

Glycemic Increment: Individualized Medicine for Diabetics*

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Abstract—Glycemic Increment is a new metric for diabetics to estimate the glycemic effect of meals they eat regularly. It is based on a log of meals with blood sugar measurements from a Continuous Glucose Monitor.

Index Terms—diabetes, biomedical measurements, medical expert system

I. INTRODUCTION

Diabetes is a common disease in the US. In 2021 38.4 million people of all ages—or 11.6% of the U.S. population—had diabetes [1]. 97.6 million people aged 18 years or older had prediabetes (38.0% of the adult U.S. population).

One of the first recommendations for people with prediabetes is lifestyle changes. People are encouraged to lose weight, exercise more, and restrict their intake of carbohydrates [2]. Easily digested carbohydrates lead to elevated blood sugar, the core diagnostic trait of both type I and type II diabetes.

A core pillar of treatment is the regular monitoring of blood sugar. Regular monitoring has been found to reduce instances of hyperglycemia (high blood sugar), and hypoglycemia (low blood sugar due to insulin spikes).

In 1962, Leland Clark and Ann Lyons from Cincinnati Children’s Hospital developed the sensor that led to the glucometer, which enabled home blood glucose monitoring (HBGM) [3]. A glucometer measures blood sugar by placing a drop of blood on a disposable sensor. Using a glucometer to monitor blood sugar requires high discipline, especially in insulin-dependent diabetes (type I and advanced type II).

Since the FDA approved the first continuous glucose monitor (CGM) in 1999 [4], there is a more convenient solution. A CGM is worn continuously for an extended period and provides automatic readings at a high frequency (typically every 5 minutes).

The apps associated with CGMs typically allow the user to record significant events such as meals or insulin doses. These meal logs are the basis for the new metric, Glycemic Increment.

II. METRICS

A. Blood Glucose and HbA1c

Blood glucose is measured in mg/dL. It is the primary metric generated by a CGM. See Figure II-A for typical values.

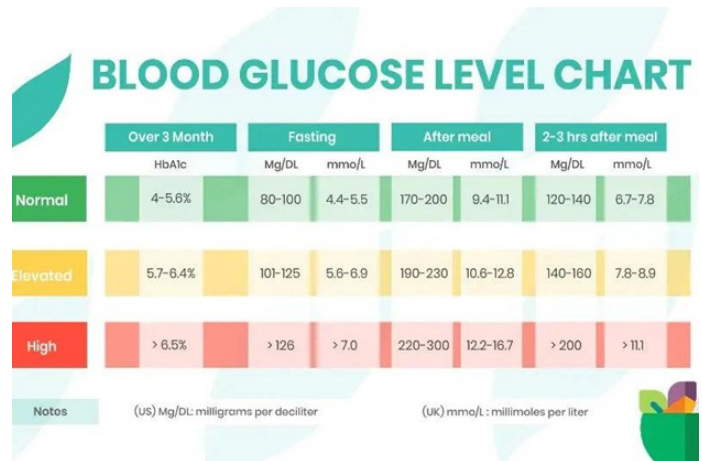


Fig. 1. Blood Glucose levels [5]

Hemoglobin A1c (HbA1c) shows average blood sugar levels over the past 2-3 months expressed as a percentage. A CGM app can calculate an equivalent metric, Glucose Management Indicator (GMI), from continuous glucose values. HbA1c is often used to diagnose prediabetes or diabetes.

B. Glycemic Index GI

An important innovation in the relationship of foods to blood glucose was the introduction of the Glycemic Index by [6]. Glycemic Index (GI) estimates how quickly a standard amount of carbohydrates (50g) is absorbed by the body from a specific food. It attempts to measure the speed with which food is absorbed. Measurements require the test subject to fast before eating the food. The amount of food varies according to its carbohydrate content. Blood glucose is then integrated over the next 2 hours. The resulting value is standardized against 50g of pure glucose, yielding a number from 0 (no effect on blood sugar) to 100 (same effect as pure glucose). There are some foods that have GI ratings higher than 100.

C. Glycemic Load GL

One limitation of GI is that it is difficult to translate into expectations for a given meal. Salmerón et. al. introduced the

concept of Glycemic Load (GL) [7], which improves upon GI by accounting for the amount of carbohydrates in a 100g serving of the food. In theory, this allows one to calculate a summary metric for any given meal to estimate the effects on blood sugar. In practice, it is a lot of work to weigh each food, look up its GL and then build a GL estimate for the meal. It can be very difficult to find the GL for certain foods. GI and GL also vary when certain foods are mixed.

