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Linearized Conversion Ratio Analysis of Finger and Sensor FPG versus Body Weight and Finger and Sensor PPG versus Carbohydrates Intake Grams Using Both Finger-Pierced and CGM Sensor Measured Glucose Data and Viscoplastic Energy Model in GH-Method: Math-Physical Medicine (No. 1024, Viscoelastic Medicine Theory #422)

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Abstract

*Recently, the author has conducted four separate analyses to **establish simplified conversion ratios for weight versus FPG and carbs versus PPG.** This research utilized finger-pricked and CGM sensor data, along with the Viscoplastic Energy Model (SD-VMT) of the GH-Method: Math-Physical Medicine approach.*

The first analysis, spanning 2016 to 2023, utilized finger glucose data. The second, covering 2017 to 2024, used CGM sensor data. The third and fourth analyses, both from 2018 to 2024, employed finger glucose and CGM sensor data, respectively. The author adopted the CGM sensor device on May 1, 2018.
The conversion ratios were calculated using simple linearized formulas:
***Glucose difference = maximum glucose - minimum glucose,** where the glucose measurements are FPG and PPG.*
***Input difference = maximum input - minimum input,** where inputs are body weight (BW) for FPG and carbohydrates for PPG.*
Conversion ratio = glucose difference / input difference

Summary of findings
***In cases 1 and 2,** every pound of weight loss corresponded to a 4.9 mg/dL decrease in finger FPG and a 2.7 mg/dL decrease in sensor FPG. **Every gram of reduced carbs intake led to a 2.4 mg/dL decrease in finger PPG and a 4.8 mg/dL decrease in sensor PPG.** However, these results are somewhat unreliable due to incomplete or estimated initial data.*
***In cases 3 and 4,** each pound of weight loss resulted in a 3.6 mg/dL decrease in finger FPG and a 3.3 mg/dL decrease in sensor FPG. **Every gram of reduced carbohydrate and sugar intake led to a 2.4 mg/dL decrease in finger PPG and a 4.8 mg/dL decrease in sensor PPG.** These results were more reliable due to the choice of more suitable time period and completeness of data.*
Regarding the SD-VMT energy results, all four cases presented similar outcomes within a narrow percentage range:
FPG = 26% - 27%
PPG = 24% - 26%
BW = 25% - 26%
Carbs = 23% - 24%

