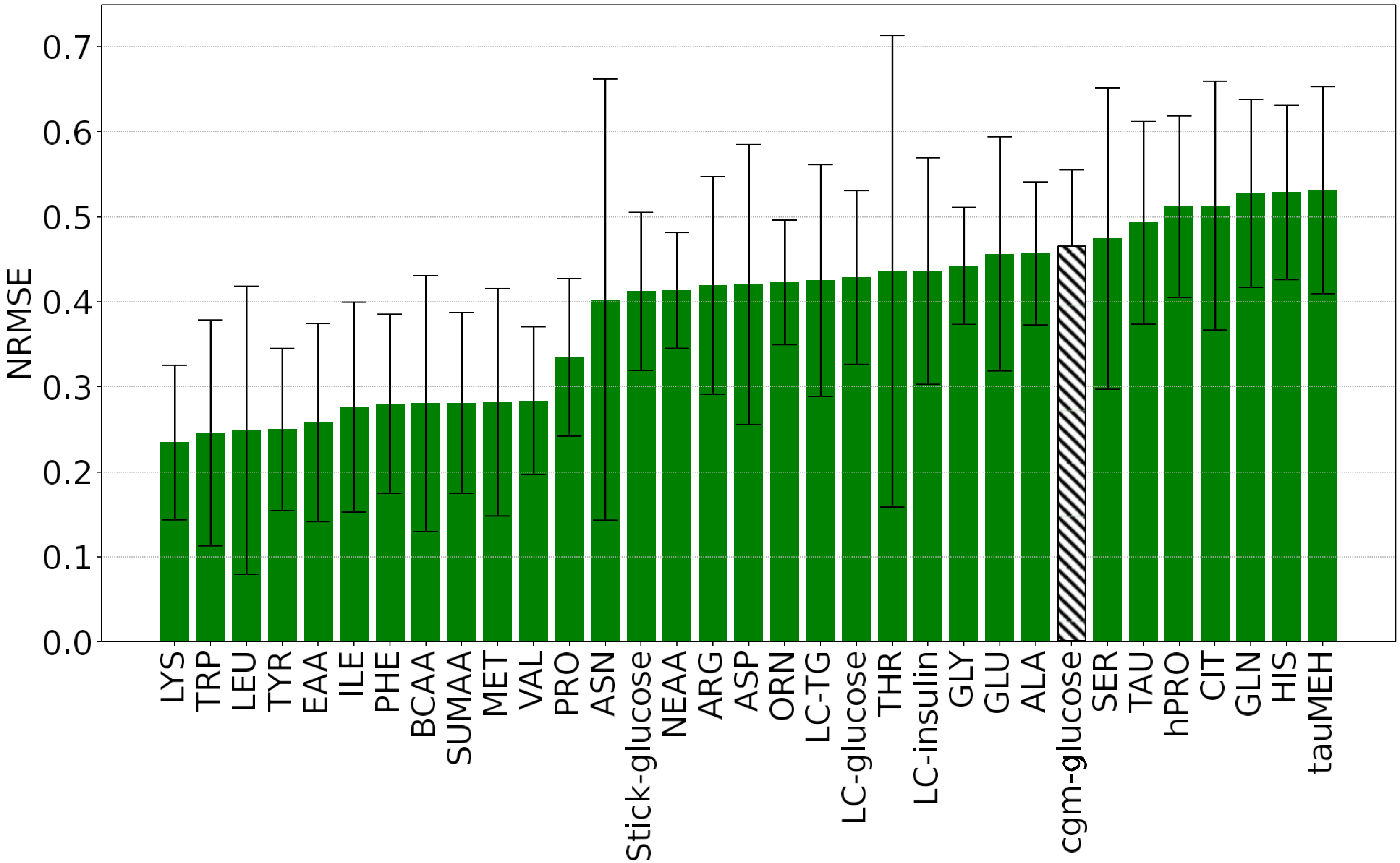
Potential biomarkers (measured in the study)

