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Research Article

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An Re-Examination of PPG Curve and its 5 Component Curves Using Signal Processing Techniques and Viscoplastic Energy Model of Gh-Method: Math-Physical Medicine (No. 1016, Viscoelastic Medicine Theory #414)

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Category: Methodology & Diabetes

Abstract

The author's first article, number 013 published on 3/17/2019, applied signal processing techniques to predict his postprandial plasma glucose (PPG) levels using data collected over four years (from 5/1/18 to 3/19/19). Subsequently, in his article number 1016, the author re-examined his PPG curve using five component waveforms of the composite PPG waveform. These five components are derived from the insulin resistance state indicated by 70% of his fasting glucose levels in the early morning (Base), sugar and carbohydrate intake (food), post-meal walking exercise (Steps), ambient temperature (Temp), and a combined curve from about 20 other minor influential factors (Others). The generation of these five component waveforms utilized signal processing techniques detailed in the Introduction section of this article. This study used a total of nine years of collected data, with approximately five additional years of data collected from the author's own body (between 3/20/19 and 12/31/23).

Additionally, the author applied the space-domain viscoplastic medicine theory's energy model (SD-VMT) to analyze these five waveforms of both major and minor influential factors.

***In summary,** the five correlations of his five component curves versus his total PPG curve are:*
Base = 88%;
Good = 97%;
Steps = 85%;
Temp = -10%;
Others = -44%.

SD-VMT energy ratios of his composite PPG curve versus
Base = 71%;
Good = 11%;
Steps = 12%;
Temp = 4%;
Others = 1%.
(Insulin resistance demonstrated through FPG is the primary factor, with food and exercise considered secondary factors, whereas temperature and other minor factors are considered insignificant).

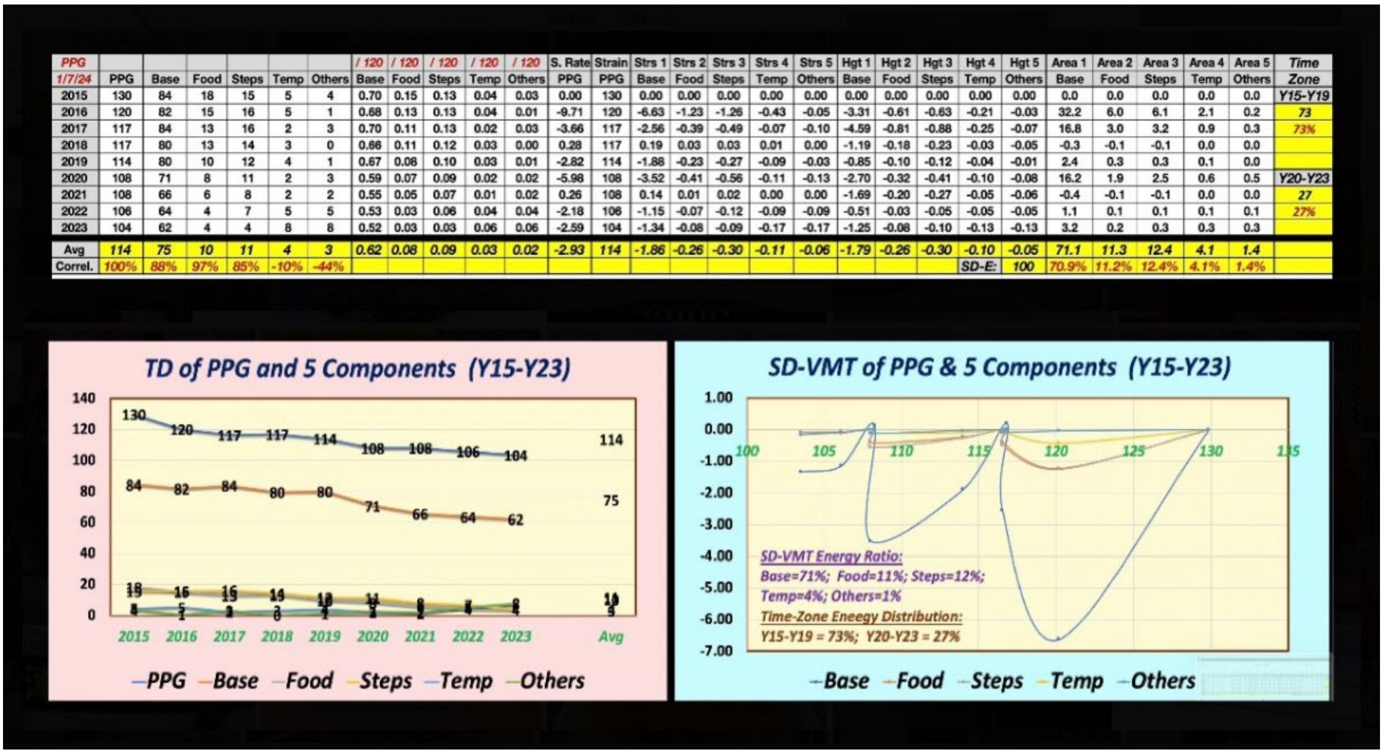
The time-zone energy distributions are:
Y2015-Y2019 = 73%
Y2020-Y2023 = 23%
(The preceding 5 years contribute three-quarters, the majority, of the total energy associated with his composite PPG curve, while the recent 4 years contribute about a quarter of the total PPG energy).