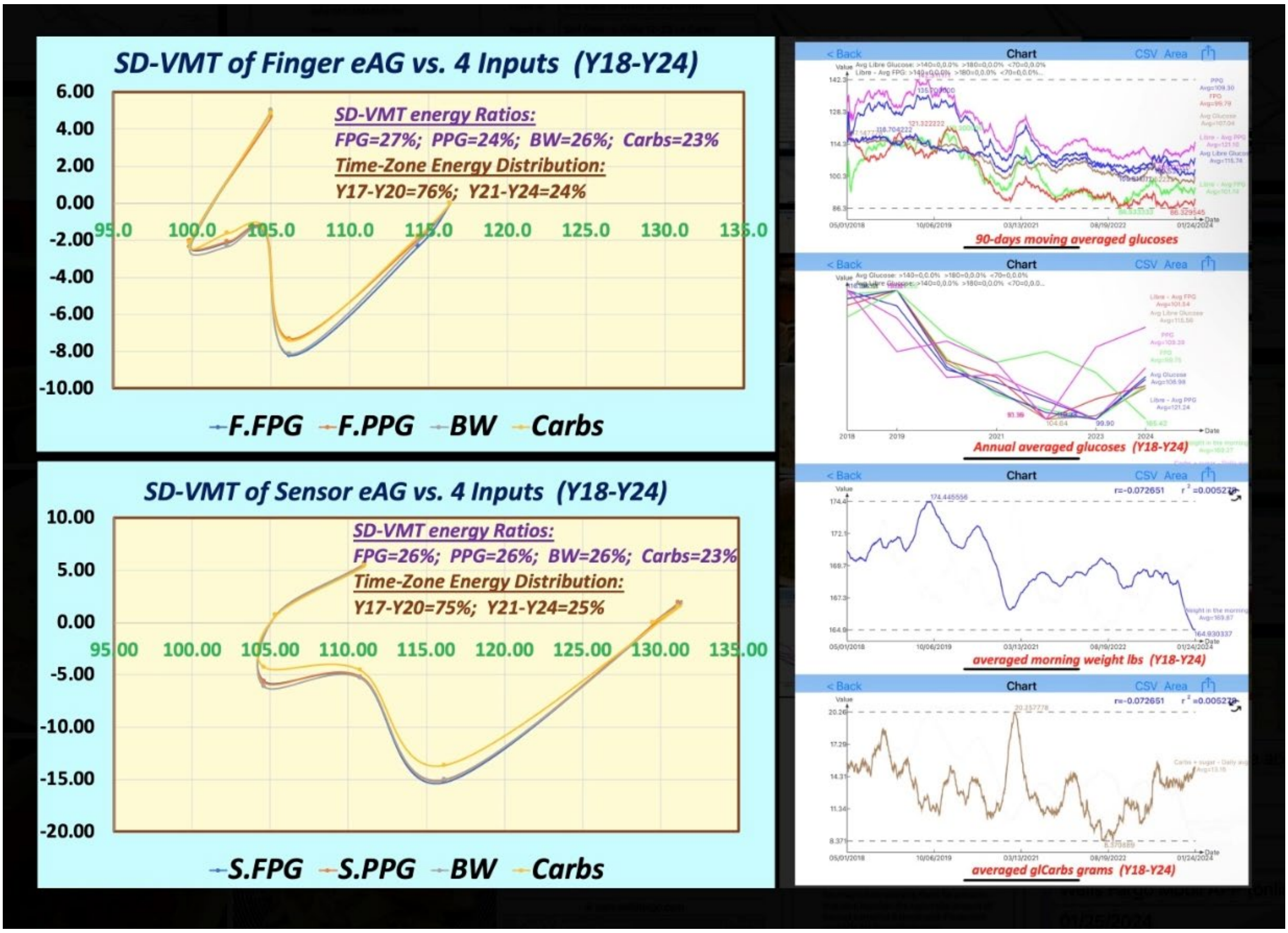
*Body weight impacts FPG, which indicates insulin resistance status and sets a baseline for PPG levels. **Together, BW, FPG, and PPG account for about 75% to 79% of daily eAG, with carbohydrate choices contributing the remaining 21% to 25%.** Part of the PPG contribution is also related to exercise, stress, ambient temperature, and other factors.*

Total sensor energy (805) is 3 times higher than total finger energy (261).

Key Message
Using Case 3 and Case 4, the following conclusions were observed:

(1) A reduction of one pound of body weight decreases FPG levels by 3.3 to 3.6 mg/dL.

(2) Lowering carbohydrate and sugar intake by one gram results in a decrease of 2.4 mg/dL in Finger PPG levels and a decrease of 4.8 mg/dL in CGM Sensor PPG levels.



1. Introduction

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The conversion ratios were calculated using simple linearized formulas:

Glucose difference = maximum glucose - minimum glucose, where the glucose measurements are FPG and PPG.

Input difference = maximum input - minimum input, where inputs are body weight (BW) for FPG and carbohydrates for PPG.

Conversion ratio = glucose difference / input difference

1.1 Biomedical and Engineering information

The following sections contain excerpts and concise information drawn from multiple medical articles, which have been meticulously reviewed by the author of this paper. The author has adopted this approach as an alternative to including a conventional reference list at the end of this document, with the intention of optimizing his valuable research time. It is essential to clarify that these sections do not constitute part of the author's original contribution but have been included to aid the author in his future reviews and offer valuable insights to other readers with an interest in these subjects.