- Amino acids (24 individual AAs + combinations)
- Triglycerides
- Insulin

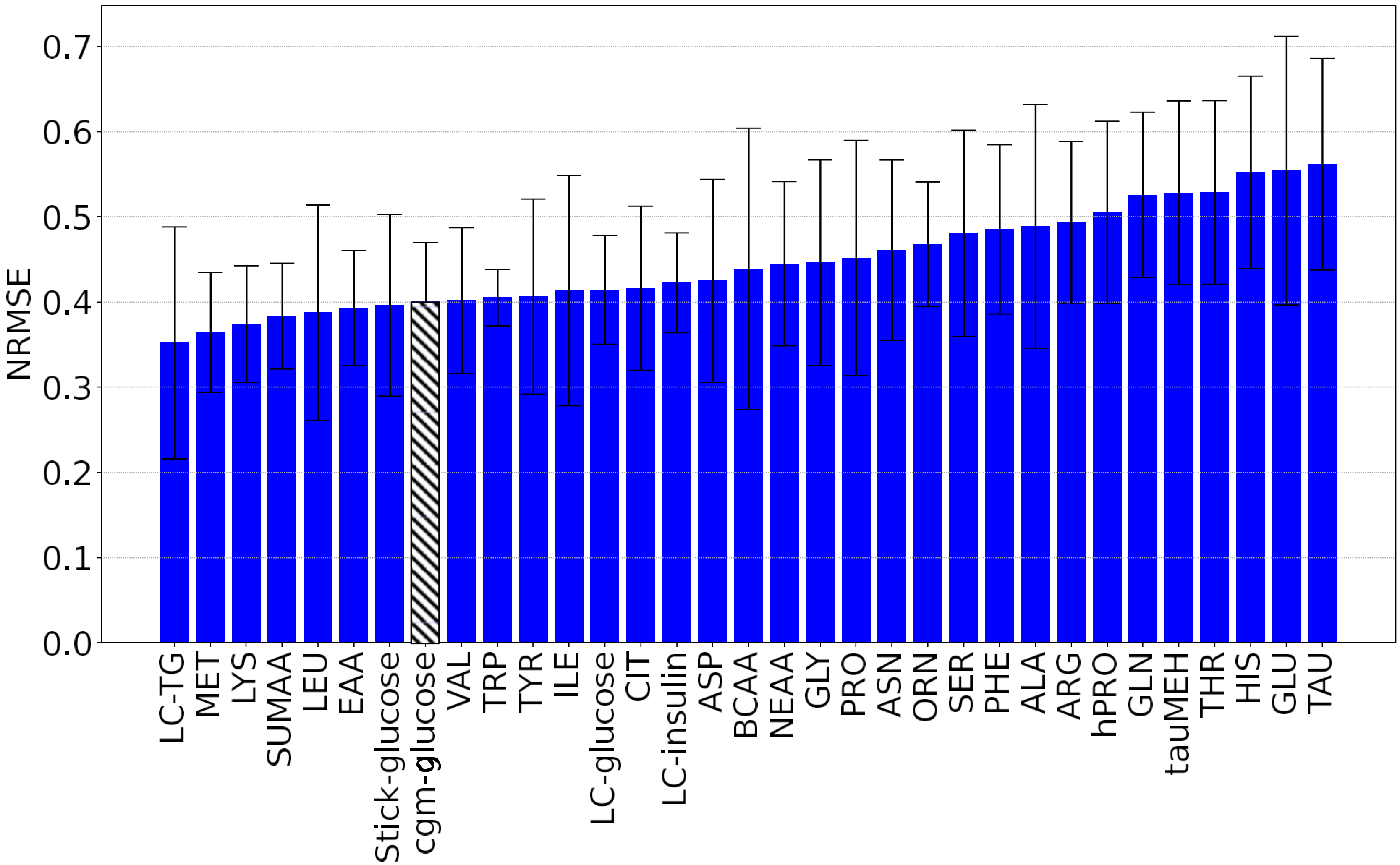
Single-marker predictions (Carbs)



