Machine-Learned Prediction of Glucose Response for 1000 Subjects

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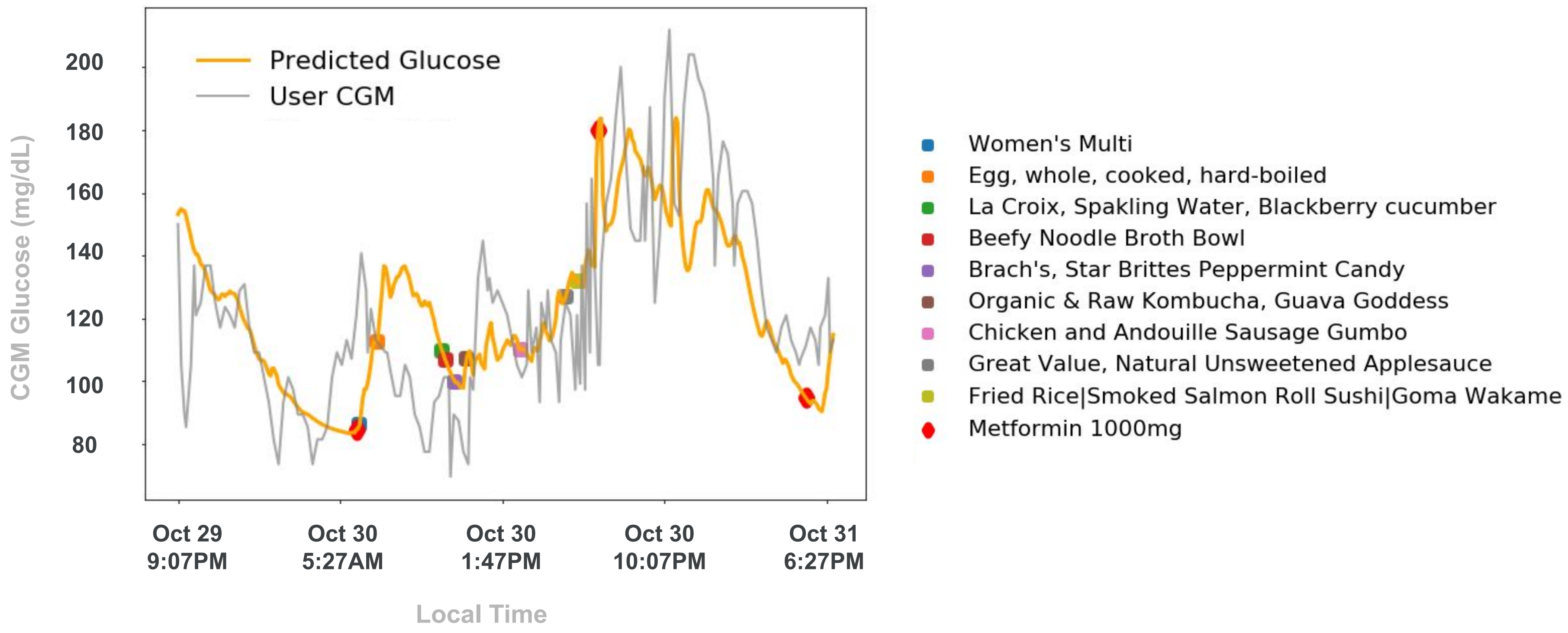
January