2. From Research Literatures, the Range of Linear Ratio between Body Weight and FPG?

The research on the linear conversion rate between body weight and fasting glucose primarily focuses on models and frameworks to understand how these two factors interact, particularly in the context of type 2 diabetes mellitus (T2DM). There isn't a straightforward linear conversion rate provided across the literature because the relationship between body weight and fasting blood sugar (FBS) levels is complex and influenced by numerous variables.

Studies have employed various mathematical models to understand this relationship. For instance, one approach involved fitting mathematical functions to clinical data, using least squares methods, to model sensitive metabolic rates. This approach was used to understand the relationship between tissue/organ response and solute concentration, such as glucose, in patients with T2DM (Nature, Scientific Reports).

Another study highlighted the importance of insulin resistance and inflammation in predicting kinetic body weight changes in response to dietary weight loss and maintenance. This study suggests that the relationship between body weight and fasting glucose is influenced by factors like insulin resistance (Nature, International Journal of Obesity).

Additionally, a study used a multivariate longitudinal marginal model to assess the relationship between FBS and glycosylated hemoglobin (HbA1c) in patients with T2DM. It found a significant positive relationship between FBS and HbA1c over time, indicating that factors such as family history of diabetes, hypertension, and duration of disease significantly influenced FBS levels (Nature, Scientific Reports).

In another research, semi-parametric mixed models were used to understand the longitudinal measurement of FBS levels in diabetic patients. These models accounted for various factors, including time-varying covariates and interaction effects, to understand the evolution of FBS levels over time (BMC Medical Research Methodology).

One study that examined glucose absorption patterns during oral glucose tolerance tests (OGTTs) found that body weight measurements and calculations of body surface area were crucial for understanding glucose metabolism. This indicates the importance of body weight in the context of glucose absorption and metabolism (Diabetes Care, American Diabetes Association).

In summary, the relationship between body weight and fasting glucose is complex and influenced by various factors including insulin resistance, inflammation, and individual metabolic responses. The studies use sophisticated mathematical and statistical models to understand this relationship, rather than providing a simple linear conversion rate.

3. From Research Literatures, the Range of Linear Ratio between Carbohydrates and Sugar Intake Grams and PPG?

The relationship between carbohydrate and sugar intake and postprandial glucose (PPG) levels is a complex one, influenced by various factors including the type of carbohydrate, its fiber content, the overall meal composition, and individual metabolic responses.

In general, carbohydrates, including sugars, are known to have a direct impact on PPG levels. The glycemic index (GI) and glycemic load (GL) are commonly used metrics to describe this impact. Foods with a high GI or GL cause a more significant and rapid increase in blood glucose levels compared to foods with a lower GI or GL.

However, specifying a linear ratio between carbohydrate/sugar intake in grams and PPG levels is challenging due to individual variations and the influence of other meal components. Additionally, such ratios might not be consistent across different research studies, as they depend on the specific types of carbohydrates and sugars being consumed.

4. MPM Background

To learn more about his developed GH-Method: math-physical medicine (MPM) methodology, readers can read the following three papers selected from his published 760+ papers.

The first paper, No. 386 (Reference 1) describes his MPM methodology in a general conceptual format. The second paper, No. 387 (Reference 2) outlines the history of his personalized diabetes research, various application tools, and the differences between biochemical medicine (BCM) approach versus the MPM approach. The third paper, No. 397 (Reference 3) depicts a general flow diagram containing ~10 key MPM research methods and different tools.

5. The Author'S Diabetes History

The author was a severe T2D patient since 1995. He weighed 220 lb. (100 kg) at that time. By 2010, he still weighed 198 lb. with an average daily glucose of 250 mg/dL (HbA1C at 10%). During that year, his triglycerides reached 1161 (high risk for CVD and stroke) and his albumin-creatinine ratio (ACR) at 116 (high risk for chronic kidney disease). He also suffered from five cardiac episodes within a decade. In 2010, three independent physicians warned him regarding the need for kidney dialysis treatment and the future high risk of dying from his severe diabetic complications.

