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A Case Study of three Equal-Length Time Periods Applying Wave Theory, Energy Theory, Fourier Transform, and Linear Elastic Glucose Theory to Estimate Risk Probability of having a Cardiovascular Disease or Stroke and Achieving Longevity Based on GH-Method: Math-Physical Medicine, Part 25 (No. 414)

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Abstract

Based on the research note, No. 413, using two distinctive periods for the pre-virus vs. virus with 417 days each, the author uses his medical research methodology once again for three distinctive periods with equal length of 77 days.

This paper describes his research method of analyzing glucose waves and glucose fluctuations in a time domain (TD), applying Fourier transform operation to convert TD waves into a frequency domain (FD), estimating the relative energy associated with both glucose value and glucose fluctuation, and then combining these derived information with his developed metabolism model using engineering finite element technique. As a result, this combined inputs can determine the impact of different relative energy levels on various internal organs in the human body to obtain a realistic estimation for the risk probability of having cardiovascular disease (CVD), stroke, kidney disease, insulin resistance from pancreatic beta cells, and also provide an expected health age versus real biological age (a longevity issue in the geriatrics branch).

The entire analysis process and research methodologies are based on mathematics, physics, and engineering as outlined in his developed GH-Method: math-physical medicine (MPM References 1 through 3).

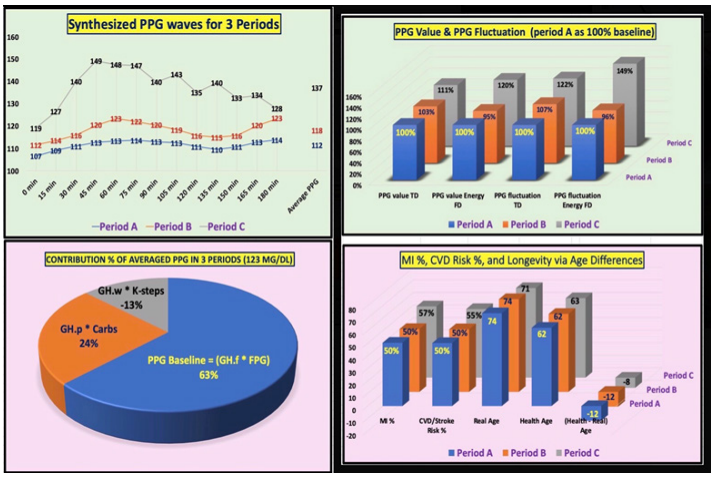
This paper provides a detailed explanation at each key step of analysis with the appropriate research method, using his collected personal biomedical data as a clinical case study for the illustration of the MPM research method.

In summary, there are 5 key points:

1. The author reviews his glucose data as a "wave" rather than a mixture of discrete data. The wave theory in TD is especially useful for analyzing many physical phenomena of biomedical characteristics for various diseases.
2. The signal processing technique of electronic engineering using fast Fourier transform (FFT) is a useful and important tool to convert a TD waveform into another waveform in FD. He examines different wave characteristics by focusing on the Y-amplitude in FD, calculating the total area underneath the FD curve, or even just calculating the square of TD's Y-amplitude (i.e., glucose value or magnitude); therefore, he can quickly obtain a reasonable sense regarding the relative energy level associated with glucose values and fluctuations, particularly by comparing different waveform patterns and moving trends.
3. This glucose energy is circulating in different organs via red blood cells through the blood vessels, both macro-vessels and micro-vessels, to provide the needed nutrition; however, in the case of "excessive energy" associated with hyperglycemia (high glucose situation), this energy damages the internal organs and threatens lives.
4. When the glucose energy combines with 4 other medical conditions, such as obesity (a major root cause for most chronic diseases, including cancer and dementia), hypertension

(blood vessel rupture or leakage), hyperlipidemia (blood vessel blockage), and 6 key lifestyle details, including diet and water intake, exercise, sleep, stress; we can then numerically assess the risk probability of having heart issues, brain problems, kidney complications, etc. Furthermore, if we combine the above metabolism information, including 4 medical and 6 lifestyle, with the required habit in maintaining a good and healthy "life-routine regularity", then we can have a better chance to achieve the goal of "longevity".

5. He has used *quantitative* data collected from his own case of three equal-length time periods (77 days each) to obtain results with high precision. These include weight, FPG, PPG value and PPG fluctuation, along with his calculated results, involving energies associated with PPG value and PPG fluctuation, metabolism index; therefore, he can actually prove that *his overall health conditions are better, internal organ damages are less, which results into a lower risk probability of having medical issues, such as* ***CVD or stroke (~5% less risk) and live a longer and healthier life (gain of 4+ years of expected lifespan).***



Introduction

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Methods

MPM Background

To learn more about his developed GH-Method: math-physical medicine (MPM) methodology, readers can read the following three papers selected from the published 400+ medical 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.

The Author'S Case of Diabetes

The author was a severe type 2 diabetes patient since 1996. 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 of 10%). During that year, his triglycerides reached to 1161 (high risk for CVD and stroke) and albumin-creatinine ratio (ACR) at 116 (high risk for chronically kidney diseases). He also suffered from five cardiac episodes within a decade. In 2010, three independent physicians warned him regarding his needs of kidney dialysis treatment and his future high risk of dying from his severe diabetic complications.

In 2010, he decided to self-study endocrinology with emphasis on diabetes and food nutrition. During 2015 and 2016, he developed four mathematical prediction models related to diabetes conditions, i.e., weight, postprandial plasma glucose (PPG), fasting plasma glucose (FPG), and HbA1C (A1C). As a result, from using his developed mathematical metabolism index (MI) model in 2014 and those four prediction tools during 2015-2016, by 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), averaged finger glucose from 250 mg/dL to 120 mg/dL, and HbA1C from 10% to ~6.5%. One of his major accomplishments is that he no longer takes any diabetes medications since 12/8/2015.

In 2017, he had achieved excellent results on all fronts, especially his glucose control. However, during the pre-COVID period of 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, through stresses, dinning out frequently, post-meal exercise disruption, jet lag, and along with the overall metabolism impact due to his irregular life patterns through a busy travel schedule; therefore, his glucose control was indeed affected during this two-year period of 2019-2020.

