

Importance Of Normalization Factors Through Post-Meal Glucose Versus Three Special PPG Waveform Patterns, Grand Canyon, Himalaya, And Twin Peaks, Using Viscoplastic Energy Model Of GH-Method: Math-Physical Medicine (No.1020, Viscoelastic Medicine Theory #418)

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Category: Methodology & Diabetes

Abstract

This paper explores the relationship between daily postprandial plasma glucose (PPG) and the three special waveform patterns of PPG.

Utilizing a CGM sensor, the author gathered 199,968 glucose data points over a period of 2,083 days (from 5/1/2018 to 1/14/2024) with approximately 96 data collections per day, at 15-minute intervals. A total of 6,249 PPG waveforms of meals were generated, consisting of 399 Himalaya meals (6%), 1,415 Grand Canyon meals (23%), and 908 Twin Peaks meals (15%) out of the total 2,722 meals (44%) analyzed. The remaining 3,527 meals (56%) were excluded from this analysis due to the complexity of combining effect from carb/sugar and walking steps, which resulted in many other waveforms.

Pattern one, "Himalaya", is characterized by a continuous plateau resulting from excessive energy intake from over-consumed meals or additional snacks/fruits, compounded by insufficient energy diffusion due to inactivity after eating.

Pattern two, "Grand Canyon", features a high peak (crest) followed by rapid decay to a low valley (trough), with the lower level sustained. This pattern is mainly associated with sufficient post-meal walking to disperse energy.

Pattern three, "Twin Peak", involves an initial peak similar to the Grand Canyon, followed by second or third peaks resulting from excessive lingering energy infusion from overeating carbs/sugar combined with inadequate energy diffusion resulting from interrupted post-meal exercise.

*Additionally, the author employed the space-domain viscoplastic medicine theory's energy model (SD-VMT) to investigate the relationships between his daily averaged PPG and the aforementioned three PPG waveform patterns using **two sets of different normalization factors**. **The first analysis utilized 120 mg/dL as the normalization factor, while the second analysis utilized the respective percentage of the three PPG waveform patterns over the total meals (6%, 23%, 15%).***

In summary, two sets of findings emerged:

*The first set, utilizing 120 mg/dL as the normalization factors, resulted in **three similar SD-VMT energies** due to the closely matched averaged PPG values for each waveform pattern.*

Himalaya: 31%

Grand Canyon: 33%

Twin peaks: 36%

The second set, using those three PPG waveform pattern's weighting factors of 6%, 23%, 15% as the three normalization factors, resulted in **three markedly different SD-VMT energies**, reflecting the contribution weight of each pattern based on the number of meals.

Himalaya: 15%
Grand Canyon: 53%
Twin peaks: 32%

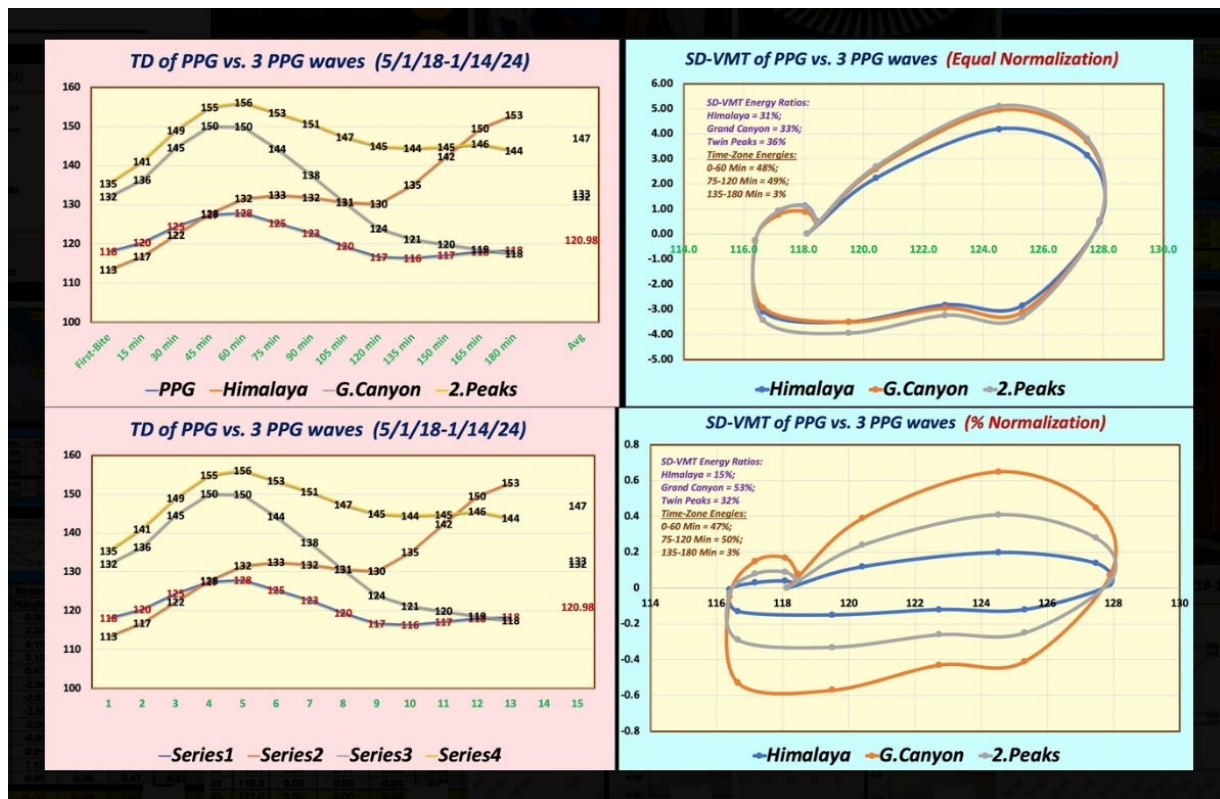
The time-zone energy distributions for these two datasets are highly similar to each other:

0-60 minutes: 47-48%
75-120minutes: 49-50%
135-180 minutes: 3%

This means that the majority of energy from carbohydrate/sugar intake is expended through post-meal walking exercise, leaving only 3% to be stored in the body.

Key Message

The optimal post-meal glucose curve resembles a "Grand Canyon," quickly rising and then dropping rapidly. The "Twin-Peaks" pattern, with two or more high peaks, poses some harm to the body. The "Himalaya" curve, rising to a high plateau and sustaining at that level, leads to the most harm to the body.



1. Introduction

This paper explores the relationship between daily postprandial plasma glucose (PPG) and the three special waveform patterns of PPG.

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3,527 meals (56%) were excluded from this analysis due to the complexity of combining effect from carb/sugar and walking steps, which resulted in many other waveforms.

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Additionally, the author employed the space-domain viscoplastic medicine theory's energy model (SD-VMT) to investigate the relationships between his daily averaged PPG and the aforementioned three PPG waveform patterns using *two sets of different normalization factors. The first analysis utilized 120 mg/dL as the normalization factor, while the second analysis utilized the respective percentage of the three PPG waveform patterns over the total meals (6%, 23%, 15%).*

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. Pathophysiological Explanations and Statistical Evidence of Differences among Daily Glucose, FPG, PPG, And Glucose beside Fasting and Post-Meal (others)

Diabetes is a metabolic disorder that is characterized by elevated levels of glucose in the blood. The understanding of different glucose levels, such as daily glucose, fasting plasma glucose (FPG), postprandial glucose (PPG), and glucose levels aside from fasting and post-meal, is crucial in managing and understanding the pathophysiology of diabetes. Here are the pathophysiological explanations and statistical evidence of the differences among these glucose levels:

2.1 Daily Glucose

Daily glucose levels represent the range of blood sugar levels throughout the day, including before and after meals as well as during periods of fasting. In individuals without diabetes, daily glucose levels typically remain within a narrow range. However, in people with diabetes, there can be significant fluctuations in daily glucose levels due to impaired insulin production or function.

2.1.1 Pathophysiological Explanation

In diabetes, the pathophysiological mechanism involves either insufficient insulin production (Type 1 diabetes) or impaired insulin action (Type 2 diabetes). This leads to an inability of cells to take up glucose effectively, resulting in elevated blood glucose levels throughout the day.

2.1.2 Statistical Evidence

Continuous glucose monitoring (CGM) studies provide statistical evidence of daily glucose fluctuations in individuals

with diabetes. CGM data show patterns of blood sugar levels throughout the day, including postprandial spikes and periods of hypoglycemia or hyperglycemia.

2.2 Fasting Plasma Glucose (FPG)

FPG refers to the glucose level measured after an overnight fast, typically before breakfast in the morning. FPG is an important clinical indicator used in the diagnosis and management of diabetes, as it reflects baseline glucose control.