In 2010, he decided to self-study endocrinology with an emphasis on diabetes and food nutrition. He spent the entire year of 2014 to develop a metabolism index (MI) mathematical model. During 2015 and 2016, he developed four mathematical prediction models related to diabetes conditions: weight, PPG, fasting plasma glucose (FPG), and HbA1C (A1C). Through using his developed mathematical metabolism index (MI) model and the other four glucose prediction tools, by the end of 2016, his weight was reduced from 220 lbs. (100 kg) to 176 lbs. (89 kg), waistline from 44 inches (112 cm) to 33 inches (84 cm), average finger-piercing glucose from 250 mg/dL to 120 mg/dL, and A1C from 10% to ~6.5%. One of his major accomplishments is that he no longer takes any diabetes-related medications since 12/8/2015.

In 2017, he achieved excellent results on all fronts, especially his glucose control. However, during the pre-COVID period, including both 2018 and 2019, he traveled to ~50 international cities to attend 65+ medical conferences and made ~120 oral presentations. This hectic schedule inflicted damage to his diabetes control caused by stress, dining out frequently, post-meal exercise disruption, and jet lag, along with the overall negative metabolic impact from the irregular life patterns; therefore, his glucose control was somewhat affected during the two-year traveling period of 2018-2019.

He started his COVID-19 self-quarantined life on 1/19/2020. By 10/16/2022, his weight was further reduced to ~164 lbs. (BMI 24.22) and his A1C was at 6.0% without any medication intervention or insulin injection. In fact, with the special COVID-19 quarantine lifestyle since early 2020, not only has he written and published ~500 new research articles in various medical and engineering journals, but he has also achieved his best health conditions for the past 27 years. These achievements have resulted from his non-traveling, low-stress, and regular daily life routines. Of course, his in-depth knowledge of chronic diseases, sufficient practical lifestyle management experiences, and his own developed high-tech tools have also contributed to his excellent health improvements.

On 5/5/2018, he applied a continuous glucose monitoring (CGM) sensor device on his upper arm and checks his glucose measurements every 5 minutes for a total of 288 times each day. Furthermore, he extracted the 5-minute intervals from every 15-minute interval for a total of 96 glucose data each day stored in his computer software.

Through the author's medical research work over 40,000 hours and read over 4,000 published medical papers online in the past 13 years, he discovered and became convinced that good life habits of not smoking, moderate or no alcohol intake, avoiding illicit drugs; along with eating the right food with well-balanced nutrition, persistent exercise, having a sufficient and good quality of sleep, reducing all kinds of unnecessary stress, maintaining a regular daily life routine contribute to the risk reduction of having many diseases, including CVD, stroke, kidney problems, micro blood vessels issues, peripheral nervous system problems, and even cancers and dementia. In addition, a long-term healthy lifestyle can even "repair" some damaged internal organs, with different required time-length depending on the particular organ's cell lifespan. For example, he has "self-repaired" about 35% of his damaged pancreatic beta cells during the past 10 years.

6. Energy Theory

The human body and organs have around 37 trillion live cells which are composed of different organic cells that require energy infusion from glucose carried by red blood cells; and energy consumption from labor-work or exercise. When the residual energy (resulting from the plastic glucose scenario) is stored inside our bodies, it will cause different degrees of damage or influence to many of our internal organs.

According to physics, energies associated with the glucose waves are proportional to the square of the glucose amplitude. The residual energies from elevated glucoses are circulating inside the body via blood vessels which then impact all of the internal organs to cause different degrees of damage or influence, e.g. diabetic complications. Elevated glucose (hyperglycemia) causes damage to the structural integrity of blood vessels. When it combines with both hypertension (rupture of arteries) and hyperlipidemia (blockage of arteries), CVD or Stroke happens. Similarly, many other deadly diseases could result from these excessive energies which would finally shorten our lifespan. For an example, the combination of hyperglycemia and hypertension would cause micro-blood vessel's leakage in kidney systems which is one of the major cause of CKD.