He started his self-quarantined life on 1/19/2020. By the end of 2020, his weight was further reduced to 165 lbs. (BMI 24.4)

and his HbA1C was at 6.2% without any medications intervention or insulin injection. Actually, during 2020 with the special COVID-19 quarantined lifestyle, not only has he published ~400 medical papers in various journals, but he has also achieved his best health conditions for the past 26 years. These good results are due to his non-traveling, low-stress, and regular daily life routines. Of course, his rich chronic diseases knowledge, sufficient practical lifestyle management experiences, and his developed various high-tech tools also contribute to his excellent health status since 1/19/2020.

On 5/5/2018, he applied a continuous glucose monitoring (CGM) sensor device on his upper arm and checks his glucose measurements every 15 minutes for a total of ~96 times each day. He has maintained the same measurement pattern to present day. Therefore, during the past 11 years, he could continuously investigate, study, and analyze his collected ~2 million data regarding his health status, medical conditions, and lifestyle details. He applies his knowledge, models, and tools from mathematics, physics, engineering, and computer science to conduct his medical research work. His entire medical research work is based on the aims of achieving both "high precision" with "quantitative proof" in the medical findings, not just through linguistic expressions of qualitative words, vague statements, or complex terminologies.

Wave Theory and Time Domain Analysis

Most data collected by people are in discrete data format or curve format in a time domain (TD), which has its x-axis showing time element, such as days and hours, while its y-axis show the amplitude or magnitude of some variables. The author has accumulated data from the last 12 years of his medical conditions and lifestyle details, including weight, FPG, PPG, carbs/sugar intake amount, exercise amount, sleep hours, and others which are data in a TD with the presentation formats of data table and curves or waves.

Once a wave is established, he can then apply concepts from wave theory in physics, such as amplitude, frequency, wavelength or period to conduct the wave analysis of this wave.

These collected glucose waves in TD can be further segregated into various types of components, such as starting glucose, ending glucose, average glucose (mean), maximum glucose (peak), minimum glucose (nadir), and maximum minus minimum (glycemic variability or GV), or GV wave over a time period (glycemic excursion).

Other GV Research Work

There are many available articles regarding GV; however, the author decided to combine five published articles into one outlined excerpt (References 4, 5, 6, 7 and 8). Reference 4 concentrates on the comparison of many published GV articles. Reference 5 focuses on an algorithm, method, and firmware design of a web-based APP software in calculating the GV values. Reference 6 evaluates the relationship between GV and pancreatic beta cell dysfunction. Reference 7 from the American Diabetes Association (ADA) describes the overall picture of GV.

Reference 8 defines the mathematical equation of MAGE.

Here is the combined simple-version of the excerpt:

"Several pathophysiological mechanisms were reported, unifying the two primary mechanisms: excessive protein glycation end products and activation of oxidative stress, which causes vascular complications. *Intermittent high blood glucose exposure, rather than constant exposure to high blood glucose, has been shown to have deleterious effects in experimental studies.* ***In in-vitro experimental settings and in animal studies, glycemic fluctuations display a more deleterious effect on the parameters of CV risk, such as endothelial dysfunction.*** *There is a significant association between GV and the increased incidence of hypoglycemia. Hypoglycemic events may trigger inflammation by inducing the release of inflammatory cytokines. Hypoglycemia also induces increased platelet and neutrophil activation. The sympathoadrenal response during hypoglycemia increases adrenaline secretion and may induce arrhythmias and increase the cardiac workload. Underlying endothelial dysfunction leading to decreased vasodilation may contribute to CV risk.* ***Published studies have demonstrated that GV, particularly when associated with severe hypoglycemia, could be harmful not only to people with diabetes but also to non-diabetic patients in critical care settings.*** *Overall, the pathophysiological evidence appears to be highly suggestive of* ***GV being an important key determinant of vascular damage.*** *In addition to HbA1c, GV may have a predictive value for the development of T1DM complications.* ***In insulin-treated T2DM, the relevance of GV varies according to the heterogeneity of the disease, the presence of residual insulin secretion and insulin resistance.*** *HbA1c is a poor predictor of hypoglycemic episodes because it only considers 8% of the likelihood of severe hypoglycemia; on the contrary, GV can account for an estimated 40% to 50% of future hypoglycemic episodes. HbA1c is a poor predictor of hypoglycemic risk, whereas* ***GV is a strong predictor of hypoglycemic episodes. GV was an independent predictor of chronic diabetic complications, in addition to HbA1c. We should note that PPG and GV are not identical, even if they are closely related.*** *The attention dedicated to GV is derived from the above evidence concerning its effects on oxidative stress and, from the latter, on chronic diabetes complications.* ***Control of GV has been the focus of a number of interventional studies aimed at "reducing this fluctuation".*** *Diet and weight reduction are the first therapeutic instrument that can be used for reducing GV.*

Despite the various formulas offered, simple and standard clinical tools for defining GV have yet to evolve *and different indexes of GV should be used, depending on the metabolic profile of the studied population.* ***Moreover, the absence of a uniformly accepted standard of how to estimate postprandial hyperglycemia and GV adds another challenge to this debate.*** *Collectively, GV is likely to be incompletely expressed by HbA1c, particularly in patients with good metabolic control.* ***It appears that GV is poised to become a future target parameter for optimum glycemic control over and above standard glycemic parameters, such as blood glucose and HbA1c.***

Avoiding both hyperglycemia and hypoglycemia by careful use of SMBG and the availability of new agents to correct hyperglycemia without inducing hypoglycemia is expected to reduce the burden

of premature mortality and disabling CV events associated with diabetes mellitus. ***However, defining GV remains a challenge primarily due to the difficulty of measuring it and the lack of consensus regarding the most optimal approach for patient management.***

The risk of developing diabetes-related complications is related not only to long-term glycemic variability, but may also be related to short-term glucose variability from peaks to nadirs. *Oscillating glucose concentration may exert more deleterious effects than sustained chronic hyperglycemia on endothelial function and oxidative stress, two key players in the development and progression of cardiovascular diseases in diabetes. Percentages of hyperglycemia (levels between 126 and 180 mg/dl) and hypoglycemia (levels below 70.2 mg/dl) episodes should be used in the GV related research.*

Mean amplitude of glycemic excursions (MAGE), together with mean and SD, is the most popular parameter for assessing glycemic variability and is calculated based on the arithmetic mean of differences between consecutive peaks and nadirs of differences greater than one SD of mean glycemia. *It is designed to assess major glucose swings and exclude minor ones.*

The features discouraging use of glycemic variability as a parameter in clinical practice and trials are the difficulty of interpreting numerous parameters describing this phenomenon and a limited number of computational opportunities allowing rapid calculation of glycemic variability parameters in CGM data.