D. Glycemic Increment G+

With the availability of CGM data, it becomes practical to directly estimate the glycemic effects of meals eaten by the patient. Actual measurements of typical meals can lead to actionable insights into diet.

This paper introduces the concept of Glycemic Increment (G+). G+ directly estimates the blood sugar consequences of particular foods and composite meals. It provides an individualized model of each patient's response to particular foods. The inputs to the model are just a list of foods in a particular meal. The output is a number that directly estimates an increase or decrease in blood sugar over a reasonable period. The model is built without requiring a fasting state or precise measurements of foods. It relies on the "typical serving" used by the patient.

Figure II-D shows how G+ is calculated. The left of the chart represents the start of a meal. The duration of the chart represents the measurement period. The values in blue are the integration of blood glucose values over the measurement period. The orange area, set at the initial blood glucose level, is subtracted from the blue. The difference is divided by the number of hours in the measurement period. The resulting unit is mg-hours/dL.

Standardization to 1 hour allows for the comparison of G+ from different measurement intervals.

Using the starting blood glucose makes it unnecessary for the patient to be fasting at measurement time.

Note that if blood glucose falls significantly below the starting glucose, G+ can yield a negative value. This can happen when a food triggers a rapid insulinic response, causing blood sugar to drop rapidly. For this reason, both very positive and very negative G+ values should be interpreted as a strong glycemic response.

It is not clear whether the low glycemic response is G+ values near zero or G+ values near the mean. Without further examination, the present work assumes the former.

III. DATA

The data set is 2 years of CGM data taken from the second author. It includes free-form food logs and blood glucose measurements taken every 5 minutes. The data is nearly complete, with only a few gaps related to the periodic challenges associated with acquiring CGM sensors.

The free-form notes have some structure due to consistent commenting by the second author. Foods are comma-separated, and there are additional notations such as restaurants, quantities, and units.

Fig. III shows a sample of raw glucose data. Fig. III shows a sample of raw meal data.

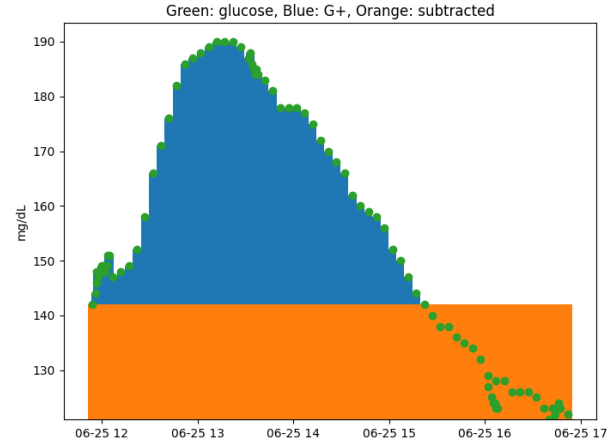


Fig. 2. Glycemic Increment

Record Type	Serial Number	Historic Glucose mg/dL	...	Notes	timestamp	glucose
0	0e154b86-bf50-4004-9ddb-123beeb2e7c4	208.0	...	NaN	2024-06-24 10:32:00	208.0
1	0e154b86-bf50-4004-9ddb-123beeb2e7c4	208.0	...	NaN	2024-06-24 10:37:00	208.0
2	0e154b86-bf50-4004-9ddb-123beeb2e7c4	219.0	...	NaN	2024-06-24 10:42:00	219.0
3	0e154b86-bf50-4004-9ddb-123beeb2e7c4	216.0	...	NaN	2024-06-24 10:47:00	216.0
4	1e154b86-bf50-4004-9ddb-123beeb2e7c4	NaN	...	NaN	2024-06-24 10:48:00	219.0
...
119479	0e154b86-bf50-4004-9ddb-123beeb2e7c4	155.0	...	NaN	2025-07-20 17:41:00	155.0
119480	0e154b86-bf50-4004-9ddb-123beeb2e7c4	154.0	...	NaN	2025-07-20 17:46:00	154.0
119481	0e154b86-bf50-4004-9ddb-123beeb2e7c4	150.0	...	NaN	2025-07-20 17:51:00	150.0
119482	0e154b86-bf50-4004-9ddb-123beeb2e7c4	143.0	...	NaN	2025-07-20 17:56:00	143.0
119483	0e154b86-bf50-4004-9ddb-123beeb2e7c4	139.0	...	NaN	2025-07-20 18:01:00	139.0