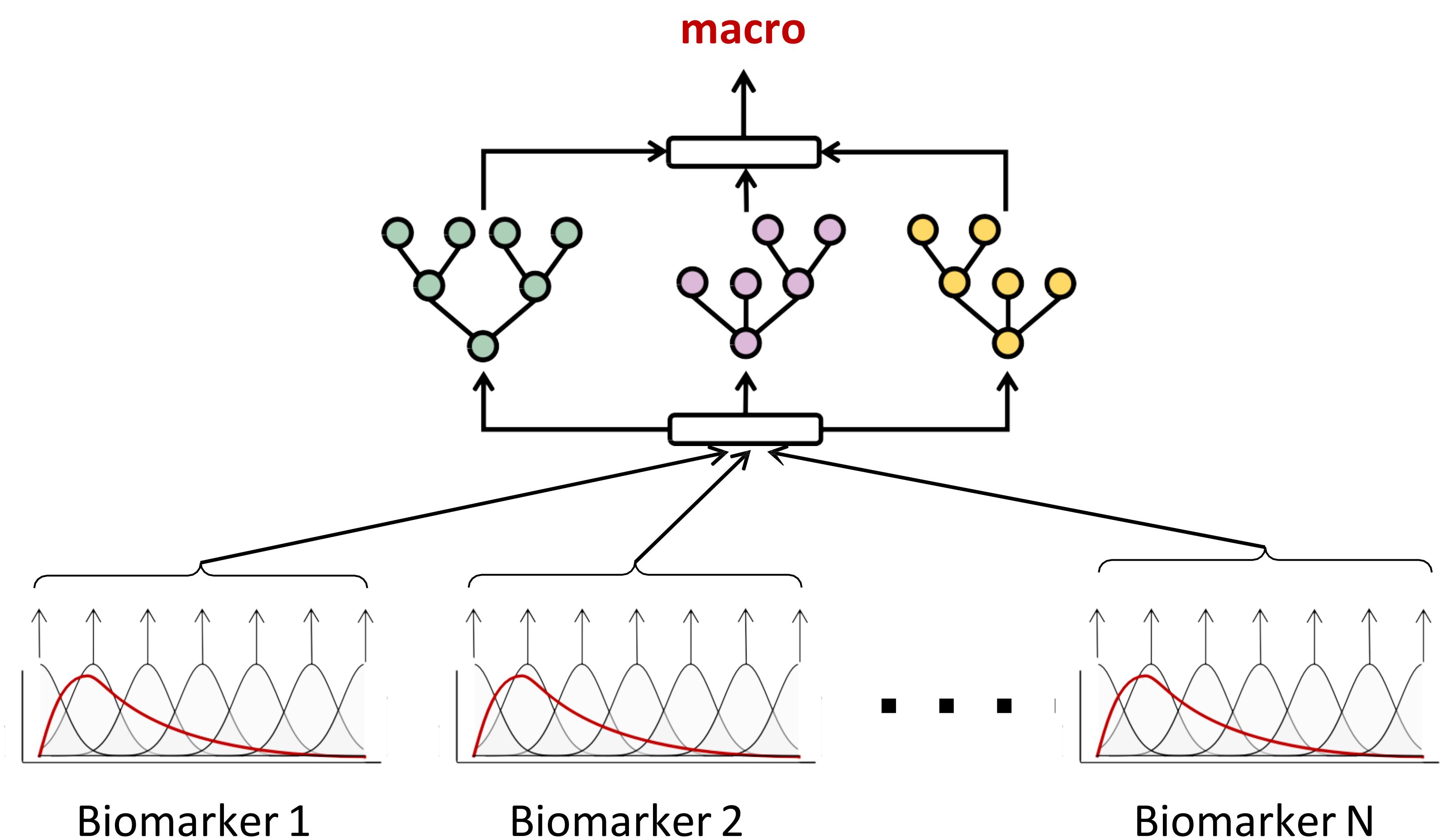
Single-marker predictions (Protein)