The UK Prospective Diabetes Study (UKPDS) showed that after an initial improvement, glycemic control continues to deteriorate despite the use of oral agents to enhance insulin secretion and to reduce insulin resistance. This deterioration can be attributed to the progressive decline of β-cell function. Even in subjects with well-controlled type 2 diabetes, 70% of the variability of A1C can be explained by abnormalities in postprandial glucose. ***Chronic sustained hyperglycemia has been shown to exert deleterious effects on the β-cells and the vascular endothelium. In vivo studies have convincingly demonstrated that hyperglycemic spikes induce increased production of free radicals and various mediators of inflammation, leading to dysfunction of both the vascular endothelium and the pancreatic β-cell."***

Mean Amplitude of Glycemic Excursions (MAGE)

Furthermore, such a measure should be simple in concept and faithful to the physiological basis for the glucose swings. ***Because interest lay in the amplitude of glycemic swings and not in the dispersion of all the glucose data, SD was considered to be unsuitable.*** *An automated algorithm has been created for the calculation of MAGE. Although created for determination from continuous BG analysis, MAGE has been applied to intermittent (7- and 22-point sampling/24 h) measurements as well as continuous interstitial glucose monitoring.*

$$\text{M-value}=\frac{\Sigma}{N}\left|\text{M}\frac{BS}{BS}\right|+\text{W}/20 \quad \text{where} \quad \text{M}\frac{BS}{BS}=\left|10\log\frac{PG}{120}\right|^3$$

The Author's view on Glucose Wave Fluctuations (Glycemic Excursions)

There is one concluding remark from one of the reference articles, which was quoted above and now is copied again at below.

"The features discouraging use of glycemic variability as a parameter in clinical practice and trials are the difficulty of interpreting numerous parameters describing this phenomenon and a limited number of computational opportunities allowing rapid calculation of glycemic variability parameters in CGM data."

The author also believes that any newly created biomarker should accurately describe the biomedical phenomena of a disease, but at the same time, it should be easily enough for physicians and/or patients to comprehend and apply it to their day-to-day diabetes control.

The concept and discussion of GV have existed more than a decade based on the clinical usage and results of the continuous glucose monitoring (CGM) device to monitor severe diabetes patients and insulin treatments in hospitals. The self-monitored glucose device (SMGD) became available and popular to outpatients for general public's diabetes control usage starting from 2016-2017. As a result, most of the published research reports are based on glucose data collected during a relatively short analysis period of 2 to 3 days from hospitalized diabetes patients. Although many GV medical papers have been published based on a larger patient numbers, who were probably hospitalized, but it lacks the needed longer time period for both clinical observation and data collection. Furthermore, there are only few of those research papers that provide connections to the intuitive comprehension and easy application on daily diabetes control. That is why the subject of GV is only a research topic in the medical research community, instead of being truly utilized as a clinical tool for practical usage by both diabetes patients and their physicians. For example, the author has had type 2 diabetes (T2D) for 26 years and has been under the care of multiple physicians associated with renown medical institutes. For the past decade, he has attended 65 medical conferences and met more than 1,000 medical doctors, professors, and clinical physicians, but he has never heard of GV mentioned once or its related discussions by the physicians he has met.

Starting on 5/5/2018, he placed a SMGD on his arm to collect two sets of glucose data. The first set of data are measured every 15 minutes with a total of 96 data per day. In addition, since 2/19/2020, he has applied Bluetooth technique to collect his second set of data which are measured every 5 minutes with a total of 288 data per day. In this article, he decided to use the 15-minute dataset with 96 data per day for his analysis due to its longer time period of available glucose data. With a longer observation timespan, he can watch for more changes on both glucose and insulin resistance situations. Statistics analysis based on 1000+ patients with only a few days can certainly provide some useful information. However, the author offers a similar analysis from a perpendicular angle, i.e., one patient with big data associated with a much longer period of time. His collected big databank of glucoses includes a shorter time span of ~3 years for sensor-collected glucoses and a much longer time span of ~10 years for finger-piercing

glucoses. The reason he chose PPG wave as his research target in this article because its fluctuations are usually the most "violent" kind in comparison with glucoses in other segments in a day. Besides, the PPG carried energy is bigger than then energies associated with either FPG or between-meals glucoses.

Defining GV remains a challenge primarily due to the difficulty of data collection with its associated follow-on necessary tasks, such as data transfer, data cleansing, data processing, and data analysis that can lead into the ambiguity of GV's existing interpretations, different versions of expressions, along with the lack of consensus regarding the optimal approach for its clinical management. For example, one of the major GV derivations, mean amplitude of glycemic excursion (MAGE), involves the usage of standard deviation (SD) from statistics. Although SD is widely used in statistics, it has some limitations since its inherited assumption of measured data are normally distributed, which is typically not the case for most glucose data and waves. Besides, choosing glucoses with certain selected SD range would mean that you must omit some of other collected data in your calculations.

All of the above-mentioned tasks are still challenging for most diabetes patients, physicians, and even some medical research scientists. Due to the lack of professional training and academic knowledge in this domain, most patients and clinical physicians have encountered difficulties in understanding the concept of GV and applying the GV related information.

The author is a professionally trained mathematician, physicist, and engineer. He has further used multiple analytical approaches to analyze and research his own health data and glucose waveforms from many different angles. Therefore, he thoroughly understands the behaviors and characteristics of those glucose data and glucose waves collected from his own body.