119484 rows × 8 columns

Fig. 3. Raw Glucose Data

Record Type	Serial Number	Historic Glucose mg/dL	Scan Glucose mg/dL	Carbohydrates (grams)	Notes	timestamp
0	0e154b86-bf50-4004-9ddb-123beeb2e7c4	NaN	NaN	NaN	Starbucks Bacon gruyere egg bites	2024-06-24 10:50:00
1	0e154b86-bf50-4004-9ddb-123beeb2e7c4	NaN	NaN	NaN	Spinach tomato omelet with Swiss, fruit cup	2024-06-24 13:53:00
2	0e154b86-bf50-4004-9ddb-123beeb2e7c4	NaN	NaN	NaN	Coconut water, 2oz prosciutto	2024-06-24 16:34:00
3	0e154b86-bf50-4004-9ddb-123beeb2e7c4	NaN	NaN	NaN	Beef Carpaccio, tomato, arugula	2024-06-24 17:48:00
4	0e154b86-bf50-4004-9ddb-123beeb2e7c4	NaN	NaN	NaN	Blueberries	2024-06-24 17:59:00
...
1869	0e154b86-bf50-4004-9ddb-123beeb2e7c4	NaN	NaN	NaN	Brueggers: skinny hot pastrami sandwich, pickle.	2025-07-19 08:20:00
1870	0e154b86-bf50-4004-9ddb-123beeb2e7c4	NaN	NaN	NaN	DLCC: ramen, chocolate chunk cookie.	2025-07-19 12:41:00
1871	0e154b86-bf50-4004-9ddb-123beeb2e7c4	NaN	NaN	NaN	Niki's Thai: 2 chicken satay, glass noodle salad.	2025-07-19 19:03:00
1872	0e154b86-bf50-4004-9ddb-123beeb2e7c4	NaN	NaN	NaN	peanut butter, honey.	2025-07-19 20:53:00
1873	0e154b86-bf50-4004-9ddb-123beeb2e7c4	NaN	NaN	NaN	Red Robin: 2 cheese twists, 2 onion rings, hot jalapeno burger no bun.	2025-07-20 15:36:00

1874 rows × 7 columns

Fig. 4. Raw Meal Data

IV. METHODS AND MODELS

This study defines a regression problem: predict a blood sugar metric based on foods in a meal.

All models use ‘LinearRegression’ so that the coefficients are interpretable. The coefficient of a food tells how much a serving of that food affects blood sugar.

This study includes models that treat the notes as unstructured and models that account for the semi-structured format used by the second author. The unstructured models are suitable for a patient who might not have recorded foods in the same format. The structured format reports foods more accurately.

The predicted value is Glycemic Increment (G+), introduced for the first time in this study.

A. Meals

There are three types of meals: *regular*, *extended*, and *unprecedented*.

For *regular* meals, each note in the data set defines a separate meal. The two hours following the note are the measurement period.

For *extended* meals, if a note occurs within 2 hours of another note, it is combined with the preceding note(s). The measurement period starts from the time of the first note to 2 hours after the last note.

If there are no notes for 4 hours before a given note, it is an *unprecedented* meal. The measurement period starts from the time of the note to 30 minutes after.

The three data sets are each split into *train* and *test* sets with `sklearn.train_test_split`, reserving 30% for the test set.

B. Tokenization and Vectorization

There are two tokenizers. The generic tokenizer is meant for use by anyone who has been using the notes to record foods that they have eaten. The full format tokenizer is intended for anyone who has been using a specific semi-structured format.

The generic tokenizer is the default tokenizer for `CountVectorizer` with unigrams, bigrams, and trigrams. The stop words are `and`, `with`, `servings`, and `leftovers`.

The full format tokenizer allows each note to start with an optional *restaurant* followed by a colon, and then the remaining string is split on the regular expression `r'[,;]|and|with'`. This allows foods to be identified by their full name. Each food can start with a quantity and an optional unit. If no quantity is specified, the parser defaults to 1.0. The default unit is *serving*.

There are two vectorizers. The simpler vectorizer is `CountVectorizer` with binary labels. It is used with the default tokenizer and the full format tokenizer.