During this selected period of 8.6 years (from 8/1/2015 to 12/31/2023), his averaged PPG values are:

Predicted: 112.80 mg/dL
Measured: 112.45 mg/dL
Prediction accuracy = 99.7%
Correlation = 79%.

Key Message

The health of pancreatic beta cells, particularly their insulin production and quality, is the primary determinant of the composite postprandial plasma glucose (PPG) waveform, accounting for 71% of its variation. Food intake and physical activity are secondary factors, contributing 11% and 12% respectively. Ambient temperature and 20 other minor factors have a negligible impact, together comprising only 5% of the composite PPG waveform's variation. The predicted PPG using signal processing techniques has exceptionally high accuracy, with a 99.7% prediction accuracy.



PPG 1/7/24	PPG	Base	Food	Steps	Temp	Others	/ 120 Base	/ 120 Food	/ 120 Steps	/ 120 Temp	/ 120 Others	S. Rate PPG	Strain PPG
2015	130	84	18	15	5	4	0.70	0.15	0.13	0.04	0.03	0.00	130
2016	120	82	15	16	5	1	0.68	0.13	0.13	0.04	0.01	-9.71	120
2017	117	84	13	16	2	3	0.70	0.11	0.13	0.02	0.03	-3.66	117
2018	117	80	13	14	3	0	0.66	0.11	0.12	0.03	0.00	0.28	117
2019	114	80	10	12	4	1	0.67	0.08	0.10	0.03	0.01	-2.82	114
2020	108	71	8	11	2	3	0.59	0.07	0.09	0.02	0.02	-5.98	108
2021	108	66	6	8	2	2	0.55	0.05	0.07	0.01	0.02	0.26	108
2022	106	64	4	7	5	5	0.53	0.03	0.06	0.04	0.04	-2.18	106
2023	104	62	4	4	8	8	0.52	0.03	0.03	0.06	0.06	-2.59	104
Avg	114	75	10	11	4	3	0.62	0.08	0.09	0.03	0.02	-2.93	114
Correl.	100%	88%	97%	85%	-10%	-44%							

PPG 1/7/24	Strs 1 Base	Strs 2 Food	Strs 3 Steps	Strs 4 Temp	Strs 5 Others	Hgt 1 Base	Hgt 2 Food	Hgt 3 Steps	Hgt 4 Temp	Hgt 5 Others	Area 1 Base	Area 2 Food	Area 3 Steps	Area 4 Temp	Area 5 Others	Time Zone
2015	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.0	0.0	0.0	0.0	0.0	Y15-Y19
2016	-6.63	-1.23	-1.26	-0.43	-0.05	-3.31	-0.61	-0.63	-0.21	-0.03	32.2	6.0	6.1	2.1	0.2	73
2017	-2.56	-0.39	-0.49	-0.07	-0.10	-4.59	-0.81	-0.88	-0.25	-0.07	16.8	3.0	3.2	0.9	0.3	73%
2018	0.19	0.03	0.03	0.01	0.00	-1.19	-0.18	-0.23	-0.03	-0.05	-0.3	-0.1	-0.1	0.0	0.0	
2019	-1.88	-0.23	-0.27	-0.09	-0.03	-0.85	-0.10	-0.12	-0.04	-0.01	2.4	0.3	0.3	0.1	0.0	
2020	-3.52	-0.41	-0.56	-0.11	-0.13	-2.70	-0.32	-0.41	-0.10	-0.08	16.2	1.9	2.5	0.6	0.5	Y20-Y23
2021	0.14	0.01	0.02	0.00	0.00	-1.69	-0.20	-0.27	-0.05	-0.06	-0.4	-0.1	-0.1	0.0	0.0	27
2022	-1.15	-0.07	-0.12	-0.09	-0.09	-0.51	-0.03	-0.05	-0.05	-0.05	1.1	0.1	0.1	0.1	0.1	27%
2023	-1.34	-0.08	-0.09	-0.17	-0.17	-1.25	-0.08	-0.10	-0.13	-0.13	3.2	0.2	0.3	0.3	0.3	
Avg	-1.86	-0.26	-0.30	-0.11	-0.06	-1.79	-0.26	-0.30	-0.10	-0.05	71.1	11.3	12.4	4.1	1.4	
Correl.									SD-E:	100	70.9%	11.2%	12.4%	4.1%	1.4%	