Based on the theoretical and technical viewpoints, the author decided to conduct this study on applying the ***basic concept, not the GV definitions*** from other sources. His definition of glycemic variability is simple as the glucose wave fluctuation between peak and trough. He then combine his defined GV with the ***primary characteristics*** of wave theory (mainly frequencies, amplitudes, phases, and associated energies of glucoses) to conduct his deeper research of glucose. This would assist in his continuous investigation on the self-recovery of his pancreatic beta cells and various internal organ impacts from the energy associated with glucose waves, including GV (i.e., glucose wave fluctuations). It also benefits his research on the subject of risk probability of having complications, e.g., cardiovascular diseases or stroke, from chronic diseases. Again, in this article, the author applies the following simple formula of glucose fluctuation rate to use for his GV study where ***the glucose fluctuation is defined as the glucose wave's peak as the maximum glucose minus the glucose wave's trough as the minimum glucose.***

Glucose fluctuation rate= [Summation (i = 1 to n) of : ((maximum glucose - minimum glucose) / average glucose)] / n

Fourier Transform and Frequency Domain Analysis

The following is excerpt from Wikipedia regarding signal processing which includes concepts related to time domain, frequency domain, wave theory, and energy theory:

"Fourier methods are named after Joseph Fourier, a French mathematician and physicist that lived from 1768 to 1830. He pioneered the use of sinusoids for representing arbitrary functions.

It is relatively easy to represent an arbitrary signal, or a wave, as a combination or sum of multiple sinusoids of different frequencies. A frequency spectral analysis is an important aspect of signal processing. The goal is to start with a signal, usually in a "time domain", and identify the strength of the sinusoidal components that make up the signal. The strength or amplitude of the sinusoids are displayed as a function of frequency which is the "frequency domain".

Fourier methods are used for two primary purposes: mathematical analysis of problems and numerical analysis of data. The Fourier transform is used to analyze problems involving continuous-time signals or mixtures of continuous- and discrete-time signals. The fast Fourier transform algorithm or FFT, is not a distinct Fourier method, but is an efficient computational technique for evaluating the discrete Fourier transform. The discrete Fourier transform may be computed very efficiently using an FFT algorithm. The computational efficiency of FFT algorithms is a direct consequence of the properties of complex sinusoids. The FFT algorithm was published by Cooley and Tukey in 1965. Computational power was quite limited in those early days of digital computing, and the FFT opened up possibilities for computer analysis of signals that were previously unimaginable. Thus, FFT algorithms fueled the rapid growth of the new field of signal processing. The FFT remains a cornerstone of modern signal processing as it allows solution of problems that are "large" with respect to available computing power.

In summary, Fourier methods are based on representing arbitrary signals as weighted sums of complex sinusoids, with a complex variable having both a real part and an imaginary part. They are intuitive, apply to a large class of interesting signal processing systems and physical effects, and numerical Fourier analysis can be performed very efficiently. They play a huge role in signal processing and are worthy of study.

A fast Fourier transform (FFT) is an algorithm that computes the discrete Fourier transform (DFT) of a sequence, or its inverse (IDFT). Fourier analysis converts a signal from its original domain (often time or space) to a representation in the frequency domain and vice versa. The DFT is obtained by decomposing a sequence of values into components of different frequencies.

In physics, electronics, control systems engineering, and statistics, the frequency domain refers to the analysis of mathematical functions or signals with respect to frequency, rather than time. ***Put simply, a time-domain graph shows how a signal changes over***

time, whereas a frequency-domain graph shows how much of the signal lies within each given frequency band over a range of frequencies."

Energy Theory and Frequency Domain Analysis

As the first step, the author calculates the "glucose fluctuation" value, defined as "the maximum glucose value minus the minimum glucose value" for the PPG values of his three meals. He then assembles them into a daily PPG fluctuation wave in a TD. After that, he calculates the square of the glucose fluctuation amplitude first, since the energy associated with a specific wave is "proportional to" (not "equal to") the square of amplitude in TD, which is the square of daily glucose fluctuation value.

For the second step, he uses the developed software program based on FFT algorithm to transform his daily glucose fluctuation signals or waves into a FD. In the FD, he then calculates the following two energy values. First, by hand, he takes the strength of frequency domain, which is the average Y-amplitude value, then multiply the total number of frequency components (N or n). Second, by computer, he calculates the total area underneath the frequency curve or frequency wave in the FD.

Since the above two methods are based on the same equation but utilizing different tools, they would produce two energy values that are remarkably close to each other due to the minor difference of accuracy between hand and computer.

However, the estimated energy based on the square of glucose Y-amplitude in TD multiplied with the total number of days (N), which is the same as the total number of frequency components in FD, results into different numerical results. In addition, the same data trend or data pattern indicates the energy level. This explanation can be found in a typical physics textbook describing the associated energy in a particular wave as directly proportional to, but not equal to, the square of amplitude of this wave in TD.

Stress, Strain, & Young's Modulus

The following excerpts come from the internet public domain, Google and Wikipedia:

Strain - ε

Strain is the "deformation of a solid due to stress" - change in dimension divided by the original value of the dimension - and can be expressed as
$\varepsilon = dL / L$
where
ε = strain (m/m, in/in)
dL = elongation or compression (offset) of object (m, in)
L = length of object (m, in)

Stress - σ

Stress is force per unit area and can be expressed as
$\sigma = F / A$
where
σ = stress (lb./in2, psi)
F = applied force (lb.)
A = stress area of object (in2)

Stress includes tensile stress, compressible stress, shearing stress, etc.

E, Young's Modulus
It can be expressed as:
$E = \text{stress} / \text{strain} = \sigma / \varepsilon$

where
E = Young's Modulus of Elasticity was named after the 18th-century English physicist Thomas Young.

Elasticity:
Elasticity is a property of an object or material indicating how it will restore it to its original shape after distortion. A spring is an example of an elastic object - when stretched, it exerts a restoring force which tends to bring it back to its original length.

Young's modules in the above table are ranked from soft material (low E) to stiff material (higher E)."

Highlights of Linear Elastic Glucose Theory

If readers are interested in the step-by-step explanation for the predicted PPG equation using linear elastic glucose theory (LEGT), they can read the author's papers listed in References 10 through 25.

The author defines the LEGT equation as:

Predicted PPG= Baseline PPG + food induced incremental PPG + exercise induced incremental PPG
or,

Predicted PPG = (FPG * GH.f) + (Carbs/sugar * GH.p) + (post-meal walking k-steps * GH.w)

Based on the experiences in utilizing the GH-Modulus, the GH.f ranges between 0.6 to 1.0 (he uses 0.97 frequently for his own cases) and *the GH.w is -5.0 for most cases. Therefore, the GH.p-Modulus is the most important variable which defines the food induced incremental PPG as follows:*

Food induced Incremental PPG= GH.p * carbs/sugar
or
GH.p = incremental PPG / carbs

In comparison with Young's modulus equation:

$E = \text{stress} / \text{strain}$

where higher E (stiff material) under the same stress would result into less strain.