2.2.1 Pathophysiological Explanation

In diabetes, elevated FPG levels are primarily attributed to increased hepatic glucose production due to reduced insulin action and increased glucagon secretion. This results in higher fasting blood glucose levels.

2.2.2 Statistical Evidence

Large-scale epidemiological studies, such as the National Health and Nutrition Examination Survey (NHANES) and the Diabetes Control and Complications Trial (DCCT), have provided statistical evidence linking elevated FPG levels with an increased risk of diabetes-related complications.

2.3 Postprandial Glucose (PPG)

PPG refers to the glucose level measured after meals, typically 1-2 hours after eating. Postprandial spikes in glucose levels are common in individuals with impaired glucose regulation.

2.3.1 Pathophysiological Explanation

After a meal, the digestion and absorption of carbohydrates lead to an increase in blood glucose. In diabetes, impaired insulin secretion or action can result in inadequate postprandial glucose control, leading to elevated PPG levels.

2.3.2 Statistical Evidence

Studies have demonstrated that high PPG levels are associated with an increased risk of cardiovascular disease and microvascular complications in diabetes patients. These studies include clinical trials such as the ACCORD trial and the DECODE study.

2.4 Glucose Levels Beside Fasting and Post-Meal (Others)

This category encompasses glucose levels measured at various times throughout the day, including random glucose measurements. These levels can provide insight into glucose variability and control at different times.

2.4.1 Pathophysiological Explanation

Fluctuations in glucose levels besides fasting and post-meal are influenced by factors such as physical activity, stress, medication dosing, and hormonal fluctuations. In diabetes, inadequate glucose control can lead to erratic glucose levels throughout the day.

2.4.2 Statistical Evidence

Ambulatory glucose monitoring and studies using continuous glucose monitoring (CGM) devices have provided statistical evidence of glucose variability and its impact on diabetes management and complications.

In summary, understanding these different glucose levels and

their pathophysiological implications is crucial for effectively managing diabetes and reducing the risk of associated complications. Statistical evidence from clinical trials, epidemiological studies, and continuous monitoring technologies has helped elucidate the impact of daily glucose fluctuations on diabetes-related outcomes.

3. Pathophysiological explanations of different PPG waveform patterns

The pathophysiological explanations for different postprandial glucose (PPG) waveform patterns are based on how the body metabolizes glucose after a meal.

"Grand Canyon" Pattern: This pattern, characterized by a quick rise and rapid drop in postprandial glucose levels, is associated with efficient insulin response and glucose uptake by the cells. It indicates a healthy metabolism, with insulin quickly acting to facilitate glucose absorption by tissues, resulting in a rapid reduction of blood sugar levels.

"Twin-Peaks" Pattern: The "Twin-Peaks" pattern, featuring two or more high peaks in postprandial glucose, may indicate a delayed or prolonged insulin response. This delayed response could result in continued glucose release from the liver into the bloodstream, leading to sustained high glucose levels after the meal, potentially causing stress on the pancreas and leading to insulin resistance over time.

"Himalaya" Pattern: The "Himalaya" pattern shows a prolonged plateau of high postprandial glucose levels, hyperglycemia, potentially indicating an inadequate or prolonged insulin response. This pattern suggests inefficient glucose uptake by tissues and prolonged presence of high glucose in the bloodstream, which can lead to chronic hyperglycemia and contribute to the development of diabetes-related complications.

In summary, the pathophysiological explanations for these three PPG waveform patterns are closely tied to the efficiency of insulin response, glucose uptake, and the subsequent impact on blood glucose levels post-meal.

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 ($d\epsilon/dt$)**

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

Figure 1 shows data tables.