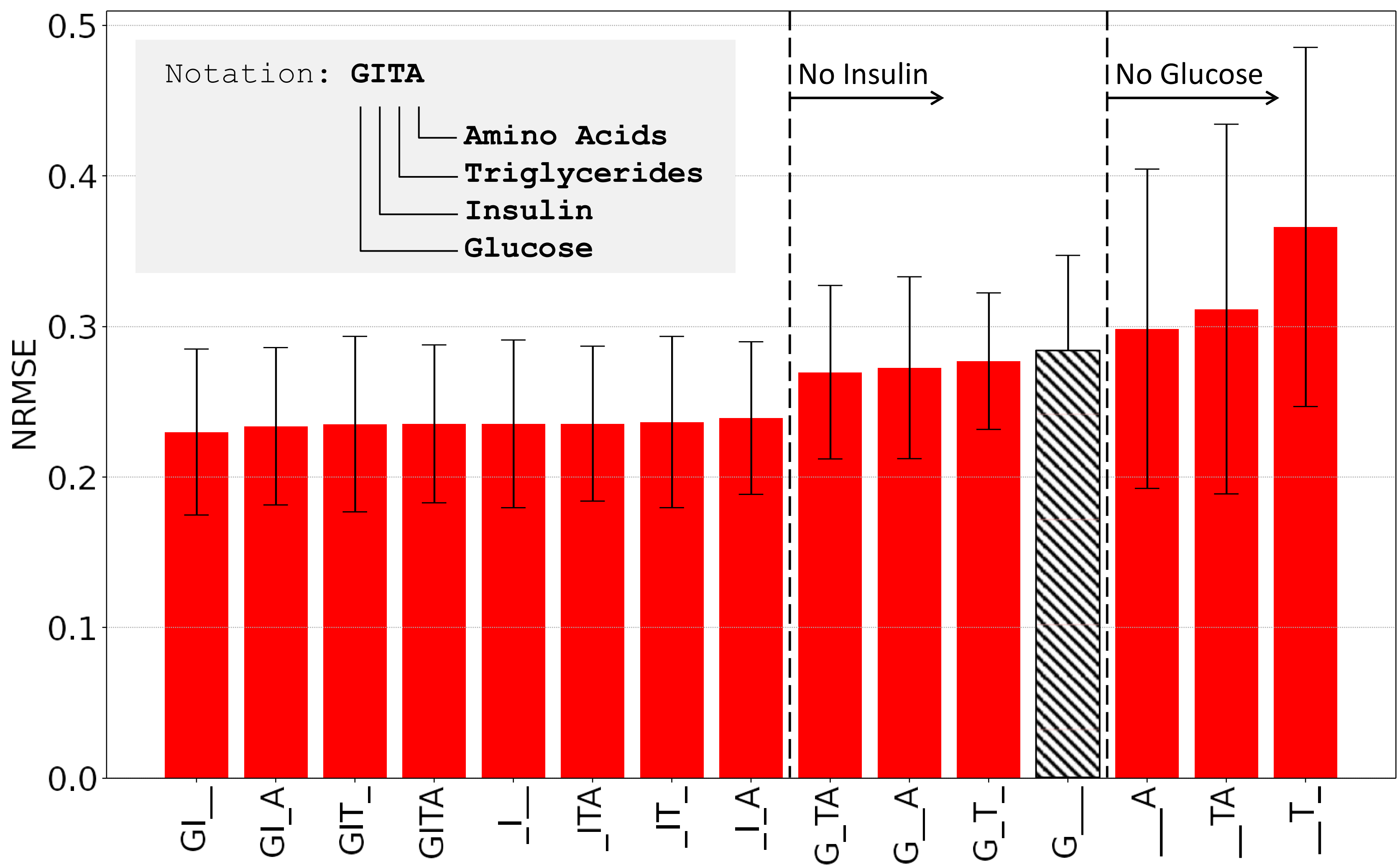
Single-marker predictions (Fat)