1. Introduction

The author's first article, number 013 published on 3/17/2019, applied signal processing techniques to predict his postprandial plasma glucose (PPG) levels using data collected over four years (from 5/1/18 to 3/19/19). Subsequently, in his article number 1016, the author re-examined his PPG curve using five component waveforms of the composite PPG waveform. These five components are derived from the insulin resistance state indicated by 70% of his fasting glucose levels in the early morning (Base), sugar and carbohydrate intake (food), post-meal walking exercise (Steps), ambient temperature (Temp), and a combined curve from about 20 other minor influential factors (Others). The generation of these five component waveforms utilized signal processing techniques detailed in the Introduction section of this article. This study used a total of nine years of collected data, with approximately five additional years of data collected from the author's own body (between 3/20/19 and 12/31/23).

Additionally, the author applied the space-domain viscoplastic medicine theory's energy model (SD-VMT) to analyze these five waveforms of both major and minor influential factors.

1.1 Engineering and 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.

2. What are Common Signal Processing Techniques?

Signal processing is a field of electronics and electrical engineering and applied mathematics that deals with the manipulation and analysis of signals. Here are some signal processing techniques commonly used:

2.1 Filtering

This technique involves the removal of unwanted noise from signals or the separation of desired frequencies from a mixture of signals.

2.2 Fourier Transform
This mathematical technique is used to decompose a signal into its constituent frequencies, allowing for frequency analysis and filtering.

2.3 Wavelet Transform
Similar to Fourier Transform, Wavelet Transform breaks down a signal into different time-frequency components, making it useful for analyzing non-stationary signals.

2.4 Digital Filtering
The process of applying digital algorithms to manipulate and enhance signals, including techniques such as Finite Impulse Response (FIR) and Infinite Impulse Response (IIR) filtering.

2.5 Time-Frequency Analysis
Methods such as Short-Time Fourier Transform (STFT) and spectrogram analysis to understand how the frequency content of a signal changes over time.

2.6 Adaptive Filtering
Techniques that adjust filter characteristics based on the changing properties of a signal, useful for applications like noise cancellation and signal enhancement.

These techniques are used in a wide range of applications, including audio and speech processing, biomedical signal analysis, communication systems, image processing, and more.

(Note by the author: The author of this article has spent 11 years on various semiconductor chip designs which dealt with signal processing applications.)

3. How to Decompose one Signal Waveform into Multiple Constitute Waveforms?
There are several methods to decompose a signal waveform into multiple component waveforms. One common approach is to use the technique of signal decomposition known as "Wavelet Transform." The Wavelet Transform breaks down a signal into different time-frequency components, which allows for the analysis of both time and frequency characteristics of the signal. Here's a high-level overview of the process:

3.1 Continuous Wavelet Transform (CWT)
The CWT is applied to a ***continuous-time signal***. It involves convolving the signal with a scaled and translated version of a mother wavelet function. The resulting coefficients correspond to the time-frequency representation of the signal.

3.2 Discrete Wavelet Transform (DWT)
The DWT applies a similar concept, but it operates on ***discrete-time signals.*** It decomposes the signal into approximation and detail coefficients at different scales and positions.

The wavelet transform allows for the extraction of information at different scales or resolutions, which can reveal the presence of specific frequency components or transient features in the signal. This makes it a powerful tool for analyzing non-stationary signals and for denoising applications.

Other techniques such as the Short-Time Fourier Transform (STFT), empirical mode decomposition (EMD), and independent component analysis (ICA) can also be used to decompose a signal into its constituent components based on different mathematical principles and assumptions. Each method has its own strengths and is suited for different types of signals and applications.