Training:
4 days with CGM, HRM, and logging

With AI personalization no time horizon limits to forecast

No CGM used in forecasting

Only heart rate, food medication logs and a personalized model to forecast

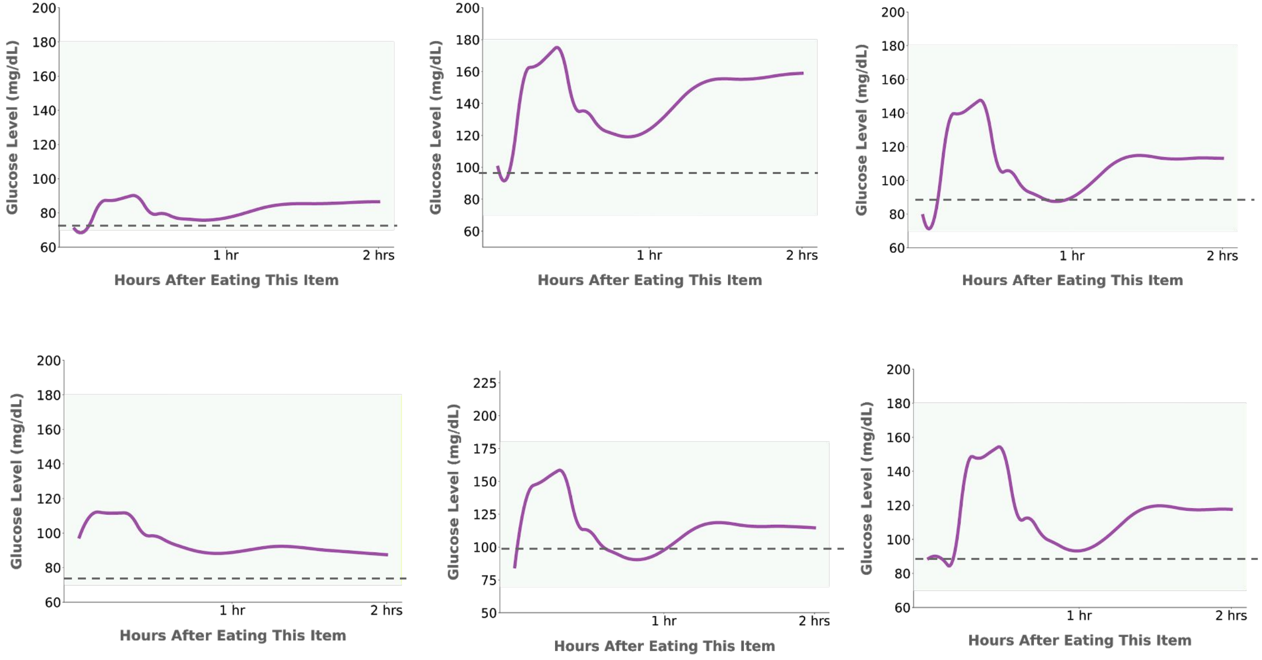
Our algorithm accurately forecasts glucose levels from logged foods