The other vectorizer, defined for this study, is `QuantifierVectorizer` which uses the quantity from the full format parser as the value of the feature. The features themselves are generated by `CountVectorizer` with the full format vectorizer. It is not possible to use the

meal type	vectorizer	tokenizer
regular	Binary	ngrams
regular	Binary	full
regular	Quantifier	full
extended	Binary	ngrams
extended	Binary	full
extended	Quantifier	full
unprecedented	Binary	ngrams
unprecedented	Binary	full
unprecedented	Quantifier	full

TABLE I
THE 9 MODELS.

generic tokenizer with the `QuantifierVectorizer` as the full format parser is needed to extract quantities from the notes.

V. EXPERIMENTAL DESIGN AND INVESTIGATION STRATEGY

Each model is presented as a scatter plot of predicted G+ vs. actual G+, with a linear fit line for reference. For a perfect model, the linear fit line would have a slope of 1.0.

The plots also include the Pearson Correlation Coefficient (1.0 is perfect correlation), and root mean squared error (0.0 is a perfect model). The root mean squared error has the same units as the domain (hour-mg/dL), allowing the comparison of error to the coefficients of individual foods.

There are 9 possible models as shown in table I. There are three meal types, and three possible combinations of vectorizer and tokenizer.

The *regular* meal type is the simplest interpretation of the data. Every note is a separate meal.

The *extended* meal type attempts to deal with the case when a second set of food has been consumed before the glucose of the preceding food has been fully processed.

The *unprecedented* meal type is an effort to create conditions closer to those used for GI calculation, where the subject is in a state of fasting before testing.

VI. RESULTS AND OBSERVATIONS

Fig. VI shows a variant on calibration curve for each of the models. Here it is used as a continuous approximation of confusion matrix. The horizontal axis is the predicted G+ and the vertical axis is the actual G+. The green line is a best linear fit. The data set for each meal type is a separate test set.

The three metrics we look at are *root mean squared error* (*rmse*), the correlation coefficient, and the slope of the best linear fit.

The value of *rmse* is in the same units as G+. A perfect model would have an *rmse* of 0.0. This metric is most useful for comparing the models.

A perfect model would have a correlation coefficient of 1.0. Here it is used as an indicator for the strength of the model.

The slope of the best linear fit shows how well the model approximates the true blood sugar behavior. A perfect model

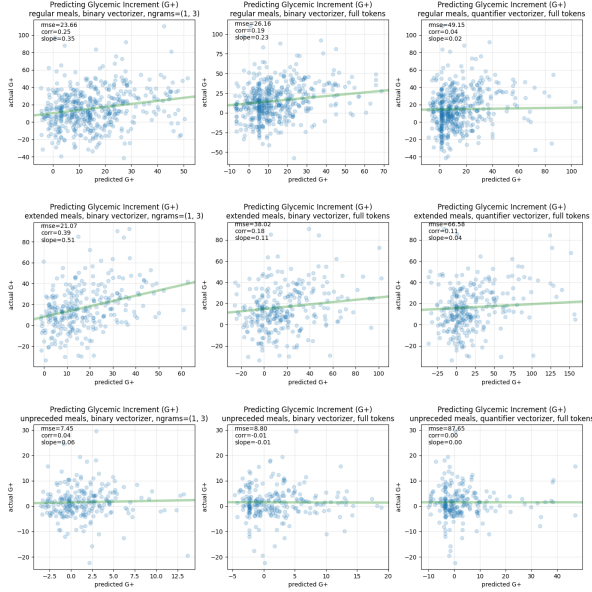


Fig. 5. Model Tests

would have a slope of 1.0. A slope near 0.0 shows a model with no predictive power.

The three *unprecedented* meal models are worthless. Their correlations and slopes are near 0. There is no discernible relationship between the predictions and the actual values.

The three models with the *QuantifierVectorizer* are similarly terrible. The *extended* meals model has a tiny positive correlation, but it does not appear to have significant predictive power.

The four remaining models appear to be usable. The two full token models have nearly identical correlations (0.19 and 0.18), and modest slopes.

The two trigram based models (*regular* meals and *extended*) have moderately higher predictive power.

Look at the low magnitude and high magnitude food coefficients to confirm that the models make sense. Only the models with reasonable predictive power are in these tables.

Fig. VI shows the foods with the lowest magnitude scores.