3 PPG: A					/ 120			S. Rate	Strain	Stress 1	Stress 2	Stress 3	Height 1	Height 2	Height 3	Area 1	Area 2	Area 3		Pred.	Pred.	Pred.
1/14/24	PPG	Himalaya	G.Canyon	2.Peaks	Himalaya	G.Canyon	2.Peaks	PPG	PPG	Himalaya	G.Canyon	2.Peaks	Himalaya	G.Canyon	2.Peaks	Himalaya	G.Canyon	2.Peaks	Time-Zone	Step 1	Step 2	PPG
First-Bite	118	113	132	135	0.95	1.1	1.13	0.00	118.1	0.00	0.00	0.00	0.00	0.00	0.00	0.0	0.0	0.0	0-60 Min	1.06	0.93	118.1
15 min	120	117	136	141	0.97	1.14	1.18	2.29	120.4	2.23	2.60	2.69	1.11	1.30	1.35	2.6	3.0	3.1	92.5	1.1	0.96	116.0
30 min	125	122	145	149	1.02	1.2	1.24	4.11	124.5	4.19	4.95	5.10	3.21	3.78	3.90	13.2	15.5	16.0	48%	1.16	1.01	122.4
45 min	127	128	150	155	1.06	1.25	1.29	2.94	127.5	3.13	3.68	3.80	3.66	4.31	4.45	10.8	12.7	13.1		1.21	1.05	127.4
60 min	128	132	150	156	1.1	1.25	1.3	0.43	127.9	0.47	0.54	0.56	1.80	2.11	2.18	0.8	0.9	0.9		1.22	1.06	128.8
75 min	125	133	144	153	1.1	1.2	1.28	-2.59	125.3	-2.86	-3.11	-3.31	-1.19	-1.29	-1.38	3.1	3.3	3.6	75-120 Min	1.2	1.05	126.5
90 min	123	132	138	151	1.1	1.15	1.26	-2.58	122.7	-2.83	-2.96	-3.24	-2.85	-3.04	-3.28	7.4	7.8	8.5	95.0	1.17	1.02	123.5
105 min	120	131	131	147	1.09	1.09	1.23	-3.22	119.5	-3.50	-3.51	-3.95	-3.17	-3.23	-3.60	10.2	10.4	11.6	49%	1.14	0.99	120.0
120 min	117	130	124	145	1.09	1.03	1.21	-2.85	116.7	-3.09	-2.94	-3.44	-3.30	-3.23	-3.70	9.4	9.2	10.5		1.11	0.97	117.2
135 min	116	135	121	144	1.13	1.01	1.2	-0.26	116.4	-0.29	-0.26	-0.31	-1.69	-1.60	-1.88	0.4	0.4	0.5	135-180 Min	1.12	0.97	117.6
150 min	117	142	120	145	1.19	1	1.21	0.77	117.2	0.91	0.77	0.93	0.31	0.25	0.31	0.2	0.2	0.2	5.5	1.13	0.99	119.2
165 min	118	150	119	146	1.25	0.99	1.21	0.90	118.1	1.12	0.89	1.09	1.02	0.83	1.01	0.9	0.8	0.9	3%	1.15	1	121.1
180 min	118	153	118	144	1.27	0.98	1.2	0.39	118.5	0.50	0.38	0.47	0.81	0.64	0.78	0.3	0.3	0.3		1.15	1	121.1
Avg	121	132	133	147	1.1	1.11	1.23	0.03	121.0	0.00	0.08	0.03	-0.02	0.06	0.01	59.2	64.5	69.2		1.15	1	121.4
Correlation	100%	-26%	94%	81%										SD-E:	192.91	31%	33%	36%	Accuracy=	98%	R =	89%