Why personalization matters: Data suggests limited value in static food ranks

User 1 | User 2 | User 3

Early Breakfast

Dinner

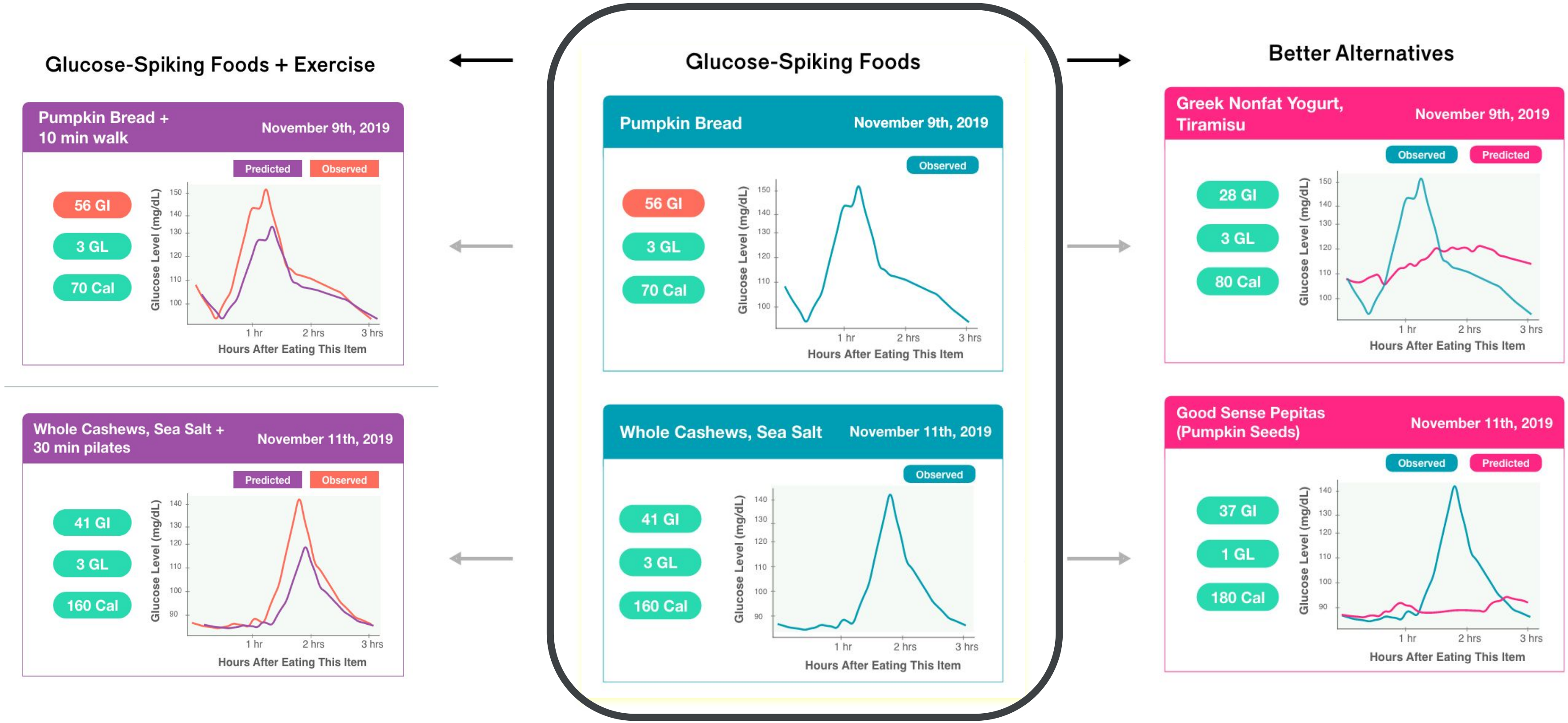


PB&J Sandwich

Glucose responses may vary by:

- User's physiology
- Meal
- Pre-prandial heart-rate
- Timing of the meal
- Prandial glucose/insulin levels
- Sleep patterns

Significant differences in food responses between users



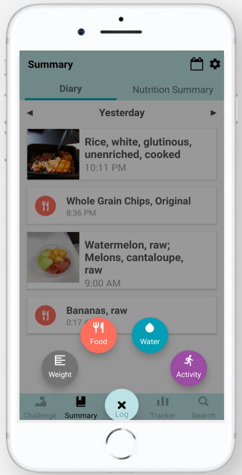
Counterfactuals allow immediate behavior feedback

Over 1,000 Participants Successfully Enrolled

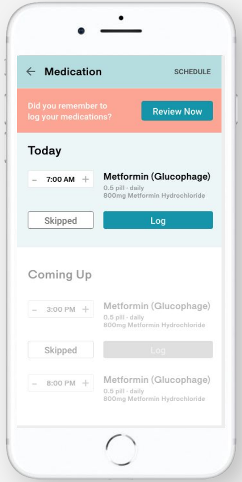
Disease Type	Gender		Age				BMI				
	Male	Female	<30	30-40	40-50	>50	<25	25-30	30-40	40-45	>45
HV	33%	67%	36%	40%	17%	7%	31%	29%	30%	8%	2%
PwPD	42%	58%	16%	44%	24%	16%	30%	21%	33%	10%	7%
PwT2D	29%	71%	5%	35%	40%	21%	7%	13%	40%	22%	19%

