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Body weight versus PPG, FPG, fluctuations of PPG and FPG and applying the viscoplastic energy model of GH-Method: mathphysical medicine (No. 949, VMT #348, 11/4/2023)

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Abstract

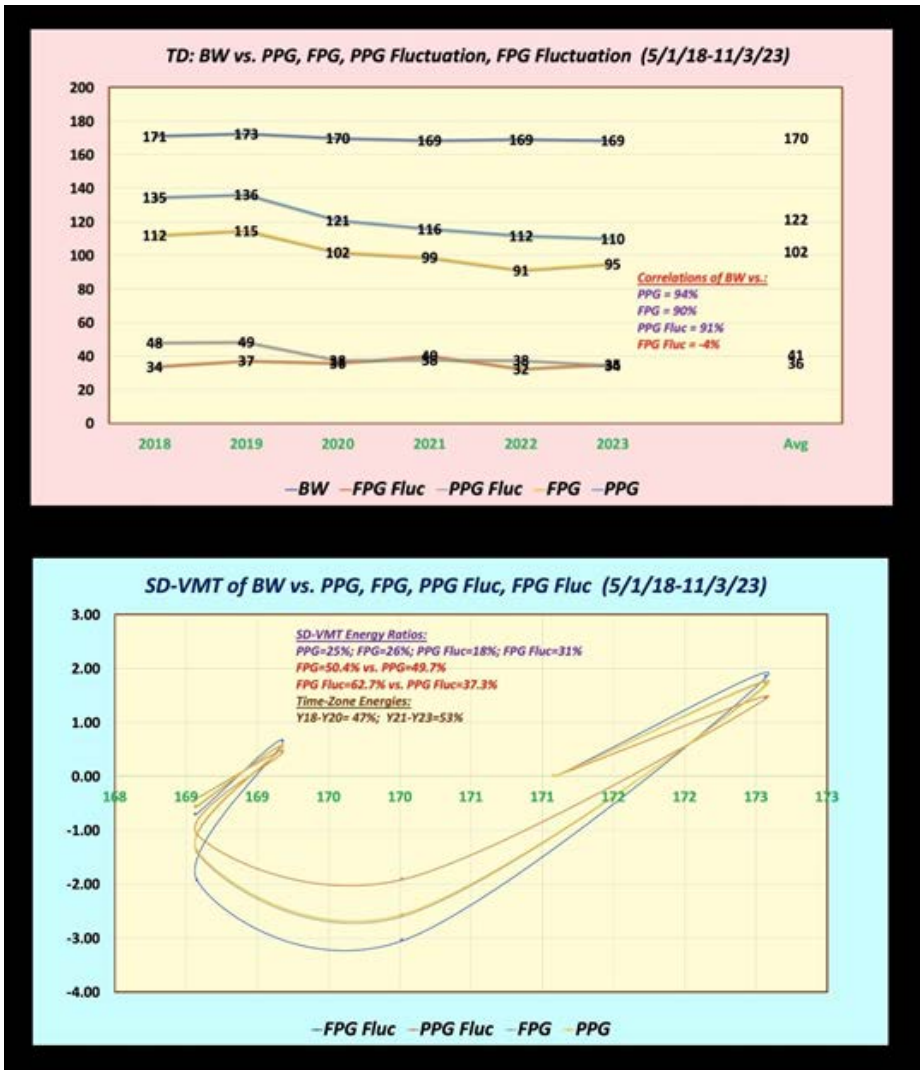
The author utilizes statistical techniques to compute correlation coefficients (R) between two variables: his body weight (BW) and four measures of his glucose levels, namely fasting plasma glucose (FPG) in the early morning, postprandial plasma glucose (PPG) from three meals, maximum PPG minus minimum PPG (PPG fluctuations), and maximum FPG minus minimum FPG (FPG fluctuations). The Timedomain (TD) analysis is conducted for two sub-periods, yielding the following subsequent findings:

8/1/2018 - 11/3/2023:
FPG vs. PPG = 95% FPG fluctuations vs. PPG fluctuations = 24% (low)
1/1/2021 - 11/3/2023:
FPG vs. PPG = 79%
FPG fluctuations vs. PPG fluctuations = 65%
Y18-Y23 annual data correlations of BW vs. 4 biomarkers:
PPG = 94%
FPG = 90%
PPG fluctuations = 91%
FPG fluctuations = -4% (none)