The author then applied Fast Fourier Transform (FFT) operations to convert the input wave from a time domain into a frequency domain. The y-axis amplitude values in the frequency domain indicate the proportional energy levels associated with each different frequency component of input occurrence. ***Both output symptom value (i.e. strain amplitude in the time domain) and output symptom fluctuation rate (i.e. the strain rate and strain frequency) are influencing the energy level (i.e. the Y-amplitude in the frequency domain).***

Currently, many people live a sedentary lifestyle and lack sufficient exercise to burn off the energy influx which causes them to become overweight or obese. Being overweight and having obesity leads to a variety of chronic diseases, particularly diabetes. In addition, many types of processed food add unnecessary ingredients and harmful chemicals that are toxic to the bodies, which lead to the development of many other deadly diseases, such as cancers. For example, ~85% of worldwide diabetes patients are overweight, and ~75% of patients with cardiac illnesses or surgeries have diabetes conditions.

In engineering analysis, when the load is applied to the structure, it bends or twists, i.e. deform; however, when the load is removed, it will either be restored to its original shape (i.e, elastic case) or remain in a deformed shape (i.e. plastic case). In a biomedical system, the glucose level will increase after eating carbohydrates or sugar from food; therefore, the carbohydrates and sugar function as the energy supply. After having labor work or exercise, the glucose level will decrease. As a result, the exercise burns off the energy, which is similar to load removal in the engineering case. In the biomedical case, both processes of energy influx and energy dissipation take some time which is not as simple and quick as the structural load removal in the engineering case. Therefore, the age difference and 3 input behaviors are "dynamic" in nature, i.e. time-dependent. *This time-dependent nature leads to a "viscoelastic or viscoplastic" situation.* ***For the author's case, it is "viscoplastic" since most of his biomarkers are continuously improved during the past 13-year time window.***

Time-dependent output strain and stress of (viscous input*output rate)

Hooke's law of linear elasticity is expressed as:

Strain (ε: epsilon)
= Stress (σ: sigma) / Young's modulus (E)

For biomedical glucose application, his developed linear elastic glucose theory (LEGT) is expressed as:

PPG (strain) = carbs/sugar (stress) * GH.p-Modulus (a positive number) + post-meal walking k-steps * GH.w-Modulus (a negative number)

Where GH.p-Modulus is reciprocal of Young's modulus E.

However, in viscoelasticity or viscoplasticity theory, the stress is expressed as:

Stress
= viscosity factor (η: eta) * strain rate (dε/dt)

Where strain is expressed as Greek epsilon or ε.

In this article, in order to construct an "ellipse-like" diagram in a stress-strain space domain (e.g. "hysteresis loop") covering both the positive side and negative side of space, he has modified the definition of strain as follows:

Strain
= (body weight at certain specific time instant)

He also calculates his strain rate using the following formula:

Strain rate
= (body weight at next time instant) - (body weight at present time instant)

The risk probability % of developing into CVD, CKD, Cancer is calculated based on his developed metabolism index model (MI) in 2014. His MI value is calculated using inputs of 4 chronic conditions, i.e. weight, glucose, blood pressure, and lipids; and 6 lifestyle details, i.e. diet, drinking water, exercise, sleep, stress, and daily routines. These 10 metabolism categories further contain ~500 elements with millions of input data collected and processed since 2010. For individual deadly disease risk probability %, his mathematical model contains certain specific weighting factors for simulating certain risk percentages associated with different deadly diseases, such as metabolic disorder-induced CVD, stroke, kidney failure, cancers, dementia; artery damage in heart and brain, micro-vessel damage in kidney, and immunity-related infectious diseases, such as COVID death.

Some of explored deadly diseases and longevity characteristics using the ***viscoplastic medicine theory (VMT)*** include stress relaxation, creep, hysteresis loop, and material stiffness, damping effect ***based on time-dependent stress and strain*** which are different from his previous research findings using ***linear elastic glucose theory (LEGT) and nonlinear plastic glucose theory (NPGT)***.

