

The GH-Method

Viscoelastic or Viscoplastic Glucose Theory (VGT #157): A Study of Longevity versus Obesity via BMI, Beta Cell Health Status via FPG, Type 2 Diabetes Conditions via PPG, Insulin Resistance Status via TyG, and Nonalcoholic Fatty Liver Disease Possibilities via TyG Using Both Space-Domain and Time-Domain Energy Analysis Tools Based on the GH-Method: Math-Physical Medicine (No. 750)

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Keywords: Viscoelastic; Viscoplastic; Obesity; Type 2 diabetes; Fasting plasma glucose; Postprandial plasma glucose; Insulin resistance; Body weight; Fast Fourier transform

Abbreviations: NAFLD: non-alcohol fatty liver disease; T2D: type 2 diabetes; FFT: fast Fourier transform; FPG: fasting plasma glucose; PPG: postprandial plasma glucose; FD: frequency domain; SD: space domain; TD: time domain; MPM: math-physical medicine

1. INTRODUCTION

When using Google search, a reader can easily locate and read the following important general information regarding health, diseases, and death:

“Studies have shown that becoming overweight or obese is a major risk factor in developing type 2 diabetes. Today, roughly 30 percent of overweight people have diabetes, and around 85 percent of diabetics patients are overweight.

Having diabetes means you are more likely to develop heart disease, such as cardiovascular diseases (CVDs) or strokes. People with diabetes are also more likely to have certain other risk factors, such as high blood pressure or high cholesterol, that increase their chances of having a heart attack or a stroke.

Heart disease is common in people with diabetes. Data from the National Heart Association from 2012 shows 65% of people with diabetes will die from some sort of heart disease or stroke.

During Y2020, the total number of US deaths was 2,506,540 (100%) which includes a new category of 350,831 (14%) from COVID death. The subtotal death cases that directly or indirectly resulted from various metabolic disorders and complications are 1,748,553 (69.8%) which includes 696,962 heart disease cases (28%), 602,350 cancers cases (24%), 160,264 stroke cases (6%), 134,242 Alzheimer’s disease & dementia cases (5%), 102,188 diabetes cases (4%), and 52,547 kidney cases (2%). (Source: Mortality in the United States, 2020, data table in Figure 4.)”

The main path to having many deadly diseases and medical complications is due to a poor lifestyle leading to body weight problems such as being overweight and obese, then developing diabetes, hypertension, and hyperlipidemia. As a result, various metabolic disorder-induced complications such as heart issues, stroke, kidney problems, and even cancers and Alzheimer’s can occur, finally leading to death or shortening a person’s lifespan/longevity. This article particularly focuses on investigating longevity via age difference (calculated health age minus biological real age) versus having obesity (via

high BMI), type 2 diabetes (via high postprandial plasma glucose), pancreatic beta cell's general health state (via fasting plasma glucose), insulin resistance (via TyG higher than 4.49) and non-alcoholic fatty liver disease (via TyG higher than 8.5). These 5 chronic diseases are part of the reasons for the leading cause of death and should be a concern for many patients.

The developed equations for the health age and the age difference are listed as follows:

$$\text{Health Age} = \text{Chronological real Age} * (1 + ((\text{MI} - 0.735) / 0.735) / 2)$$

$$\text{Age difference} = \text{health age} - \text{real age}$$

where MI is the metabolism index value calculated using 500 detailed elements of 4 categories of medical conditions and 6 categories of lifestyle details, with over 3 million data stored in his database of collected biomarker values and extended data. The numerical digit of 0.735 is the dividing line of MI value between healthy and unhealthy conditions. Regarding this output strain of longevity, the age difference, in 2010, his calculated health age was 73 while his biological real age was only 63 (therefore, his age difference was +10 or q0 years older). Currently, in 2022, his health age becomes 65 while his biological real age is already 75 (therefore, his age difference is -10 or 10 years younger). In other words, over the past 13 years, he has extended his life expectancy by almost 20 years (i.e. 10+10).

The defined triglyceride-glucose index (TyG) biomarker using the triglycerides (TG) input and fasting plasma glucose (FPG) input is defined as follows:

$$\text{TyG} = (\ln(\text{TG}) + \ln(\text{FPG})) / 2$$

A more detailed explanation of TyG can be found in the methods section.

In many of the author's previous medical papers, he has already addressed the following 3 important pieces of information.

(1) Fasting plasma glucose or FPG, i.e. the glucose value measured first thing in the morning before eating or drinking anything,

actually indicates the overall health status of a diabetes patient's pancreatic beta cells.