All of the aforementioned correlations surpass 90%, signifying the presence of significant similarities in curve-shape between BW and PPG, FPG, as well as PPG fluctuations. However, there is no correlation (-4%) observed between BEW and FPG fluctuations. This indicates that not only does his FPG fluctuation exhibit a higher average value (36 mg/dL, exceeding the threshold of normal value of 30 mg/ dL), but it also lacks shape similarity (correlation) with his body weight curve. Consequently, ***the biomarker of his FPG fluctuation warrants special attention.***

In summary, *the space-domain Viscoplastic energy analysis reveals that* ***the SD-VMT energy ratios between his FPG and PPG are remarkably similar:***
In 4-inputs diagram:
PPG = 25% & FPG = 26%
In 2-inputs diagram:
PPG = 50.4% & FPG = 49.7%
The energy ratios between his FPG fluctuations and his PPG fluctuations are 1.7 in both 4-inputs and 2-inputs SD-VMT diagrams:
In 4-inputs diagram: PPG fluctuation = 18% & FPG fluctuation = 31% (32/18=1.7)
In 2-inputs diagram:
PPG fluctuation = 37.3% & FPG fluctuation = 62.7% (63.7/37.3=1.7) *In conclusion, the FPG fluctuation stands out as a distinctive biomarker for his diabetes conditions, with no correlation to his body weight and* ***nearly double the amount of energy generated compared to PPG fluctuations.***

This study offers a crucial insight to the author, emphasizing the need for special attention to be given to his FPG fluctuations during nighttime sleep.



1. Introduction

The author utilizes statistical techniques to compute correlation coefficients (R) between two variables: his body weight (BW) and four measures of his glucose levels, namely fasting plasma glucose (FPG) in the early morning, postprandial plasma glucose (PPG) from three meals, maximum PPG minus minimum PPG (PPG fluctuations), and maximum FPG minus minimum FPG (FPG fluctuations). The Timedomain (TD) analysis is conducted for two sub-periods, yielding the following subsequent findings:

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All of the aforementioned correlations surpass 90%, signifying the presence of significant similarities in curve-shape between BW and PPG, FPG, as well as PPG fluctuations. However, there is no correlation (-4%) observed between BEW and FPG fluctuations. This indicates that not only does his FPG fluctuation exhibit a higher average value (36 mg/dL, exceeding the threshold of normal value of 30 mg/ dL), but it also lacks shape similarity (correlation) with his body weight curve. Consequently, ***the biomarker of his FPG fluctuation warrants special attention.***

1.1. Biomedical 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.

1.2. Pathophysiological explanations of high PPG fluctuations

Higher postprandial plasma glucose (PPG) fluctuations in diabetes can be explained by various pathophysiological factors. Here are some key explanations for these fluctuations:

1. Delayed Insulin Response: In diabetes, especially type 2

diabetes, there can be a delay in the insulin response to rising blood sugar levels after a meal. This delayed insulin release can lead to higher PPG levels.

2. Insulin Resistance: Insulin resistance, which is common in type 2 diabetes, means that the body's cells do not respond effectively to insulin. This resistance can make it difficult for glucose to enter cells, leading to higher PPG levels after meals.

3. Glucose Absorption: In the small intestine, carbohydrates from the meal are broken down into glucose and absorbed into the bloodstream. In diabetes, this absorption may not be well-regulated, leading to rapid spikes in PPG levels.

4. Inadequate Insulin Production: In type 1 diabetes, where the pancreas doesn't produce insulin, or in advanced stages of type 2 diabetes, there may be insufficient insulin production to manage the rise in blood sugar after a meal, resulting in higher PPG levels.

5. Hormonal Imbalances: Hormones like glucagon, amylin, and incretins (such as GLP-1) play a role in regulating blood sugar levels after meals. In diabetes, the balance of these hormones can be disrupted, leading to higher PPG levels.

6. Meal Composition: The type and amount of carbohydrates in a meal can significantly affect PPG levels. High-carbohydrate meals, especially when combined with low fiber and low protein, can lead to rapid and high PPG spikes.

7. Gut Hormones: Some gut hormones can influence the rate of digestion and glucose absorption. In diabetes, the regulation of these hormones may be impaired, contributing to PPG fluctuations.

8. Medication or Insulin Timing: The timing and effectiveness of diabetes medications or insulin injections can impact PPG levels. If medication doses are not timed correctly with meals, it can result in higher PPG levels.

9. Glycogen Release: The liver stores glucose as glycogen and releases it into the bloodstream between meals and during exercise. In diabetes, especially during periods of low insulin action, the liver may inappropriately release glycogen, causing higher PPG levels.

Understanding the specific factors contributing to higher PPG fluctuations in an individual with diabetes is crucial for effective management.