7. Results

Finger						/ 100	/ 120	/ 170	/ 15	S. Rate	Strain	Strs 1	Strs 2	Strs 3	Strs 4	Hgt 1	Hgt 2	Hgt 3	Hgt 4	Area 1	Area 2	Area 3	Area 4	Time
1/25/24	F.eAG	F.FPG	F.PPG	BW	Carbs	F.FPG	F.PPG	BW	Carbs	F.eAG	F.eAG	F.FPG	F.PPG	BW	Carbs	F.FPG	F.PPG	BW	Carbs	F.FPG	F.PPG	BW	Carbs	Zone
2018	116.4	113.7	116.8	171.1	15.8	1.14	0.97	1.01	1.05	0.00	116.4	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0	0	0	0	Y18-Y21
2019	114.4	114.6	114.0	172.6	13.2	1.15	0.95	1.02	0.88	-2.01	114.4	-2.30	-1.91	-2.04	-1.77	-1.15	-0.95	-1.02	-0.89	2.31	1.92	2.05	1.78	197
2020	106.2	101.0	108.0	170.0	13.7	1.01	0.90	1.00	0.91	-8.14	106.2	-8.22	-7.33	-8.14	-7.42	-5.26	-4.62	-5.09	-4.60	42.82	37.59	41.44	37.44	75%
2021	104.6	93.8	108.3	168.6	12.8	0.94	0.90	0.99	0.85	-1.61	104.6	-1.51	-1.45	-1.60	-1.37	-4.86	-4.39	-4.87	-4.40	7.83	7.07	7.84	7.08	
2022	102.3	90.8	105.9	169.2	10.4	0.91	0.88	1.00	0.69	-2.35	102.3	-2.13	-2.07	-2.34	-1.63	-1.82	-1.76	-1.97	-1.50	4.28	4.14	4.62	3.52	Y22-Y24
2023	99.9	88.9	103.8	168.0	13.4	0.89	0.86	0.99	0.90	-2.38	99.9	-2.11	-2.06	-2.35	-2.13	-2.12	-2.07	-2.35	-1.88	5.06	4.92	5.58	4.47	64
2024	105.0	95.6	109.0	165.4	14.3	0.96	0.91	0.97	0.95	5.13	105.0	4.90	4.66	4.99	4.88	1.39	1.30	1.32	1.37	7.16	6.67	6.77	7.05	25%
Avg	107.0	99.8	109.4	169.3	13.4	1.00	0.91	1.00	0.89	-1.62	107.0	-1.63	-1.45	-1.64	-1.35	-1.98	-1.78	-2.00	-1.70	69.46	62.31	68.3	61.35	
Correl.	100%	98%	99%	70%	58%													SD-E:	261	27%	24%	26%	23%	

Avg. BW	Avg. F.FPG	F.FPG / BW	Avg. Carbs	Avg. F.PPG	F.PPG / Carbs
169.3	99.8	0.6	13.4	109.4	8.2
BW Diff.	F.FPG Diff.	F.FPG / BW	Carbs Diff.	F.PPG Diff.	F.PPG / Carbs
7.2	25.7	3.6	5.4	13.1	2.4