Sugar AI app was used to collect data

Food



Medication



Heart-Rate & CGM

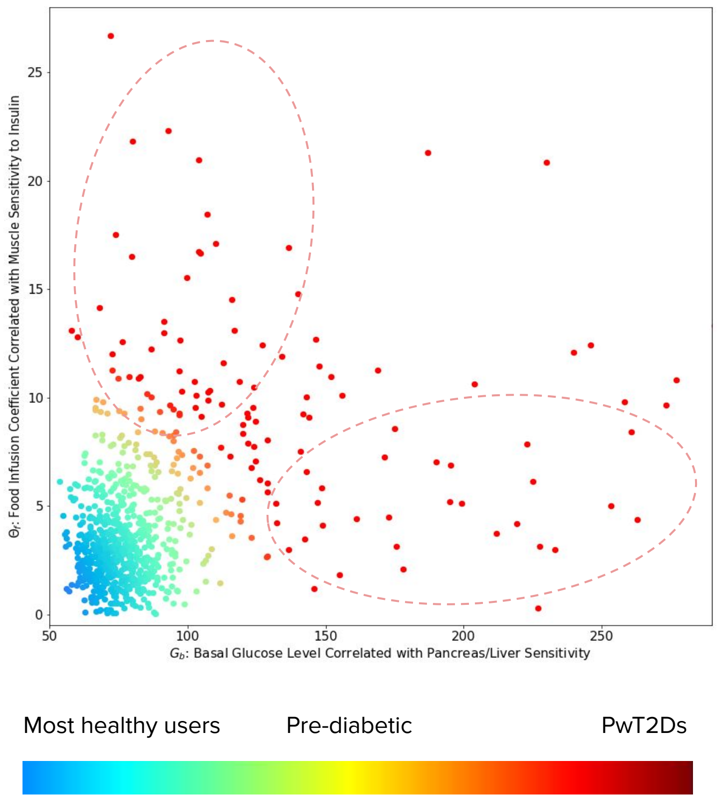
Over 22,500 individual applied to the study

Over **22,000 individuals applied** to participate in the Sugar Challenge across the **50 states** of the United States. We enrolled self-reported healthy, people with prediabetes, and people with Type 2 diabetes on metformin, glucagon-like peptide 1 agonist (GLP-1a), or sodium-glucose co-transporter 2 inhibitor (SGLT-2i) therapy. In addition, participants wore a continuous glucose monitor (CGM) and a heart rate monitor 20-24 hours/day, provided body weight at baseline and agreed to comprehensive logging of their activity, food, medication, and water consumption for 10 consecutive days.

ML infers parameters that suggest wide physiological differences in users

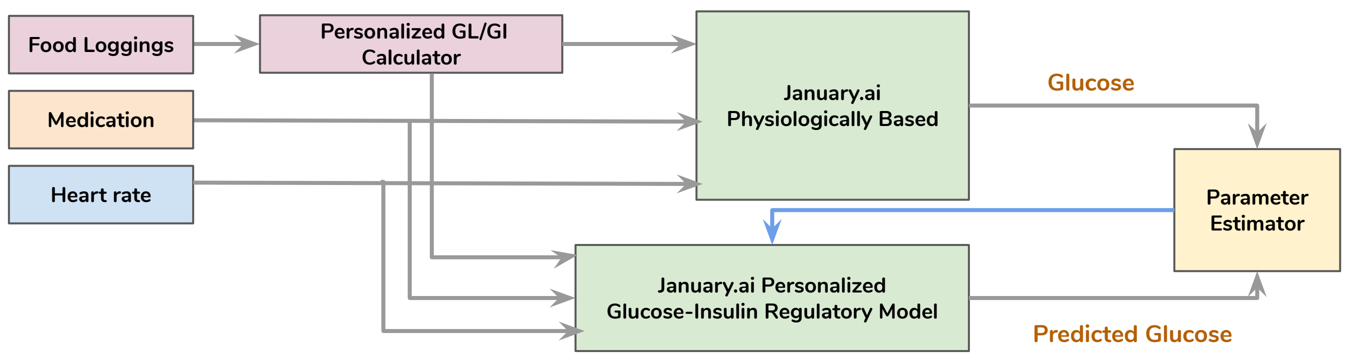
- Machine learning combined with our novel biophysical model learns personalization parameters having physiological analogs.
- These parameters provide several clinical insights:
    - Map patient histories to health transitions (e.g. Healthy Volunteers to PwT2D)
    - PwT2D's dysregulation is caused by different underlying conditions (seen in two ellipses)
    - Provide a path towards more personalized food and activity recommendations

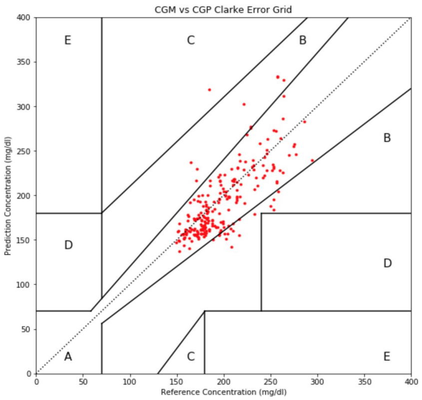
For visualization, **2** out of **24** parameters are depicted on the right (Note that **high basal value,** does not equate to relatively **higher spikes**)