1.3. Pathophysiological explanations of high FPG fluctuations

Higher fluctuations in fasting plasma glucose (FPG) levels can be attributed to various pathophysiological factors, including:

1. Insulin Resistance: When cells in the body become resistant to the effects of insulin, glucose uptake is impaired, leading to elevated FPG levels. Insulin resistance is commonly seen in conditions like type 2 diabetes.

2. Dawn Phenomenon: The dawn phenomenon is a natural increase in FPG in the early morning hours due to the release of counterregulatory hormones (e.g., cortisol and growth hormone), which raise blood sugar levels.

3. Somogyi Effect: This occurs when hypoglycemia (low blood sugar) during the night prompts the body to release stress hormones, causing rebound hyperglycemia in the morning.

4. Liver Glucose Output: The liver can release glucose into the bloodstream, and an overactive liver can contribute to high FPG levels.

5. Glycogenolysis: The breakdown of glycogen stored in the liver and muscles can release glucose into the bloodstream, especially during fasting periods.

6. Incretin Hormones: Abnormalities in incretin hormones, like glucagon-like peptide-1 (GLP-1) and glucose-dependent insulinotropic polypeptide (GIP), can affect postmeal glucose regulation and consequently FPG.

7. Medications and Hormones: Certain medications (e.g., corticosteroids) and medical conditions (e.g., Cushing's syndrome) can lead to elevated FPG levels.

8. Stress and Illness: Physical or emotional stress, as well as illness, can lead to the release of stress hormones, which can increase FPG.

9. Diet and Lifestyle: Dietary choices, physical activity, and other lifestyle factors can influence FPG fluctuations. High-carbohydrate meals can cause postprandial hyperglycemia, which may affect FPG. FPG and PPG are inter-related from some perspectives.

10. Hormonal Imbalances: Conditions that affect hormones, such as thyroid disorders or polycystic ovary syndrome (PCOS), can impact glucose regulation.

Understanding the underlying pathophysiology of FPG fluctuations is crucial for effective management and treatment in individuals with diabetes or other glucose-related disorders.

2. Methods

2.1. 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.

2.2. 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 fingerpiercing 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 preCOVID 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 selfquarantined 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 indepth 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 5minute intervals from every 15minute 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 wellbalanced 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.

2.3. 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 laborwork 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. timedependent. *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.***

2.4. 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 ksteps * 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 stressstrain 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:

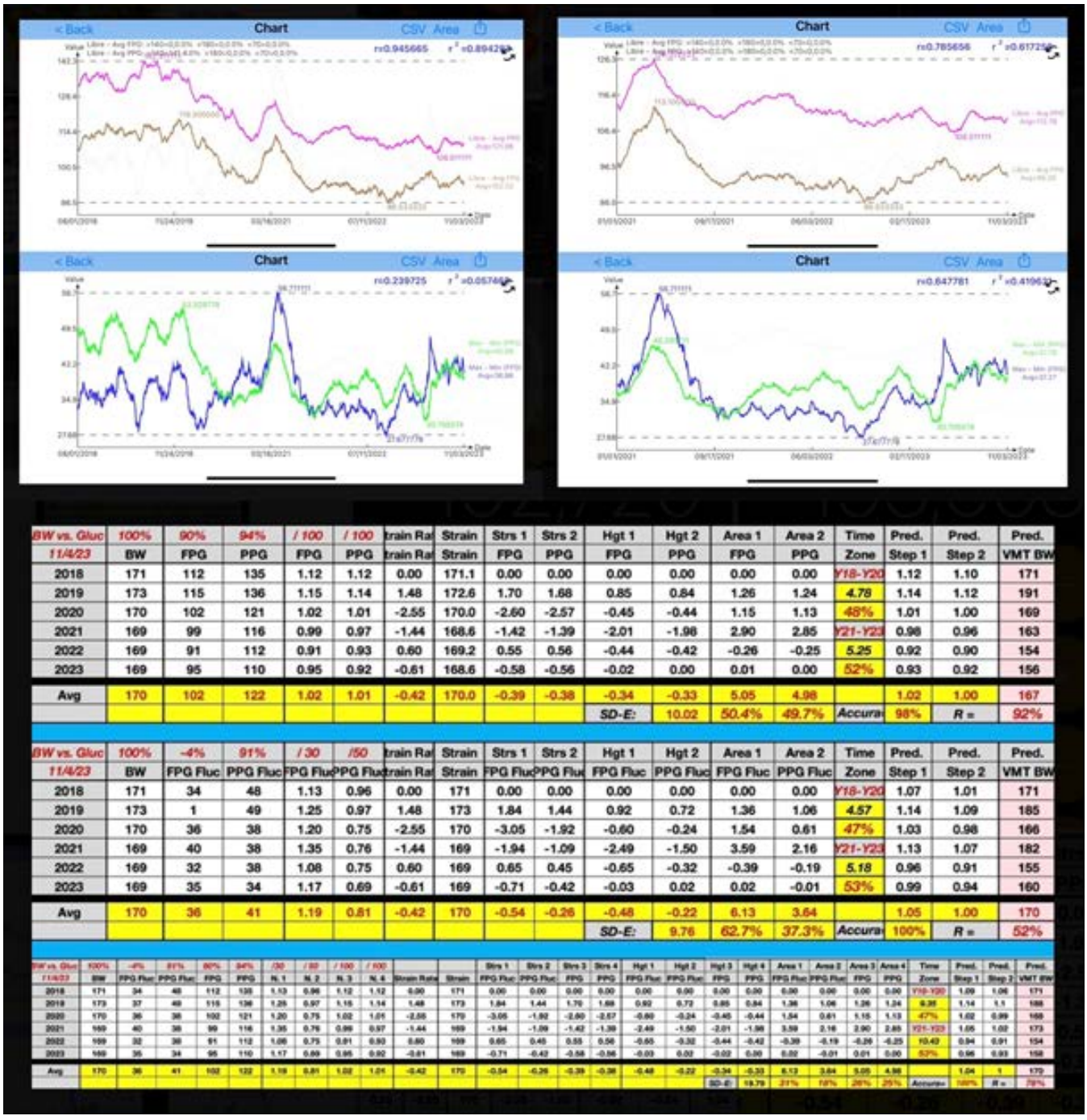
Strain rate = (body weight at next time instant) - (body weight at present time instant)