4. How to decompose a Combined Signal into Several Component Waveforms Using Signal Processing Techniques?
It is possible to decompose a combined signal wave into several component waveforms using signal processing techniques. This process is known as ***signal decomposition or signal demodulation***, and it is a common practice in fields such as communications, audio processing, and biomedical signal analysis.

One of the widely used techniques for decomposing signals is the ***Fourier transform,*** which can express a signal as a combination of sinusoids of different frequencies. The signal can be decomposed into its frequency components, allowing for the separation of individual waveforms present in the original mixed signal.

Another common approach is the use of ***wavelet transforms***, which are particularly useful for signals that contain components of varying frequency and time localization. Wavelet transforms can decompose a signal into various scales and provide a time-frequency representation of the signal, making it easier to identify and isolate specific components.

Additionally, techniques such as independent component analysis (ICA) and empirical mode decomposition (EMD) are used to decompose a signal into statistically independent or intrinsic mode functions, respectively, which represent the underlying components of the signal.

These techniques are valuable for extracting meaningful information and identifying specific features within complex signals. The decomposed components can then be analyzed individually or processed further to extract relevant information for various applications, such as noise reduction, ***feature extraction, or pattern recognition.***

Overall, signal processing techniques offer powerful tools for decomposing combined signals into their component waveforms, enabling a deeper understanding and analysis of the underlying information contained within the original signal.

5. Statistical Correlation Strengths Between PPG Versus Insulin Resistance, Food, Exercise, and Ambient Temperature
The strength of statistical correlations between PPG (postprandial plasma glucose) and various factors such as insulin resistance, food, exercise, and ambient temperatures can vary based on individual characteristics, study populations, and measurement methods. ***Correlation does not necessarily imply causation.*** However, here are some general trends:

5.1 Insulin Resistance
There is typically a strong correlation between postprandial

glucose levels and insulin resistance. Insulin resistance can lead to impaired glucose uptake by cells, resulting in elevated postprandial glucose levels.

5.2 Food

Postprandial glucose levels are directly affected by the composition and quantity of food consumed. Especially, carbohydrate or sugar rich meals tend to have a stronger impact on postprandial glucose levels compared to protein or fat-rich meals. Therefore, ***there can be a moderate to strong correlation between food intake and PPG levels.***

5.3 Exercise

Regular exercise can have a positive impact on glucose metabolism, leading to better glucose control. As a result, ***there may be a moderate negative correlation between exercise and postprandial glucose levels.*** However, the immediate effect of exercise on postprandial glucose can vary based on the timing, intensity, and duration of the activity. ***(Note from the author: He typically begins his post-meal walking exercise 60 minutes after taking his first bite of the meal. Sugary foods tend to elevate his PPG starting around 5-10 minutes after eating, while carbohydrate-rich foods typically elevate his PPG starting around 15-30 minutes after eating.)***

5.4 Ambient Temperatures

While ambient temperatures may have some influence on metabolism, ***the direct correlation between ambient temperatures and postprandial glucose levels is generally not well-defined.*** However, extreme temperatures can affect physical activity levels, which in turn could impact postprandial glucose levels.

It is important to note that these correlations can be influenced by numerous confounding factors, including individual variations, medication use, and other lifestyle factors. Therefore, it is always important to consider the complex interplay of multiple variables when studying the relationship between postprandial glucose and external factors.

6. Pathophysiologically, What Strength of Biomedical Connections Between PPG Versus Insulin Resistance, Carbs and Sugar Intake Amount, Post-Meal Exercise Level, and Ambient Temperature?

The pathophysiological connections between postprandial plasma glucose (PPG) levels and various factors such as insulin resistance, carbohydrate/sugar intake, post-meal exercise, and ambient temperature are complex and multifaceted. Here is a brief overview based on current understanding:

6.1 Insulin Resistance

Insulin resistance is a key pathophysiological factor influencing postprandial glucose levels. In individuals with insulin resistance, cells may not respond efficiently to insulin, leading to reduced glucose uptake and increased PPG levels. Over time, chronic hyperglycemia can contribute to the progression of insulin resistance, creating a cyclical relationship between PPG and insulin resistance. ***(Note from the author: According to his research, insulin resistance may be indicated through its linkage with the fasting glucose levels in the early morning which without significant influences from lifestyle details. Insulin responses is the most critical influencing factor for PPG levels and the daily average glucose levels. This underscores the significance of the health state of pancreatic beta cells.)***

6.2 Carbohydrates and Sugar

Carbohydrate-rich foods are directly linked to PPG levels due to their impact on blood glucose. Carbohydrates are broken down into glucose, leading to a rapid rise in blood sugar levels. Similarly, foods high in added sugars can exacerbate postprandial hyperglycemia, especially in individuals with compromised glucose metabolism.