If we consider our carbs/sugar intake similar to stress, the incremental PPG similar to strain, then ***the biomedical GH.p-modulus and engineering E of Young's Modulus would have a "reciprocal" connection.***

Therefore, a higher E of Young's modulus value is equivalent to

a lower GH.p-Modulus value. If a higher E (stiff material) is under the same stress level, then it would result into a lower strain. This is similar to a lower GH.p-Modulus under the same carbs/sugar intake amount resulting into a smaller amount of incremental PPG.

The above explanation provides an analogy of LEGT in biomedicine with the theory of elasticity in engineering.

Metabolism and Risk of having CVD/Stroke and Longevity Study

In 2014, the author applied the topology concept of mathematics and finite-element method of engineering, to develop a ten-dimensional complex mathematical model of metabolism which contains four output categories (weight, glucose, BP, and lipids) and other lab-tested data (ACR, TSH, and others), and six input categories (food, water intake, exercise, sleep, stress, and routine life patterns), and ~500 detailed elements. He further defined two new parameters, metabolism index (MI), as the combined score of the above 10 metabolism categories (dimensions) and 500 detailed elements, and general health status unit (GHSU), as the 90-days moving average value of MI. Please note that Mi (where i = 1 through 10) represents individual metabolism score of each category. Since 2012, he has collected ~2 million data of his own biomedical conditions and personal lifestyle details. He only utilized a part of his big database for analysis work in this article.

Next, he developed a few suitable algorithms containing some different weighting factors which include a patient's baseline data (gender, age, race, family genetic history, medical history, bad habits, BMI, weight, and waistline), medical conditions (diabetes, hypertension, and hyperlipidemia), and lifestyle details (food, exercise, and others). After continuously collecting sufficient input data for a decade, he can then conduct the following three sets of calculations:

(A) Medical conditions - individual M2 through M4 for diabetes, hypertension, hyperlipidemia and others. These 3 metabolic disorder values include a patient's self-collected biomedical data and the lab-tested medical examination results. Through his previous research for the past 5-years, he already detected that glucose is the "principal criminal" and blood pressure with lipids are the "accessory criminals" in terms of induced complications from chronic diseases, specifically CVD, stroke, renal problems, diabetic retinopathy, and even cancers. More precisely, his mathematical model for CVD or stroke includes two biomedical scenarios. The first scenario is the artery blockage situation which involves diabetes (glucose), hypertension (blood pressure or BP), and hyperlipidemia (lipids) where he applied his acquired fluid dynamics concepts for his engineering modeling of artery blockage. The second biomedical scenario is the artery rupture situation which involves diabetes (glucose), and hypertension (BP) where he applied his acquired solid dynamics and fracture mechanics concepts for his engineering modeling of artery rupture.

(B) Lifestyle details - individual M5 through M10 which affect medical conditions directly or indirectly. In this category, he includes the following three sub-categories with a total of nine detailed elements. (B-1) 3 foods: quantity, quality, and carbs/sugar intake amount; (B-2) two exercises: daily walking steps and post-meal waking steps; (B-3) 4 others: water intake, sleep, stress, and daily life routines.

(C) MI & GHSU scores - MI is a combined score of M1 through M10 using engineering finite element method. GHSU is the 90-days moving average MI curve which can show the MI's trend clearly. The break-even point for MI is 73.5%, while *the break-even level of risk percentage for the separated groups of medical conditions and lifestyle details are 62%.* In other words, an undesirable situation is being above the break-even line while staying below the break-even line is an ideal situation.

With this developed mathematical risk assessment tool, he can obtain three separate risk probability percentages associated with each of these three calculation models mentioned above. As a result, this tool would offer a range of the risk probability predictions of having CVD or stroke, depending on the patient's medical conditions, lifestyle details, or the combined metabolism impact on the human body.

Link Glucose Energy with Complications of Chronic Diseases

Using either one of the three calculations of associated energies, in combination with his developed metabolism index (MI) model in 2014, we can then estimate his risk probabilities of having a cardiovascular disease (CVD), stroke, diabetic chronic kidney disease (DKD or CKD), and insulin resistance. We can use the similar approach to determine the expected health age to compare against the real biological age to see the expected longevity.

Pancreatic Beta-Cells Study

Since 2019, the author focused on his continuous medical research work for the "self-recovery" of his pancreatic beta cells. He uses the term "self-recovery" because he has kept his carbs/sugar intake amount less than 15 grams per meal and his post-meal walking exercise more than 4,000 steps for the past five years. Since 12/8/2015, he has also ceased taking any diabetes medication, which is the strongest influential factor for the phenomena of glucose fluctuations. Therefore, his body is totally free of any external chemical intervention that may alter or interrupt the internal organ's biochemical process and reactions. Under this strict controlled lifestyle and environment, his damaged pancreatic beta cells must go through the self-repairing process in order to show any meaningful improvement signs of his diabetes conditions through glucose value changes. This is his chosen approach since 2016 that "fixing his diabetes conditions from their root causes via a stringent lifestyle management" instead of "using a tranquilizer to calm down the external symptom or behavior of his glucose problems".

Furthermore, during the FPG period, e.g., between 00:00 midnight through 07:00 next morning, glucose is not under any influence from external factors, mainly food and exercise. However, the FPG values would still fluctuate through the hours of sleep. Of course, there are some other factors, such as sleep conditions, stress, illness, or room environments that can alter FPG, which are secondary influential factors. The weight is the major influential

factor of FPG which occupies ~85% of FPG formation. However, we also know that weight is highly correlated to insulin resistance phenomenon. The left-over and major influential factor of FPG formation is "insulin" which is produced by the pancreatic beta cells. Therefore, the ability to analyze and interpret FPG and then extend it to connect with PPG is important for understanding his situation of insulin resistance.

Data used in this Analysis

In order to have equal number of days in TD and frequency components in FD (i.e., N or n), he has selected a pre-virus period of 417 days from 5/5/2018 to 6/25/2019 and a special COVID-19 virus period of 417 days from 1/19/2020 to 3/10/2021. The major difference between these two periods is the peaceful and stabilized lifestyle without traveling, busy schedule, life routine interruption, and excessive stress during the virus period. These improved lifestyle details contribute to the lower values during the COVID-19 virus period regarding his body weight, FPG, PPG value and fluctuation, glucose associated energy (relative energy), and metabolism indexes; therefore, the final result is a lower risk probability of having a CVD or stroke and prolonging his life expectancy.