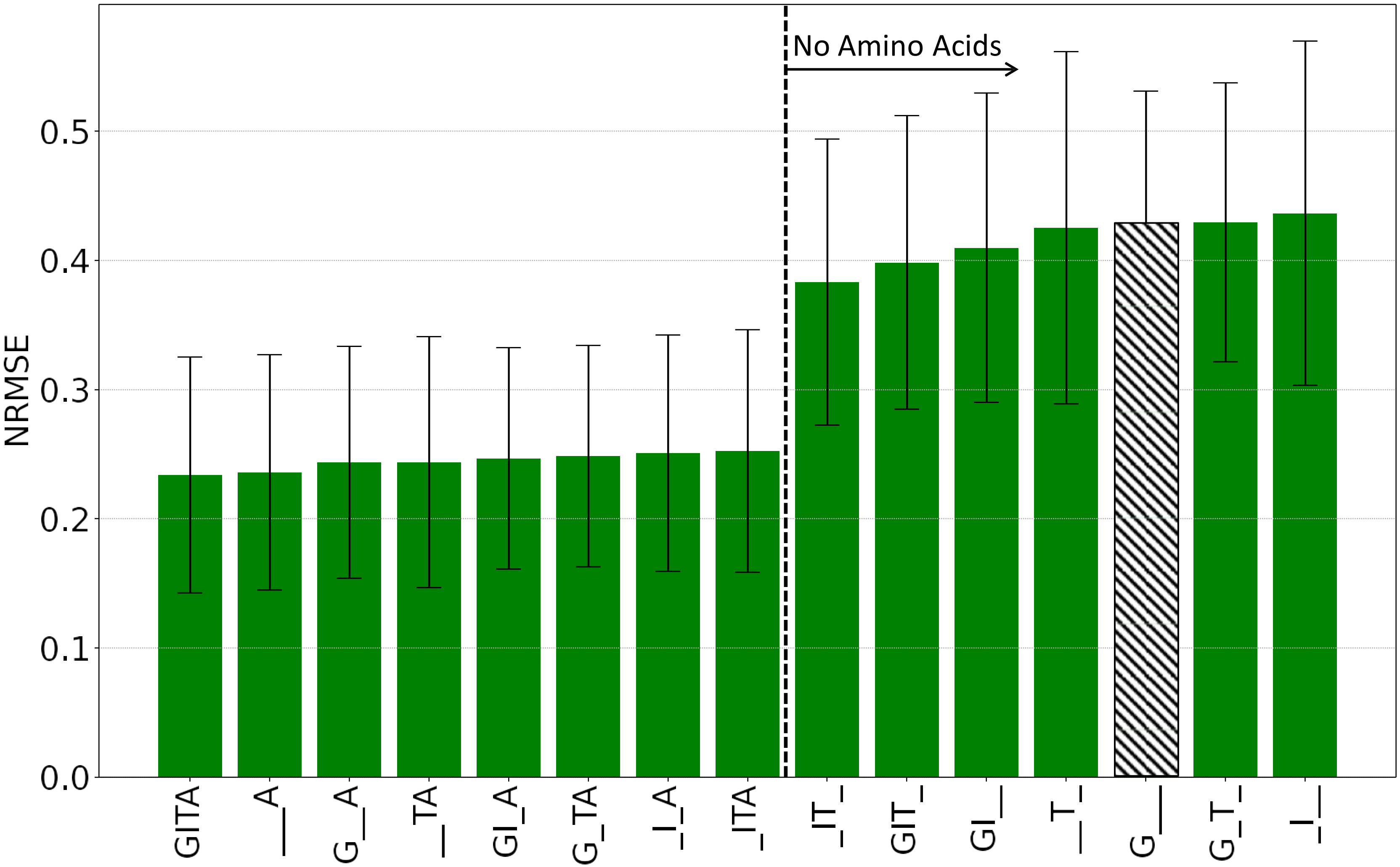
Model for multi-marker predictions