6.3 Post-Meal Exercise

Physical activity following a meal can influence PPG levels through several mechanisms. Exercise increases glucose uptake by skeletal muscles, thus reducing PPG levels in blood vessels. Additionally, it can enhance insulin sensitivity, potentially mitigating the impact of insulin resistance on postprandial glucose.

6.4 Ambient Temperature

The relationship between ambient temperature and PPG levels is not as well defined from a pathophysiological perspective. However, extreme temperatures can affect physical activity levels, medication absorption rates, and other metabolic processes, which may indirectly impact PPG regulation.

It's important to recognize that these factors interact with one another in a dynamic and individual-specific manner. For example, in individuals with insulin resistance, the impact of carbohydrate intake and post-meal exercise on PPG levels may be particularly pronounced. Additionally, other factors such as medication use, hormonal influences, and overall metabolic health can further modulate the connections between these variables.

Ultimately, the pathophysiological connections between PPG and these factors underscore the importance of a comprehensive approach to managing postprandial glucose levels, encompassing dietary interventions, physical activity, medication management, and individualized lifestyle modifications.

7. 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.

8. 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.

9. 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:

S***tress***
= 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:

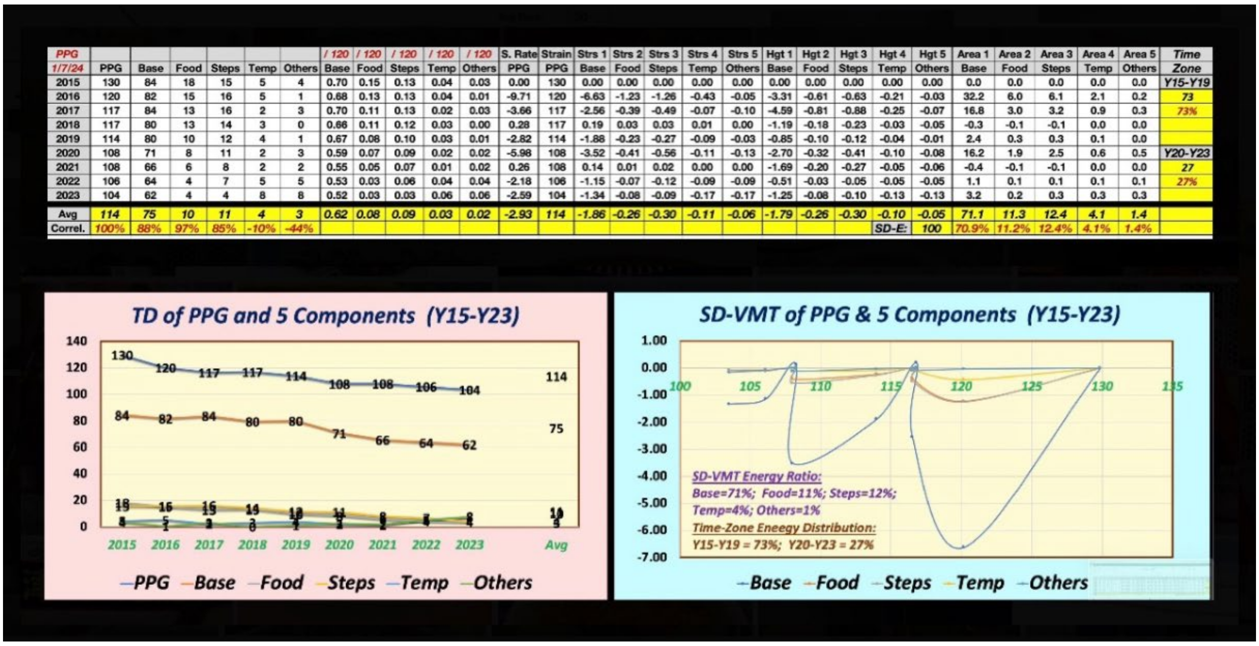
Strain rate
= (body weight at next time instant) - (body weight at present time instant)

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).***

10. Results

Figure 1 shows data table, inputs and SD-VMT energy output diagram.