The *regular* meals with ngram tokenizer model shows one of the limitations of this tokenizer. All of the small negative values come from a single meal: Miracle Noodle, butter, dill, 3 eggs, 8 ciliegine. Miracle Noodles are a form of konjac, a food with a GI of 0.

The positive values only represent two meals: Wendy's: Dave's triple no bun and 2 chicken thighs, artichoke, corn with butter, 6 dried apricots. 6 prunes.

The full tokenizer model holds no surprises. It seems likely that braised bed is a typo for braised beef.

regular meals, binary vectorizer, ngrams=(1, 3)		regular meals, binary vectorizer, full tokens	
low_coef	low_food	low_coef	low_food
-0.0024	noodle butter dill	-0.1516	triple burger no bun
-0.0024	miracle noodle butter	-0.1516	chipotle bbq sauce
-0.0024	miracle noodle	-0.1205	toasted ezeikel english muffin
-0.0024	butter dill eggs	-0.1205	buratta
-0.0024	noodle	-0.0008	peleano
0.0081	apricots prunes	0.0261	scrambled eggs
0.0081	dried apricots prunes	0.0261	braised bed
0.0130	wendy dave triple	0.0627	fried jalapeno
0.0130	dave triple no	0.0627	eggs sunny side up
0.0130	triple no	0.0738	whole milk cottage cheese
extended meals, binary vectorizer, ngrams=(1, 3)		extended meals, binary vectorizer, full tokens	
low_coef	low_food	low_coef	low_food
-0.0045	mozzarella sticks fried	-0.2822	two cherry tomatoes
-0.0045	sticks fried fish	-0.2599	sauerkraut
-0.0019	shaking	-0.1841	halumi slices
-0.0016	150g of	-0.1280	campari tomatoes
-0.0016	150g of greek	-0.0527	greens
0.0004	glaze donuts	0.0458	tate's bake shop oatmeal raisin cookies
0.0004	balsamic glaze	0.0924	jico
0.0004	truffle balsamic glaze	0.2293	thai sai fun salad
0.0004	skin	0.2293	hot chocolate milk sweetened
0.0004	skin salad	0.3625	lobster bisque

Fig. 6. Foods with scores near 0.0

The *extended* meals with ngram tokenizer model holds one surprise. The positive values all come from a combined meal of Grilled salmon, salmon skin, salad, black olives, truffle balsamic glaze and almost an hour later 2 donuts. Inexplicably, the donuts appear to have had little effect on blood sugar.

The shaking is from a note unrelated to food, so unsurprisingly did not affect blood sugar.

The *extended* meals with full tokenizer model holds only one surprise, Tate's Bake Shop oatmeal raisin cookies. This food definitely raises blood sugar so it is not clear how it has such a low score. All the other foods make sense. Note that hot chocolate milk sweetened is followed by with stevia in the raw data. The parser treats with as a food separator.

The high magnitude scores are mostly unsurprising. Eating at Speedway is generally bad for blood sugar. The masoor beef shows another limitation—that food is always eaten with rice, which increases blood sugar.

While not perfect, these models are useful for predicting the effects of specific meals on blood sugar.

VII. CONCLUSIONS

Individualized medicine is a growing field. The availability of inexpensive sensors that can provide information from activity, blood pressure, blood oxygen, and blood glucose has created a plethora of data.

Patients can use their own data to produce guidance suitable for controlling their blood sugar through diet.

APPENDIX

A. On negative values

[This section could use illustrative examples.]

All 9 models produce negative values for certain foods. Spot-checking shows that these foods are mostly high-GI and high-GL.

regular meals, binary vectorizer, ngrams=(1, 3)		regular meals, binary vectorizer, full tokens	
high_coef	high_food	high_coef	high_food
-71.7892	apricots banana	66.4125	flavor bomb tomatoes
-36.6472	chicken tenders donut	42.3769	dairy queen dilly bar
-36.6472	tenders donut	37.0013	RESTAURANT speedway
-35.5440	prunes dried apricots	36.6239	sauna
-31.7564	apple banana	30.6041	meatloaf beef
27.5434	apple plum	74.0197	singapore noodles mixed meats
36.8195	donut	74.3032	maple bear claw
45.2271	croissant	78.3518	cheese powder
57.8512	slices raisins peanut	83.7768	1/2 spicy chicken tenders
97.0738	dried apricots banana	92.9081	apple strudel

extended meals, binary vectorizer, ngrams=(1, 3)		extended meals, binary vectorizer, full tokens	
high_coef	high_food	high_coef	high_food
-46.5724	cruller	-75.5220	corn
-13.1386	thai beef	-72.7618	pot roast
-13.1386	thai beef sai	47.0276	chicken tenders
-12.9476	kumato	46.3326	peach preserves
-12.8285	milk peanut	40.1470	cooked carrots
14.6522	butter honey butter	85.5229	gravy
14.6758	honey butter	93.3223	strudel
14.7949	cinnamon	114.8571	biscuits
27.6110	giordano	128.0414	chicken cassava gloop
51.2691	croissant	138.9475	cinnamon roll