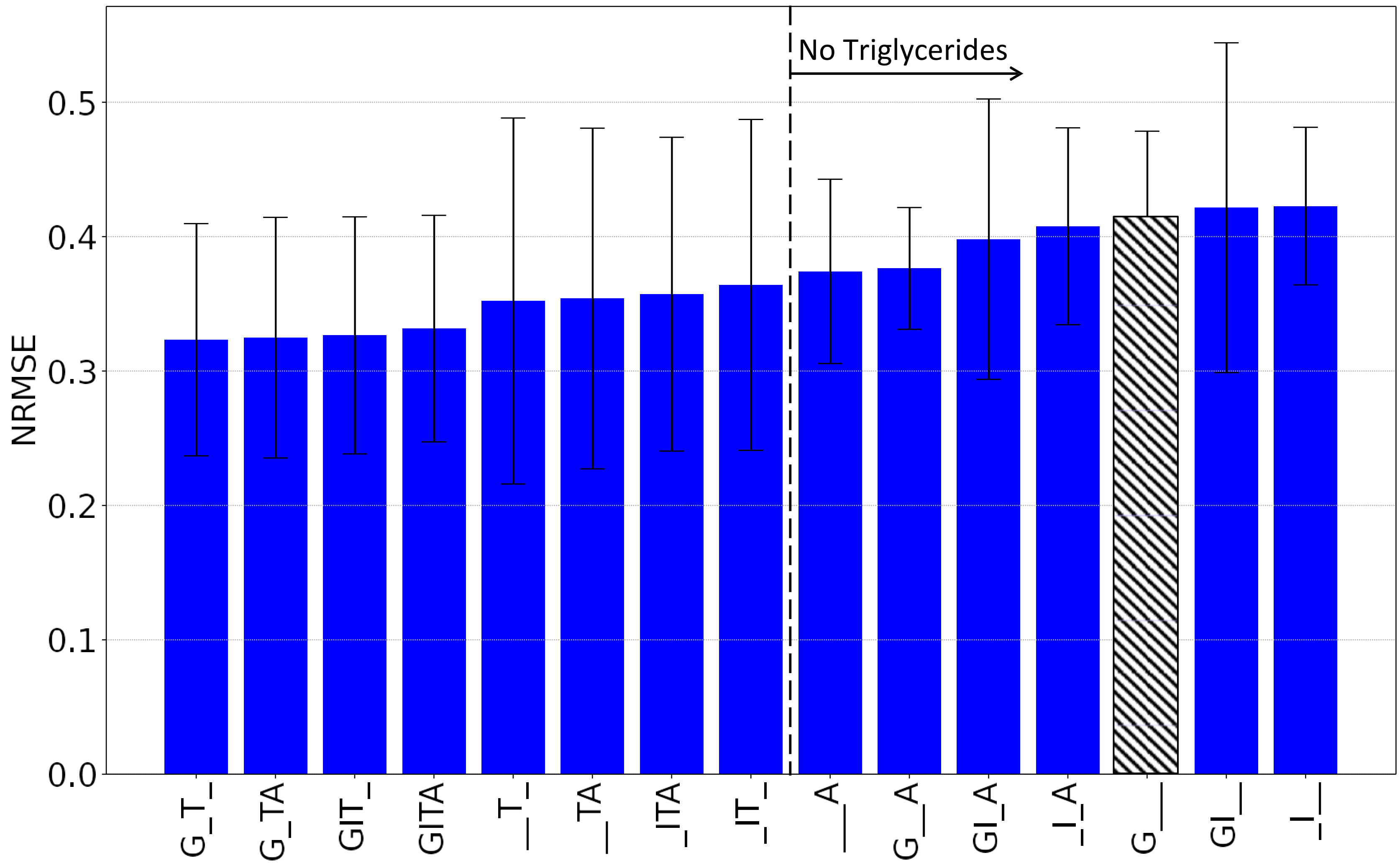
Multi-marker predictions (Carbs)



Multi-marker predictions (Protein)