Results

Figure 1 shows a big data table that contains 4 parts. The upper-left table is the input data of weight, FPG, PPG value and fluctuation (max PPG - min PPG). *The lower-left table is the LEGT calculation with an unusually high GH.p-Modulus of 87.4 for fasting case due to its extremely low carbs/sugar intake amount of 0.4 gram (a lower- bound of near zero carbs amount). The other two periods have similar normal GH.p-Modulus between 4 to 6.* The upper-right table is his metabolism data of these two periods, from m1 through 10, with the combined MI score using finite element method (FEM) from engineering. The lower-right table is a bar chart diagram of the summarized data illustrated in Figure 6, which contains the PPG value and fluctuation in TD (magnitude) and FD (energy), metabolism index (MI), along with the CVD risk and age difference for longevity investigation.

Breakfast (3 periods)	11/8/20-3/12/21 Recent Fasting	10/7/20-3/12/21 Recent Non-Fasting	5/5/18-7/21/18 Earlier Non-Fasting
Energy Study (TD2FD)	Period A	Period B	Period C
Breakfast Meals	77	77	77
Weight	167	167	170
Finger PPG	106	110	119
Carbs/Sugar grams	0.4	6.2	11.5
Post-meal Walking Steps	4114	4275	4573
Sensor FPG	103	103	107
Sensor PPG	117	120	133
Sensor (PPG-FPG)	14	17	26
K-line Max	174	135	160
K-line Min	108	105	113
K-line PPG Fluc.	66	31	47
Libre PPG TD-Y	117	120	133
Libre PPG FD-Y	94	87	103
Libre PPG FD Area	6835	6465	7756
Libre PPG Max-Min TD-Y	37	40	49
Libre PPG Max-Min FD-Y	103	96	142
Libre PPG Max-Min FD Area	7616	7286	10889
CVD/Stroke Risk	50%	50%	55%

Prepared on 3/13/2021	Recent Fasting	Recent Non-Fasting	Earlier Non-Fasting
LEGT Study (GH.p)	Period A	Period B	Period C
Sensor FPG	103	103	107
GH.f	1.0	1.0	1.0
PPG Baseline = (GH.f*FPG)	103	103	107
Carbs/Sugar (grams)	0.4	6.2	11.5
GH.p	87.4	6.3	4.2
GH.p*Carbs	35	39	49
Walking K-steps	4.1	4.3	4.6
GH.w	-5.0	-5.0	-5.0
K-steps*(-5)	-21	-21	-23
Predicted PPG (mg/dL)	116.93	120.25	132.88
Measured PPG (mg/dL)	116.93	120.25	132.88

Breakfast (3 periods)	11/8/20-3/12/21 Recent Fasting	10/7/20-3/12/21 Recent Non-Fasting	5/5/18-7/21/18 Earlier Non-Fasting
Metabolism Study	Period A	Period B	Period C
M1 (weight)	0.9916	0.9923	1.0008
M2 (glucose)	0.8521	0.8733	0.9625
M3 (blood pressure)	0.8290	0.7951	0.8412
M4 (lipid)	0.7261	0.7261	0.7261
Avg. Medical	0.8497	0.8467	0.8827
FEM Medical	0.7183	0.7147	0.7776
M5 (exercise)	0.6102	0.5840	0.6028
M6 (water)	0.7041	0.7138	0.7205
M7 (sleep)	0.6021	0.5974	0.6372
M8 (stress)	0.5014	0.5015	0.5046
M9 (food & meal)	0.5212	0.5385	0.6685
M10 (daily routine)	0.7000	0.7000	0.7442
Avg. Lifestye	0.6065	0.6059	0.6463
FEM Lifestyle	0.3681	0.3664	0.4164
MI (via FEM)	0.5043	0.5009	0.5681
Real Age	74	74	71
Health Age	62	62	63
(Health - Real) Age	-12	-12	-8

Energy Graphs (TD2FD)	Period A	Period B	Period C
Libre PPG TD-Y	117	120	133
Libre PPG FD Area	6835	6465	7756
Libre PPG Max-Min TD-Y	37	40	49
Libre PPG Max-Min FD Area	7616	7286	10889
PPG value TD	100%	103%	111%
PPG value Energy FD	100%	95%	120%
PPG fluctuation TD	100%	107%	122%
PPG fluctuation Energy FD	100%	96%	149%
CVD/Stroke Risk %	50	50	55
Real Age	74	74	71
Health Age	62	62	63
(Health - Real) Age	-12	-12	-8

Figure 1: Data table for TD to FD, wave and energy theories, LEGT, Metabolism, CVD/stroke risk, and Longevity Studies (Three 77-days periods)

The data comparison summary for the higher Period C values versus the lower Period A values are listed below:

PPG value in TD: 110%
PPG value energy in FD: 120%
PPG fluctuation in TD: 122%
PPG fluctuation energy in FD: 149%

It should be noted that the energy for Period B associated with both PPG value and PPG fluctuation are slightly lower than Period A but are remarkably close to each other. This has indicated that *a slightly higher glucose in recent non-fasting Period B actually generated a slightly lower glucose energy than recent fasting Period A.*

The positive consequences regarding CVD/stroke risk and prolonged lifespan resulted from the improved (means less) amount of glucose associated energies and overall improvement on metabolism are summarized below:

Health vs. Real age: gain of 4 years
CVD/stroke risk%: reduce 5%

Figure 2 depicts dates, days, carbs/sugar intake amount, and post-meal walking steps of these 3 periods.

Figure 2: Three 77-days periods, Period A (fasting) and Period B

(no fasting in 2020-2021 with Period C (non-fasting) in 2018
Figure 3 illustrates three synthesized PPG waves in TD within a 3-hour timespan of these three periods. From the upper line-chart, it is evident that *the overall PPG waveform and its mean value of earlier non-fasting Period C is higher than the recent non-fasting Period B; the recent fasting Period A is further lower than the recent non-fasting Period B.* This proves that, from a similar recent timespan including both Periods A and B, the intermittent fasting has an immediate benefit on PPG reduction. However, the overall metabolism status including both medical conditions and lifestyle details of the earlier non-fasting Period C was much worse than the recent Periods A and B. This causes the synthesized PPG waveform of Period C to be located at the highest position.