3 PPG: B					6 /			S. Rate	Strain	Stress 1	Stress 2	Stress 3	Height 1	Height 2	Height 3	Area 1	Area 2	Area 3		Pred.	Pred.	Pred.
1/14/24	PPG	Himalaya	G.Canyon	2.Peaks	N. 1	N. 2	N. 3	PPG	PPG	Himalaya	G.Canyon	2.Peaks	Himalaya	G.Canyon	2.Peaks	Himalaya	G.Canyon	2.Peaks	Time-Zone	Step 1	Step 2	PPG
First-Bite	118	113	132	135	0.05	0.17	0.11	0	118.1	0	0	0	0	0	0	0	0	0	0-60 Min	0.14	1.03	118.13
15 min	120	117	136	141	0.05	0.17	0.11	2.29	120.4	0.12	0.39	0.24	0.06	0.19	0.12	0.1	0.4	0.3	8.4	0.13	0.99	120.15
30 min	125	122	145	149	0.05	0.16	0.1	4.11	124.5	0.20	0.65	0.41	0.16	0.52	0.33	0.7	2.1	1.4	47%	0.12	0.94	113.6
45 min	127	128	150	155	0.05	0.15	0.1	2.94	127.5	0.14	0.45	0.28	0.17	0.55	0.35	0.5	1.6	1.0		0.12	0.9	109.3
60 min	128	132	150	156	0.05	0.15	0.1	0.43	127.9	0.02	0.07	0.04	0.08	0.26	0.16	0.0	0.1	0.1		0.12	0.9	109.0
75 min	125	133	144	153	0.05	0.16	0.1	-2.59	125.3	-0.12	-0.41	-0.25	-0.05	-0.17	-0.11	0.1	0.5	0.3	75-120 Min	0.12	0.93	112.3
90 min	123	132	138	151	0.05	0.17	0.1	-3.22	119.5	-0.12	-0.43	-0.26	-0.12	-0.42	-0.26	0.3	1.1	0.7	8.7	0.13	0.96	116.7
105 min	120	131	131	147	0.05	0.18	0.1	-3.22	119.5	-0.15	-0.57	-0.33	-0.13	-0.50	-0.29	0.4	1.6	0.9	50%	0.13	1.01	121.7
120 min	117	130	124	145	0.05	0.19	0.1	-2.85	116.7	-0.13	-0.53	-0.29	-0.14	-0.55	-0.31	0.4	1.6	0.9		0.14	1.05	126.8
135 min	116	135	121	144	0.04	0.19	0.1	-0.26	116.4	-0.01	-0.05	-0.03	-0.07	-0.29	-0.16	0.0	0.1	0.0	135-180 Min	0.14	1.06	128.7
150 min	117	142	120	145	0.04	0.19	0.1	0.77	117.2	0.03	0.15	0.08	0.01	0.05	0.03	0.0	0.0	0.0	0.6	0.14	1.07	129.4
165 min	118	150	119	146	0.04	0.19	0.1	0.90	118.1	0.04	0.17	0.09	0.03	0.16	0.09	0.0	0.1	0.1	3%	0.14	1.07	129.9
180 min	118	153	118	144	0.04	0.2	0.1	0.39	118.5	0.02	0.08	0.04	0.03	0.13	0.07	0.0	0.1	0.0		0.14	1.08	131.0
Avg	121	132	133	147	0.05	0.17	0.1	0.03	121.0	0.00	0.00	0.00	0.00	-0.01	0.00	2.7	9.3	5.7		0.13	1	120.5
Correlation	100%	-26%	94%	81%										SD-E:	17.62	15%	53%	32%	Accuracy=	98%	R =	-92%

Figure 1: Two data tables

Figure 2 shows three POG waveform patterns and summary table.

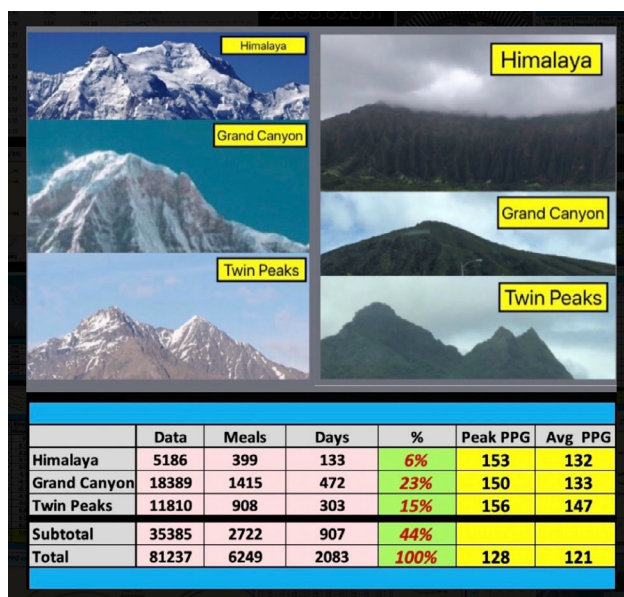


Figure 2: Three POG waveform patterns and summary table

Figure 3 shows two inputs and SD-VMT energy output diagrams.