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2018	117	80	13	14	3	0	0.66	0.11	0.12	0.03	0.00	0.28	117
2019	114	80	10	12	4	1	0.67	0.08	0.10	0.03	0.01	-2.82	114
2020	108	71	8	11	2	3	0.59	0.07	0.09	0.02	0.02	-5.98	108
2021	108	66	6	8	2	2	0.55	0.05	0.07	0.01	0.02	0.26	108
2022	106	64	4	7	5	5	0.53	0.03	0.06	0.04	0.04	-2.18	106
2023	104	62	4	4	8	8	0.52	0.03	0.03	0.06	0.06	-2.59	104
Avg	114	75	10	11	4	3	0.62	0.08	0.09	0.03	0.02	-2.93	114
Correl.	100%	88%	97%	85%	-10%	-44%							

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2015	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.0	0.0	0.0	0.0	0.0	Y15-Y19
2016	-6.63	-1.23	-1.26	-0.43	-0.05	-3.31	-0.61	-0.63	-0.21	-0.03	32.2	6.0	6.1	2.1	0.2	73
2017	-2.56	-0.39	-0.49	-0.07	-0.10	-4.59	-0.81	-0.88	-0.25	-0.07	16.8	3.0	3.2	0.9	0.3	73%
2018	0.19	0.03	0.03	0.01	0.00	-1.19	-0.18	-0.23	-0.03	-0.05	-0.3	-0.1	-0.1	0.0	0.0	
2019	-1.88	-0.23	-0.27	-0.09	-0.03	-0.85	-0.10	-0.12	-0.04	-0.01	2.4	0.3	0.3	0.1	0.0	
2020	-3.52	-0.41	-0.56	-0.11	-0.13	-2.70	-0.32	-0.41	-0.10	-0.08	16.2	1.9	2.5	0.6	0.5	Y20-Y23
2021	0.14	0.01	0.02	0.00	0.00	-1.69	-0.20	-0.27	-0.05	-0.06	-0.4	-0.1	-0.1	0.0	0.0	27
2022	-1.15	-0.07	-0.12	-0.09	-0.09	-0.51	-0.03	-0.05	-0.05	-0.05	1.1	0.1	0.1	0.1	0.1	27%
2023	-1.34	-0.08	-0.09	-0.17	-0.17	-1.25	-0.08	-0.10	-0.13	-0.13	3.2	0.2	0.3	0.3	0.3	
Avg	-1.86	-0.26	-0.30	-0.11	-0.06	-1.79	-0.26	-0.30	-0.10	-0.05	71.1	11.3	12.4	4.1	1.4	
Correl.									SD-E:	100	70.9%	11.2%	12.4%	4.1%	1.4%	

Figure 1: Data table, inputs and SD-VMT energy output diagram

11. Conclusions

In summary, the five correlations of his five component curves versus his total PPG curve are:

Base = 88%;
Good = 97%;
Steps = 85%;
Temp = -10%;
Others = -44%.

SD-VMT energy ratios of his composite PPG curve versus
Base = 71%;
Good = 11%;
Steps = 12%;
Temp = 4%;
Others = 1%.

(Insulin resistance demonstrated through FPG is the primary factor, with food and exercise considered secondary factors, whereas temperature and other minor factors are considered insignificant).

The time-zone energy distributions are:

Y2015-Y2019 = 73%
Y2020-Y2023 = 23%
(The preceding 5 years contribute three-quarters, the majority, of the total energy associated with his composite PPG curve, while the recent 4 years contribute about a quarter of the total PPG energy).

During this selected period of 8.6 years (from 8/1/2015 to 12/31/2023), his averaged PPG values are:

Predicted: 112.80 mg/dL
Measured: 112.45 mg/dL
Prediction accuracy = 99.7%
Correlation = 79%.

Key Message

T he health of pancreatic beta cells, particularly their insulin production and quality, is the primary determinant of the composite postprandial plasma glucose (PPG) waveform, accounting for 71% of its variation. Food intake and physical activity are secondary factors, contributing 11% and 12% respectively. Ambient temperature and 20 other minor factors have a negligible impact, together comprising only 5% of the composite PPG waveform's variation. The predicted PPG using signal processing techniques has exceptionally high accuracy, with a 99.7% prediction accuracy.

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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