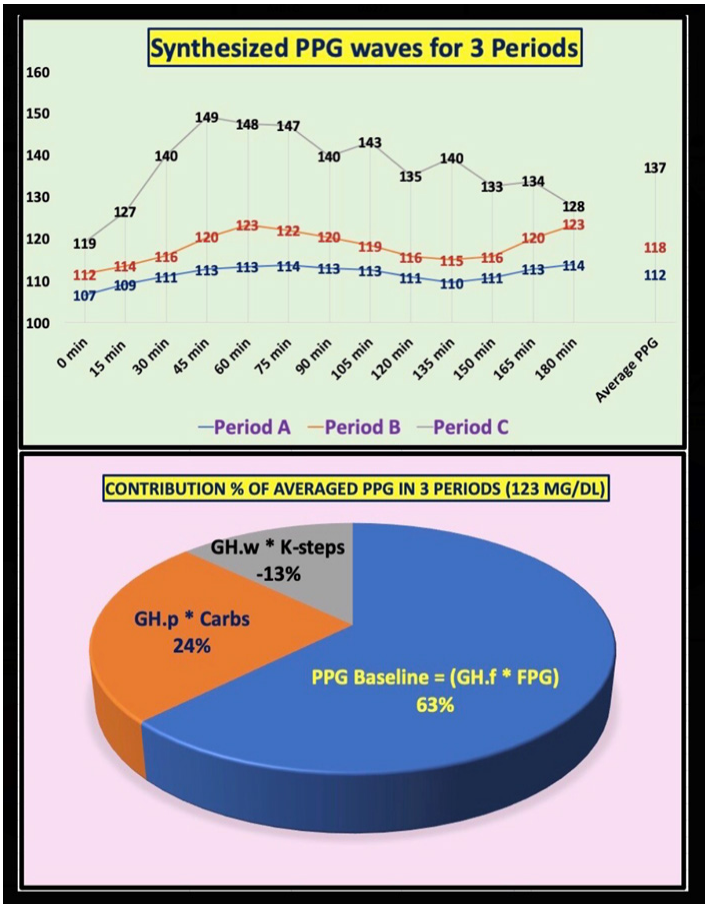

Figure 3: Three synthesized PPG waves in TD with PPG formation's contribution % of pancreatic beta cells via FPG, diet, and exercise

The lower pie chart in Figure 3 reveals an additional observation from the LEGT calculations, the PPG formation element's contribution percentages are as follows:

FPG (using 1.0 for GH.f): 63%
Diet (using 4.2-6.3 for GH.p): 24%
Exercise (using -5.0 for GH.w): -13%

This demonstrates the pancreatic beta cells insulin secretion and insulin resistance through the FPG presentation as the major influential factor for the PPG formation. After the FPG factor, both diet and exercise from lifestyle comes into the picture as the next-tier of important influential factors. Delving into this picture from a reversed angle in order to understand the physical phenomenon deeper, both diet and exercise of lifestyle can ultimately help the pancreas to slowly heal itself such that FPG will eventually become lower.

Figure 4 reflects 3 TD diagrams of PPG values. Figure 5 offers the corresponding 3 FD diagrams of PPG value's energy. Figure 6 shows 3 TD diagrams of PPG fluctuations (i.e., maximum PPG minus minimum PPG). Figure 7 indicates the corresponding 3 FD diagrams of the PPG fluctuation 's energy.

Figure 4: PPG value in TD of 3 periods

Figure 5: PPG value Energy in FD of 3 periods

Figure 6: PPG fluctuation in TD of 3 periods

The following table summarizes key results from Figure 4 through Figure 7, in a format of Period A, Period B, and Period C:

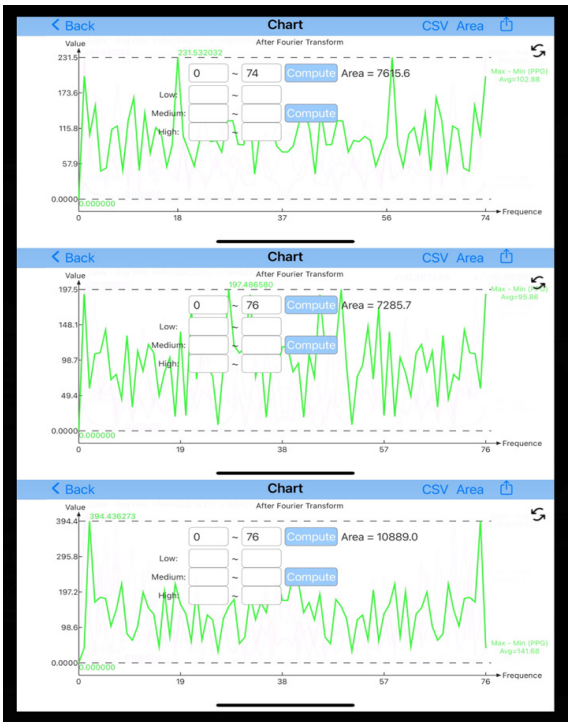

Figure 7: PPG fluctuation Energy in FD of 3 periods

PPG Y-value in TD: (117, 120, 133)
PPG Y-value in FD: (94, 88, 103)
PPG Area in FD: (6835, 6464, 7756)

and

PPG fluctuation in TD: (37, 40, 49)
PPG fluctuation in FD: (103, 87, 142)
PPG Area in FD: (7616, 6465, 10889)

It is apparent that all values in Period C is higher than both Periods A and B. In other words, *from the viewpoint of PPG and its associated energy, the author's conditions in the recent Periods A and B are healthier than the earlier Period C.* Another key observation is that despite the PPG value and PPG fluctuation in Period B is slightly higher than Period A, the associated energy of the PPG value and PPG fluctuation of Period B is slightly lower than Period A.