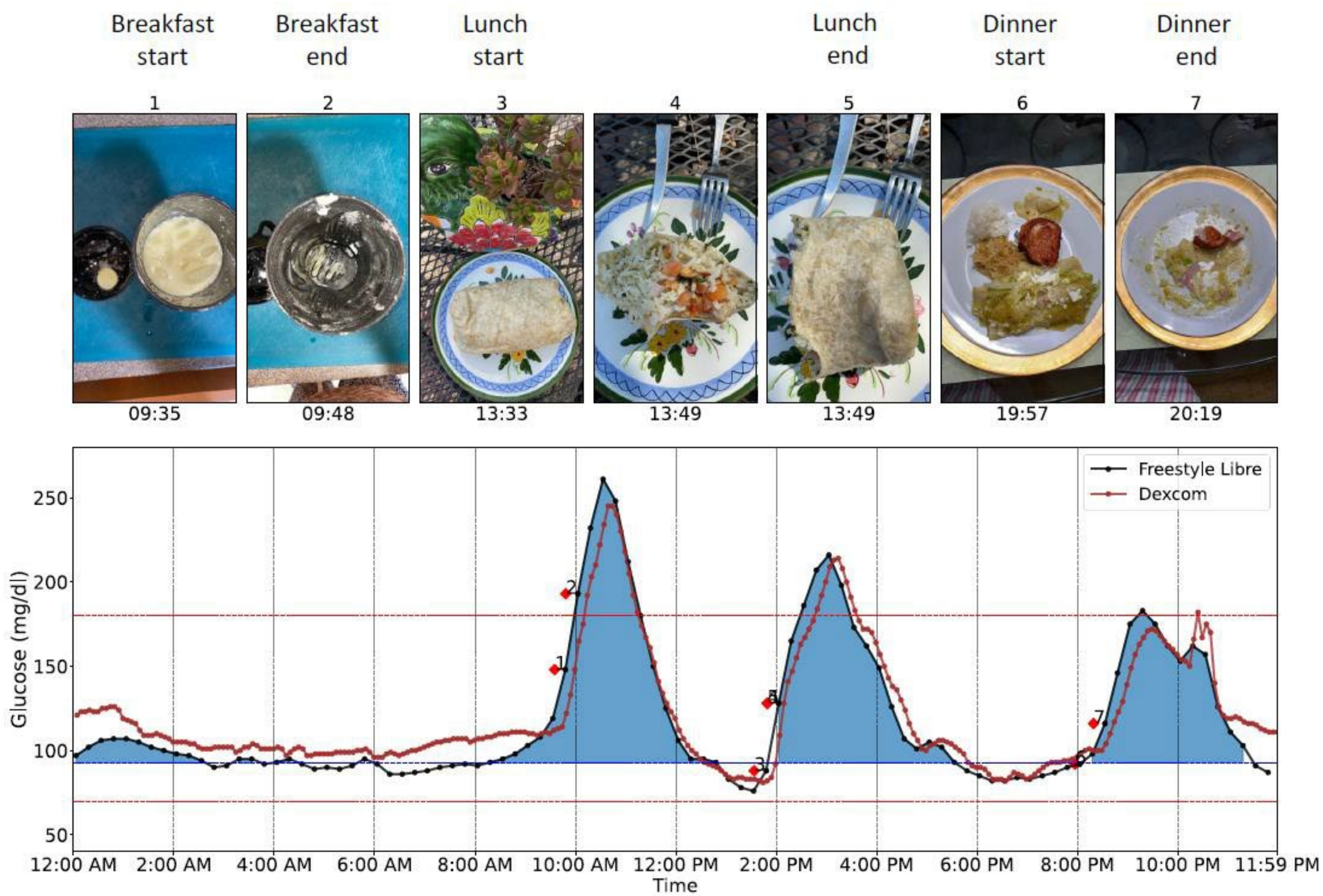


Multi-marker predictions (Fat)