Sensor						/ 100	/ 120	/ 170	/ 15	S. Rate	Strain	Strs 1	Strs 2	Strs 3	Strs 4	Hgt 1	Hgt 2	Hgt 3	Hgt 4	Area 1	Area 2	Area 3	Area 4	Time
1/25/24	S.eAG	S.FPG	S.PPG	BW	Carbs	S.FPG	S.PPG	BW	Carbs	S.eAG	S.eAG	S.FPG	S.PPG	BW	Carbs	S.FPG	S.PPG	BW	Carbs	S.FPG	S.PPG	BW	Carbs	Zone
2018	129.6	112.0	134.6	171.1	15.8	1.12	1.12	1.01	1.05	0.00	129.56	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0	0	0	0	Y18-Y21
2019	131.2	114.7	136.3	172.6	13.2	1.15	1.14	1.02	0.88	1.63	131.19	1.87	1.85	1.65	1.44	0.94	0.93	0.83	0.72	2	2	1	1	611
2020	116.2	101.9	120.9	170.0	13.7	1.02	1.01	1.00	0.91	-14.99	116.20	-15.27	-15.10	-14.99	-13.67	-6.70	-6.63	-6.67	-6.12	100	99	100	92	76%
2021	110.8	98.9	115.9	168.6	12.8	0.99	0.97	0.99	0.85	-5.38	110.82	-5.32	-5.19	-5.34	-4.58	-10.30	-10.15	-10.16	-9.13	55	55	55	49	
2022	104.6	91.2	111.7	169.2	10.4	0.91	0.93	1.00	0.69	-6.18	104.64	-5.63	-5.75	-6.15	-4.28	-5.48	-5.47	-5.74	-4.43	34	34	35	27	Y22-Y24
2023	105.4	94.9	110.3	168.0	13.4	0.95	0.92	0.99	0.90	0.76	105.40	0.72	0.70	0.75	0.68	-2.46	-2.53	-2.70	-1.80	-2	-2	-2	-1	194
2024	111.1	97.3	119.0	165.4	14.3	0.97	0.99	0.97	0.95	5.68	111.08	5.52	5.63	5.53	5.40	3.12	3.16	3.14	3.04	18	18	18	17	24%
Avg	115.6	101.5	121.2	169.3	13.4	1.02	1.01	1.00	0.89	-2.64	115.56	-2.59	-2.55	-2.65	-2.14	-2.98	-2.95	-3.04	-2.53	207	205	207	185	
Correl.	1.0	1.0	1.0	0.8	0.6						1.00							SD-E:	805	26%	26%	26%	23%	

Avg. BW	Avg. S.FPG	S.FPG / BW	Avg. Carbs	Avg. S.PPG	S.PPG / Carbs
169.3	101.5	0.6	13.4	121.2	9.1
BW Diff.	S.FPG Diff.	S.FPG / BW	Carbs Diff.	S.PPG Diff.	S.PPG / Carbs
7.2	23.6	3.3	5.4	26.0	4.8

Case	From	To	Type	FPG / BW	PPG / Carbs
Case 1	1/1/16	12/31/23	Finger	4.9	2.4
Case 2	1/1/17	1/23/24	Sensor	2.7	4.8
Case 3	5/1/18	1/24/24	Finger	3.6	2.4
Case 4	5/1/18	1/24/24	Sensor	3.3	4.8
Average				3.6	3.6