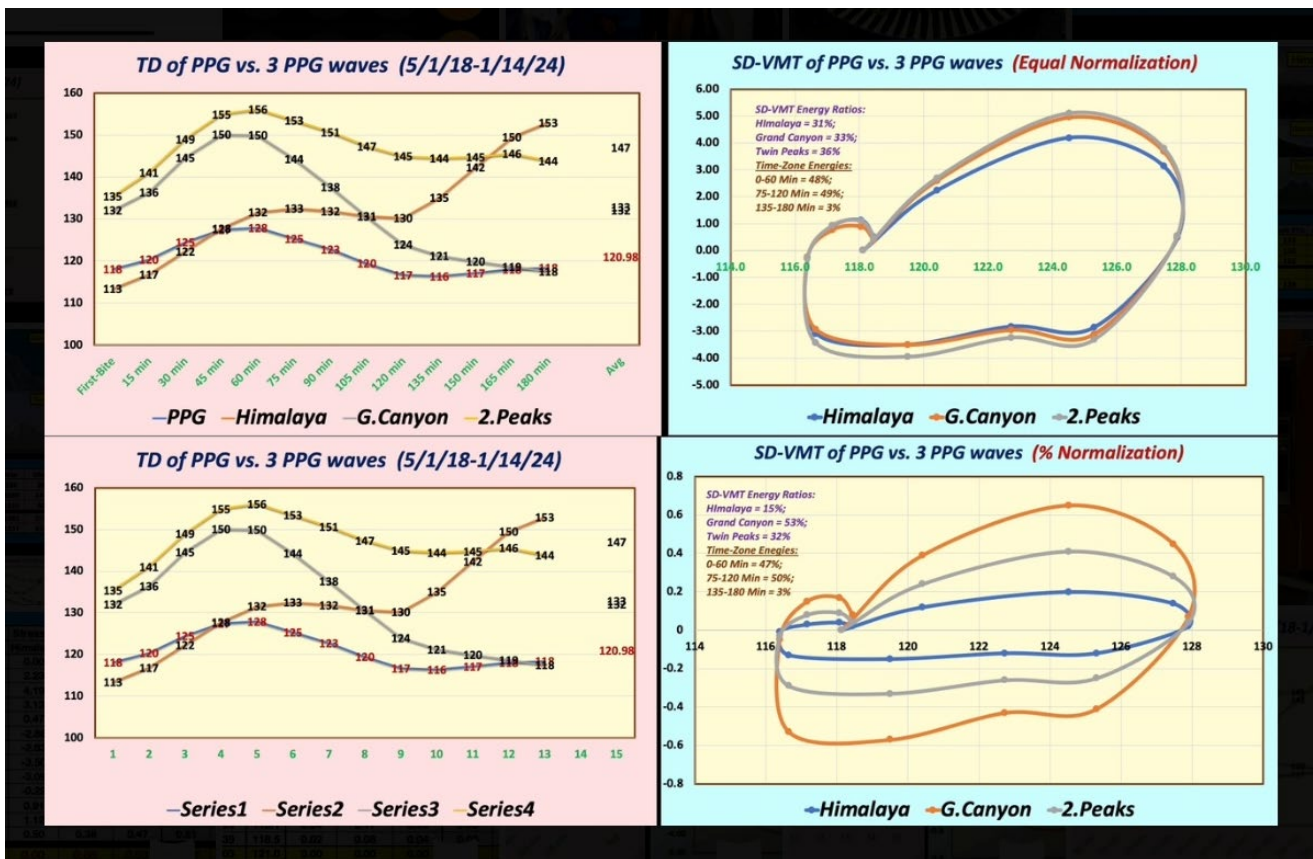


Figure 3: Two input and SD-VMT energy output diagrams

8. Conclusions

In summary, two sets of findings emerged:

The first set, utilizing 120 mg/dL as the normalization factors, resulted in *three similar SD-VMT energies* due to the closely matched averaged PPG values for each waveform pattern.

Himalaya: 31%

Grand Canyon: 33%

Twin peaks: 36%

The second set, using those three PPG waveform pattern's weighting factors of 6%, 23%, 15% as the three normalization factors, resulted in *three markedly different SD-VMT energies*, reflecting the contribution weight of each pattern based on the number of meals.

Himalaya: 15%

Grand Canyon: 53%

Twin peaks: 32%

The time-zone energy distributions for these two datasets are highly similar to each other:

0-60 minutes: 47-48%

75-120minutes: 49-50%

135-180 minutes: 3%

This means that the majority of energy from carbohydrate/sugar intake is expended through post-meal walking exercise, leaving only 3% to be stored in the body.

Key Message

The optimal post-meal glucose curve resembles a "Grand Canyon," quickly rising and then dropping rapidly. The "Twin-Peaks" pattern, with two or more high peaks, poses some harm to the body. The "Himalaya" curve, rising to a high plateau and sustaining at that level, leads to the most harm to the body.

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.eclairermd.com.

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