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 disorderinduced 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).***

3. Results

Figure 1 shows TD chart and SD data tables.



BW vs. Gluc	100%	90%	94%	/ 100	/ 100	train Rat	Strain	Strs 1	Strs 2	Hgt 1	Hgt 2	Area 1	Area 2	Time	Pred.	Pred.	Pred.
11/4/23	BW	FPG	PPG	FPG	PPG	train Rat	Strain	FPG	PPG	FPG	PPG	FPG	PPG	Zone	Step 1	Step 2	VMT BW
2018	171	112	135	1.12	1.12	0.00	171.1	0.00	0.00	0.00	0.00	0.00	0.00	Y18-Y20	1.12	1.10	171
2019	173	115	136	1.15	1.14	1.48	172.6	1.70	1.68	0.85	0.84	1.26	1.24	4.78	1.14	1.12	191
2020	170	102	121	1.02	1.01	-2.55	170.0	-2.60	-2.57	-0.45	-0.44	1.15	1.13	48%	1.01	1.00	169
2021	169	99	116	0.99	0.97	-1.44	168.6	-1.42	-1.39	-2.01	-1.98	2.90	2.85	Y21-Y23	0.98	0.96	163
2022	169	91	112	0.91	0.93	0.60	169.2	0.55	0.56	-0.44	-0.42	-0.26	-0.25	5.25	0.92	0.90	154
2023	169	95	110	0.95	0.92	-0.61	168.6	-0.58	-0.56	-0.02	0.00	0.01	0.00	52%	0.93	0.92	156
Avg	170	102	122	1.02	1.01	-0.42	170.0	-0.39	-0.38	-0.34	-0.33	5.05	4.98		1.02	1.00	167
										SD-E:	10.02	50.4%	49.7%	Accura	98%	R =	92%

BW vs. Gluc	100%	-4%	91%	/ 30	/50	train Rat	Strain	Strs 1	Strs 2	Hgt 1	Hgt 2	Area 1	Area 2	Time	Pred.	Pred.	Pred.
11/4/23	BW	FPG Fluc	PPG Fluc	FPG Fluc	PPG Fluc	train Rat	Strain	FPG Fluc	PPG Fluc	FPG Fluc	PPG Fluc	FPG Fluc	PPG Fluc	Zone	Step 1	Step 2	VMT BW
2018	171	34	48	1.13	0.96	0.00	171	0.00	0.00	0.00	0.00	0.00	0.00	Y18-Y20	1.07	1.01	171
2019	173	1	49	1.25	0.97	1.48	173	1.84	1.44	0.92	0.72	1.36	1.06	4.57	1.14	1.09	185
2020	170	36	38	1.20	0.75	-2.55	170	-3.05	-1.92	-0.60	-0.24	1.54	0.61	47%	1.03	0.98	166
2021	169	40	38	1.35	0.76	-1.44	169	-1.94	-1.09	-2.49	-1.50	3.59	2.16	Y21-Y23	1.13	1.07	182
2022	169	32	38	1.08	0.75	0.60	169	0.65	0.45	-0.65	-0.32	-0.39	-0.19	5.18	0.96	0.91	155
2023	169	35	34	1.17	0.69	-0.61	169	-0.71	-0.42	-0.03	0.02	0.02	-0.01	53%	0.99	0.94	160
Avg	170	36	41	1.19	0.81	-0.42	170	-0.54	-0.26	-0.48	-0.22	6.13	3.64		1.05	1.00	170
										SD-E:	9.76	62.7%	37.3%	Accura	100%	R =	52%