ML Analysis: Precise **In silico** glycemic response prediction for PwT2D on Metformin

Glucose Infusion Rate





In-silico users generated by uniformly sampling from:
BMI: 20-55, Age: 25-75,
Gender: Male, Female
Race: Asian, Black, Mexican, White

In absence of user logging errors such as time of log or item logged, January AI's in-silico forecasting shows excellent accuracy across a wide range of physiologies.

In-silico	RMSE	MAE	Reg. A	Reg. B	Reg. C	Reg. D	Reg. E	Reg. C-D
120 mins prediction	19.8	14.2	87.6	11.6	0.8	0.0	0.0	0.8

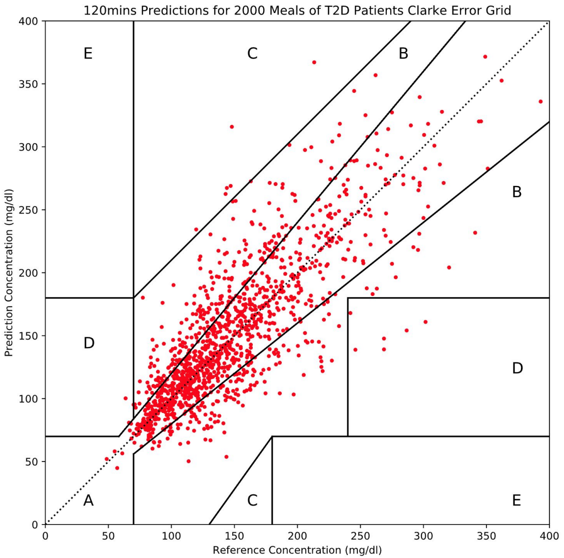
ML Analysis: Precise **In vivo** glycemic response prediction for PwT2D on Metformin

After filtering for data integrity, January AI used data from 579 human participants

We used these criteria to evaluate the accuracy of our model compared to literature:

- 4 days of training data for each user
- Food, heart-rate, medication were inputs for personalized prediction
- Evaluations were only for **postprandial glucose** to predict the response of users after their logged meals

	Gender		Age				BMI				
	Male	Female	<30	30-40	40-50	>50	<25	25-30	30-40	40-45	>45
HV (#467)	38%	62%	34%	43%	15%	8%	35%	32%	26%	6%	2%
PwPDs (#26)	38%	62%	35%	42%	19%	4%	4%	12%	61%	23%	0%
PwT2Ds (Metformin #86)	34%	66%	1%	27%	48%	24%	5%	8%	40%	29%	17%



User errors include:

- Missing food and medication logs
- Improper time logging
- Improper food selection

Systematic errors include:

- Exclusion of sleep pattern modeling
- Exclusion of stress and other known secondary factors to glucose regulation

We tested different subgroups to find a correlation between the errors with **Age**, **Gender**, **BMI**, and **Race**. However, no significant correlation was found.

PwT2D	RMSE	MAPE	Reg. A	Reg. B	Reg. C	Reg. D	Reg. E	Reg. C-E
60 mins prediction	26.6	12.3	78.0	21.3	0.2	0.5	0.0	0.7
120 mins prediction	31.9	15.0	72.0	26.8	0.3	0.9	0.0	1.2

PwPD	RMSE	MAPE	Reg. A	Reg. B	Reg. C	Reg. D	Reg. E	Reg. C-E
60 mins prediction	18.2	12.4	78.5	19.9	0.0	1.6	0.0	1.6
120 mins prediction	20.6	14.5	73.1	25.3	0.0	1.6	0.0	1.6

Healthy	RMSE	MAPE	Reg. A	Reg. B	Reg. C	Reg. D	Reg. E	Reg. C-E
60 mins prediction	15.6	11.2	81.4	17.3	0.0	1.3	0.0	1.3
120 mins prediction	17.7	13.3	76.5	21.7	0.0	1.8	0.0	1.8

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