Figure 8 is the conclusive diagram of this paper. The upper bar chart illustrates the comparison among the PPG values and fluctuations, using recent data from the fasting Period A as the baseline of 100%, for the 3 periods. The magnitude comparison percentages are shown in a format of Period B and Period C, with 100% for Period A, as listed:

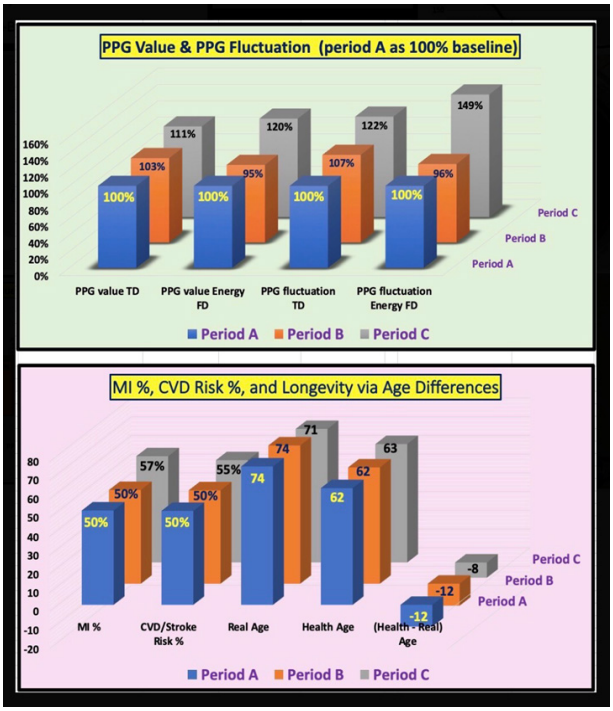

Figure 8: Conclusions of PPG values and fluctuations and their associated energies in combined with metabolism to influence the risk of CVD/Stroke and longevity

PPG value TD: (103%, 111%)
PPG energy FD: (95%, 120%)
PPG fluctuation TD: (107%, 122%)
PPG fluctuation energy FD: (96%, 149%)

The lower bar chart uncovers the comparison among the 3 periods of metabolism index (MI), risk probability of having a CVD/stroke, real biological age, effective health age, and age difference of longevity. The different ratios are listed below in the format of Period A, Period B, and Period C:

MI: (50%, 50%, 57%)
CVD/Stroke: (50%, 50%, 55%)
Real age: (74, 74, 71)
Health age: (62, 62, 63)
Age difference: (-12, -12, -8)

In summary, in terms of his heart attack risk, it has been reduced by 5% resulted mainly from the overall metabolism improvement by 5%, and in terms of his prolonged lifespan, it has been increased by 4 years from -8 years to -12 years.

Figure 9 reflects the computer output pages from his CVD risk analysis which serves as the base for Figures 1 and 8. It should be pointed out that both the CVD risk and longevity calculations have included his metabolism data. This means that ***during the recent COVID-19 virus Periods A and B, he improved his glucose control and has achieved better performances in all areas of his metabolism conditions, including weight, blood pressure, lipids, diet, exercise, sleep, stress, water intake, and daily life routines, which result into a reduced CVD risk and a prolonged expected life.***

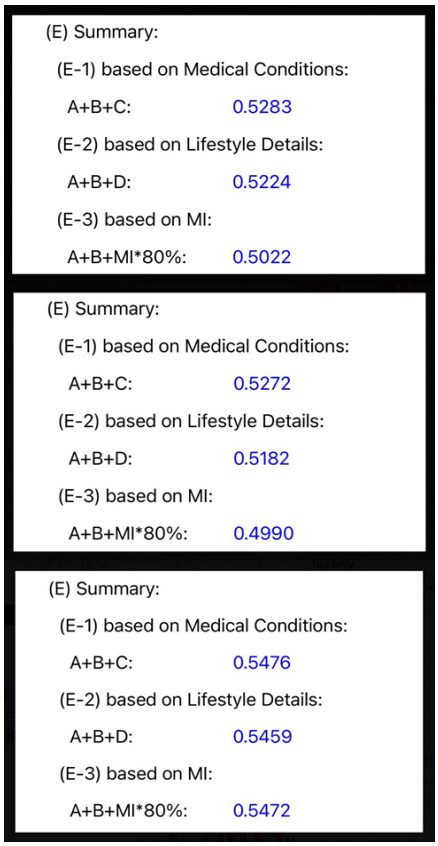

Figure 9: Comparison of risk probability of having a CVD or Stroke among three periods

Conclusions

In summary, there are 5 key points:

1. The author reviews his glucose data as a "wave" rather than a mixture of discrete data. The wave theory in TD is especially useful for analyzing many physical phenomena of biomedical characteristics for various diseases.
2. The signal processing technique of electronic engineering using fast Fourier transform (FFT) is a useful and important tool to convert a TD waveform into another waveform in FD. He examines different wave characteristics by focusing on the Y-amplitude in FD, calculating the total area underneath the FD curve, or even just calculating the square of TD's Y-amplitude (i.e., glucose value or magnitude); therefore, he can quickly obtain a reasonable sense regarding the relative energy level associated with glucose values and fluctuations, particularly by comparing different waveform patterns and moving trends.
3. This glucose energy is circulating in different organs via red blood cells through the blood vessels, both macro-vessels and micro-vessels, to provide the needed nutrition; however, in the case of "excessive energy" associated with hyperglycemia (high glucose situation), this energy damages the internal organs and threatens lives.
4. When the glucose energy combines with 4 other medical conditions, such as obesity (a major root cause for most chronic diseases, including cancer and dementia), hypertension (blood vessel rupture or leakage), hyperlipidemia (blood vessel blockage), and 6 key lifestyle details, including diet and water intake, exercise, sleep, stress; we can then numerically assess the risk probability of having heart issues, brain problems, kidney complications, etc. Furthermore, if we combine the above metabolism information, including 4 medical and 6 lifestyle, with the required habit in maintaining a good and healthy "life-routine regularity", then we can have a better chance to achieve the goal of "longevity".
5. He has used quantitative data collected from his own case of three equal-length time periods (77 days each) to obtain results with high precision. These include weight, FPG, PPG value and PPG fluctuation, along with his calculated results, involving energies associated with PPG value and PPG fluctuation, metabolism index; therefore, he can actually prove that his overall health conditions are better, internal organ damages are less, which results into a lower risk probability of having medical issues, such as CVD or stroke (~5% less risk) and live a longer and healthier life (gain of 4+ years of expected lifespan) [1-39].

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