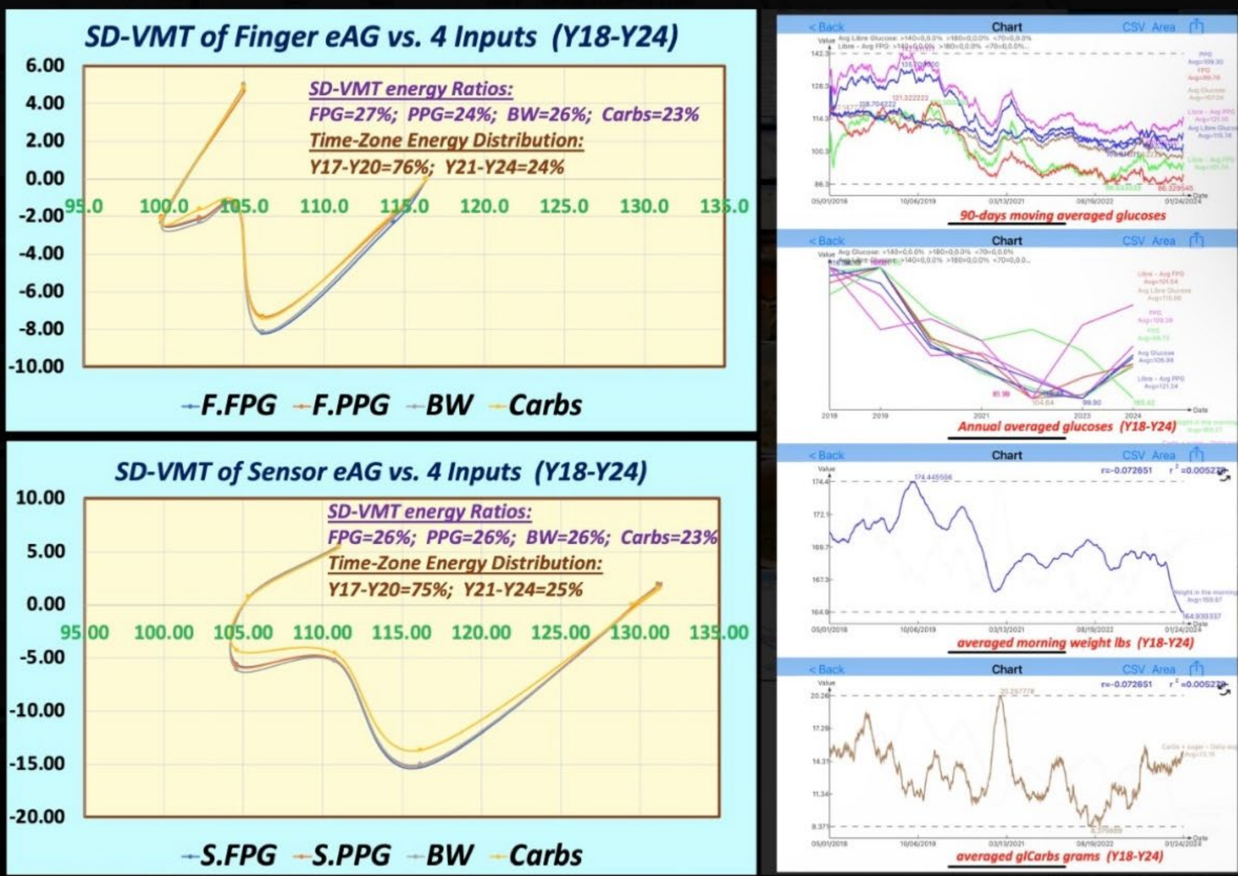

Figure 1: Shows Data, TD and SD results.

8. Conclusions

In cases 1 and 2, every pound of weight loss corresponded to a 4.9 mg/dL decrease in finger FPG and a 2.7 mg/dL decrease in sensor FPG. ***Every gram of reduced carbs intake led to a 2.4 mg/dL decrease in finger PPG and a 4.8 mg/dL decrease in sensor PPG.*** However, these results are somewhat unreliable due to incomplete or estimated initial data.

In cases 3 and 4, each pound of weight loss resulted in a 3.6 mg/dL decrease in finger FPG and a 3.3 mg/dL decrease in sensor FPG. ***Every gram of reduced carbohydrate and sugar intake led to a 2.4 mg/dL decrease in finger PPG and a 4.8 mg/dL decrease in sensor PPG.*** These results were more reliable due to the choice of more suitable time period and completeness of data.

Regarding the SD-VMT energy results, all four cases presented similar outcomes within a narrow percentage range:

FPG = 26% - 27%
PPG = 24% - 26%
BW = 25% - 26%
Carbs = 23% - 24%

Body weight impacts FPG, which indicates insulin resistance status and sets a baseline for PPG levels. ***Together, BW, FPG, and PPG account for about 75% to 79% of daily eAG, with carbohydrate choices contributing the remaining 21% to 25%***. Part of the PPG contribution is also related to exercise, stress, ambient temperature, and other factors.

Total sensor energy (805) is 3 times higher than total finger energy (261).

Key Message

Using Case 3 and Case 4, the following conclusions were observed:

(1) A reduction of one pound of body weight decreases FPG levels by 3.3 to 3.6 mg/dL.

(2) Lowering carbohydrate and sugar intake by one gram results in a decrease of 2.4 mg/dL in Finger PPG levels and a decrease of 4.8 mg/dL in CGM Sensor PPG levels.

References

For editing purposes, majority of the references in this paper, which are self-references, have been removed for this article. Only references from other authors' published sources remain. The bibliography of the author's original self-references can be viewed at www.eclairemd.com.

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