Figure 1: TD Chart and SD Data Tables

Figure 2 shows SD-VMT output energies.

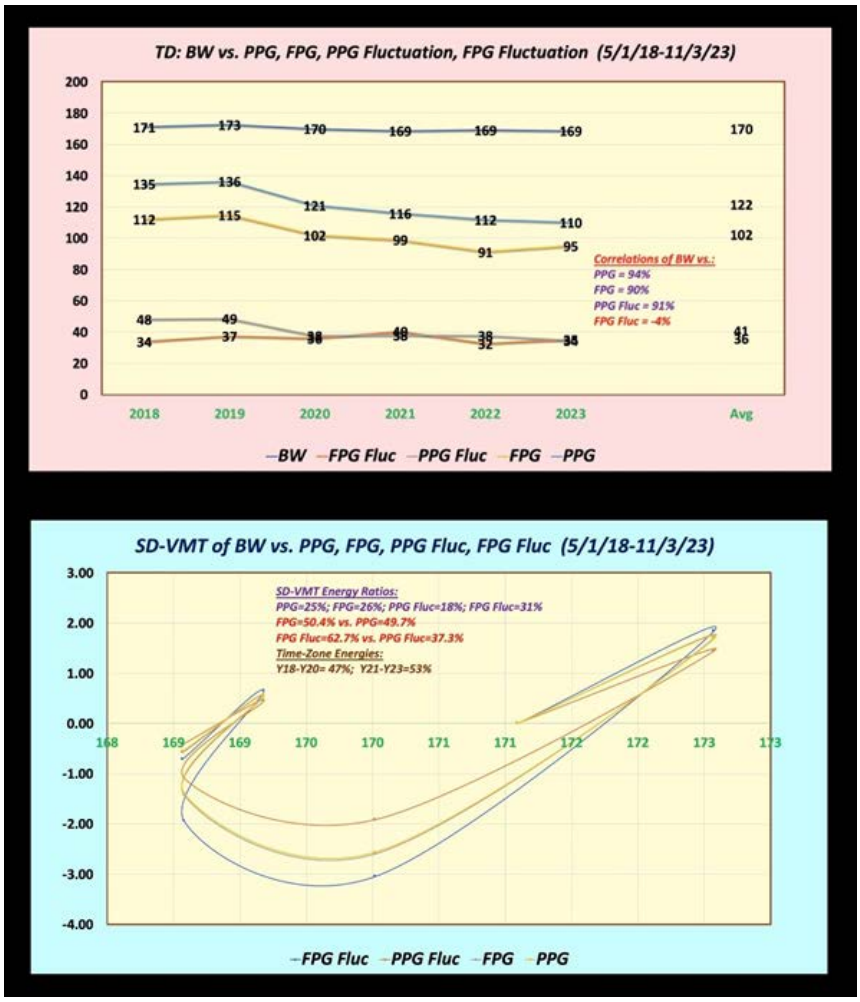


Figure 2: SD-VMT Output Energies

4. Conclusions

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<u>In 4-inputs diagram:</u>

PPG = 25% & FPG = 26%

<u>In 2-inputs diagram:</u>

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<u>In 4-inputs diagram:</u> PPG fluctuation = 18% & FPG fluctuation = 31% (32/18=1.7)

<u>In 2-inputs diagram:</u>

PPG fluctuation = 37.3% & FPG fluctuation = 62.7% (63.7/37.3=1.7) In conclusion, the FPG fluctuation stands out as a distinctive biomarker for his diabetes conditions, with no correlation to his body weight and ***nearly double the amount of energy generated compared to PPG fluctuations.***

This study offers a crucial insight to the author, emphasizing the need for special attention to be given to his FPG fluctuations during nighttime sleep.

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. Readers may use this article as long as the work is properly cited, and their use is educational and not for profit, and the author's original work is not altered.

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