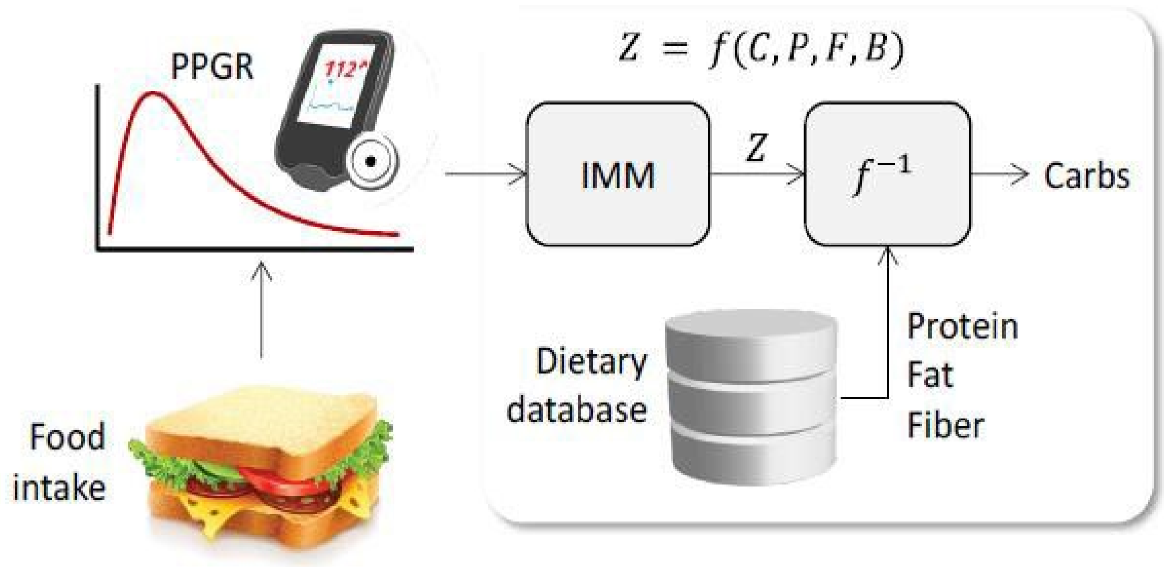
Ongoing work

Ambulatory study



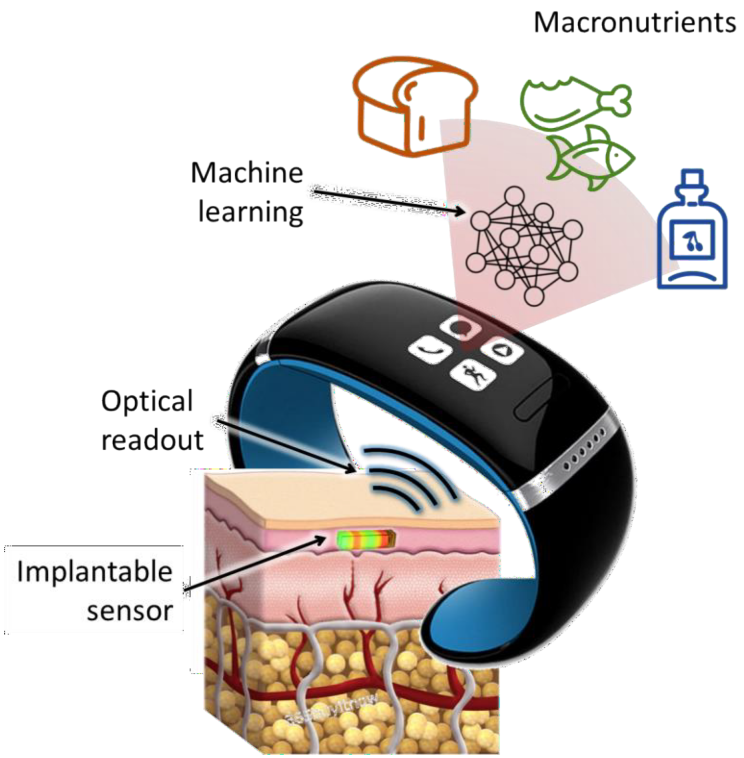
Ongoing work

Accounting for macronutrient correlations



Ongoing work

Implantable sensors for glucose and amino acids



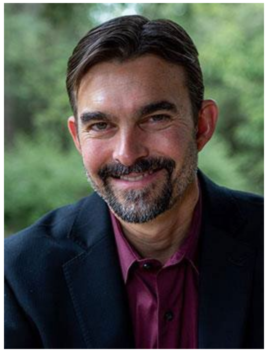
Caveats…

Technology can reduce burden

- But is burden always bad?
  - There appears to be a tradeoff between reducing user burden and enabling users to form the critical habit of monitoring their diet [Turner-McGrievy et al., 2021]
- Law of attrition
  - eHealth trials tend to experience higher dropout rates than drug trials [Eysenbach, 2005]
  - Adherence to diet monitoring is likely to decrease with time, no matter how low-burden the tool is

Thank you







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Raquel Durban, MS, RDN, LD/N
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Carolina Asthma and Allergy Center

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Q&A

Moderator:
Lisa Diewald, MS, RDN, LDN
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