Fig. 7. Foods with scores of high magnitude

Investigation of specific cases suggests three phenomena: insulin reaction, rapid successive meals, and variations in blood sugar not associated with eating.

If a high-GL food is eaten, typically there is a spike in blood sugar followed by a decrease. High-GL foods typically cause rapid rise followed by rapid decrease (hypoglycemia, an insulin reaction).

Some of the foods with negative $G+$ values are often eaten in the hours following the consumption of a high GL food, so if they have a low GL, their $G+$ values will still be negative due to the falling blood glucose from the earlier meal.

The *unprecedented* meals are an effort to isolate only those meals that do not have a predecessor, and therefore have an expectation of stable blood sugar. In fact, blood sugar is not stable for these meals. There are daily variations that do not have an immediate food-related cause.

The *extended* meals are an effort to go the other direction, combining the effects of chained meals, those eaten before the effects of the previous meal have worn off.

The fact that the most negative values are for high-GL foods suggests that the insulin reaction is the dominant effect.

A possible future metric is Absolute $G+$, in which the absolute difference between the blood sugar measurement and each subsequent measurement is integrated. A food that has no glycemic effect throughout the measurement interval is not the same as a food which has positive and negative effects on blood sugar of equal magnitude. However, both would show $G+$ of 0.

B. On singletons and rare foods

[This section could use more illustrative examples.]

An early run of a full token model yielded `lamb mattar` (lamb with peas sauce) as a very high $G+$ dish. Although peas are not particularly low-GL, they should not have been considered extreme. A close examination of the data revealed that the one meal of `lamb mattar` in the data set also

includes 5 servings of diabetic rice, which is undoubtedly the cause of the high score.

Dealing with rare cases like this remains an open topic of investigation.

REFERENCES

- [1] Centers for Disease Control and Prevention, “Diabetes Data and Research.” <https://www.cdc.gov/diabetes/php/data-research/index.html>, 2024. Accessed on September 15, 2025.
- [2] Centers for Disease Control and Prevention, “Diabetes Meal Planning.” <https://www.cdc.gov/diabetes/healthy-eating/diabetes-meal-planning.html>, 2024. Accessed: 2025-09-11.
- [3] L. C. Clark Jr. and C. Lyons, “Electrode Systems for Continuous Monitoring in Cardiovascular Surgery,” *Annals of the New York Academy of Sciences*, vol. 102, no. 29, pp. 29–45, 1962.
- [4] N. B. Reddy, N. M. Verma, and K. M. Dungan, “Monitoring Technologies- Continuous Glucose Monitoring, Mobile Technology, Biomarkers of Glycemic Control,” in *Endotext*, MDText.com, Inc., 2023. Accessed: 2025-09-11.
- [5] A. Agarwal, “Understanding Blood Sugar Levels: A Guide to Normal Sugar Levels Chart.” <https://www.medkart.in/blog/normal-blood-sugar-levels-chart>, 2025. Accessed: 2025-09-15.
- [6] D. J. A. Jenkins, T. M. S. Wolever, R. H. Taylor, H. M. Barker, H. Fielden, J. M. Baldwin, A. C. Bowling, H. C. Newman, A. L. Jenkins, and D. F. Goff, “Glycemic index of foods: a physiological basis for carbohydrate exchange,” *American Journal of Clinical Nutrition*, vol. 34, no. 3, pp. 362–366, 1981. Archived from the original on 2017-07-02. Accessed: 2025-09-11.
- [7] J. Salmerón, A. Ascherio, E. B. Rimm, G. A. Colditz, D. Spiegelman, D. J. Jenkins, M. J. Stampfer, A. L. Wing, and W. C. Willett, “Dietary Fiber, Glycemic Load, and Risk of NIDDM in Men,” *Diabetes Care*, vol. 20, no. 4, pp. 545–550, 1997.