(2) Postprandial plasma glucose or PPG, i.e. 3 hours time duration after the first bite of each meal or even 5 hours time duration if the patient eats snacks or fruit in between meals, contributes about 38%, 63% or 75% of the estimated daily average glucose (eAG) depends on measurement situation. FPG alone contributes about 25% or 29% of the eAG depending on finger-piercing or CGM sensor. Therefore, the PPG value itself is not only a key player of HbA1C value but also offers information regarding the levels and trending of both eAG and HbA1C, i.e. T2D.

(3) The TyG biomarker uses values from both FPG and TG, excluding values of blood pressure, heart rate, HDL, LDL, total cholesterol, body temperature, etc. But, at least, the TyG is a good indicator for insulin resistance (IR) and non-alcohol fatty liver disease (NAFLD).

After completing his data preparation task, the actual data processing for energy analysis work itself is 100% dependent on his recently developed VGT software tool on his iPhone which has reduced his data processing time from a normal 5-6 hours to less than 1 minute. Therefore, he can spend this saved amount of extra time to conduct a deeper investigation and/or explore a better interpretation of his observed phenomena and analyzed findings.

It should be mentioned that normalization factors (NF) are usually the dividing line between healthy and unhealthy conditions. The NF used in this articles are: BMI = 25; PPG = 140 mg/dL; FPG = 100 mg/dL; TyG = 4.49 for IR; TyG = 8.5 for NAFLD.

In the methods section, the author describes three different energy models regarding this single output of age difference versus five inputs, which are obesity, T2D, beta cells, insulin resistance, and NAFLD. He can utilize the three different energy models, but he selects the TD-squared amplitude model and SD-VGT model for this study.

The first time-domain (TD) model uses a rudimentary physics definition of energy associated with a wave that is directly proportional to the square of wave amplitude. The second space-domain (SD) model utilizes

the hysteresis loop area of the time-dependent strain-stress curve with viscoelastic and viscoplastic engineering material behaviors. The third frequency-domain (FD) model uses his defined new variable of strain (output) multiplying with stress (stress input is the strain change rate multiplying with the normalized viscosity input) and the fast Fourier transform (FFT) operation of wave theory in physics.

In summary, there are 5 noticeable findings regarding the energy study regarding the output of longevity via age difference versus 5 selected input diseases, obesity, T2D, pancreatic beta cell damage, insulin resistance, and NAFLD.

(1) From the collected data and waveforms of age difference output versus 5 selected inputs, his average age difference is 19.84 years (~20 years of life extension). The age difference here is defined as the maximum health age minus the minimum health age. The calculated correlation coefficients between age difference versus 5 inputs are: Obesity = 93%; T2D = 86%; Beta-cell = 85%; IR = 81%, NAFLD = 81%. All 5 correlations are above 80%.

(2) From the TD-squared amplitude analysis results, his TD energy ratios are: Obesity = 24%; T2D = 16%; Beta-cell = 28%; IR = 24%, NAFLD = 7%. The TD energy ranking order from high to low is: Beta-cell > Obesity = IR > T2D > NAFLD.

(3) From the SD-VGT analysis results, his SD energy ratios are: Obesity = 22%; T2D = 19%; Beta-cell = 25%; IR = 22%, NAFLD = 12%. The SD energy ranking order from high to low is: Beta-cell > Obesity = IR > T2D > NAFLD which is identical as the TD energy ranking. The absolute numerical values for each input have about 2% to 5% differences between these 2 energy tool results, but the energy ranking orders or the contribution/influence patterns from these two different energy methods are identical.

(4) The interpretation of biomedical behaviors or illustrations of observed biophysical phenomena are described as follows: His 28-year T2D conditions have revealed his severely damaged beta cell functions. Even though he has self-repaired his beta cells by 30-35% over the past 8 years, his beta cell input is still the most significant

threat to his longevity concern. The second highest contributors, both Obesity and IR having an equal score, resulted from his heavier body weight and higher FPG levels during the earlier 4 years which have pushed his SD hysteresis loop area to become larger. Besides, there is another fact that he does not like to continuously reduce his body weight in recent years because he needs more muscle strength in his old-age life. His triglyceride (TG) values have been kept around the borderline between healthy/unhealthy conditions; therefore, TG is not the main cause for IR being in the second-ranking position. His T2D via PPG is ranked as the number 4 energy contributor due to the higher normalization factor of 140 mg/dL as the Normalization factor or the dividing line between diabetes and normal condition by the existing medical community. However, the author's personal goal has always been 120 mg/dL. He does not have a fatty liver condition; therefore, NAFLD in the bottom-ranking position (the smallest hysteresis loop area) is understandable which also matches his routine medical checkup results.

(5) The time-zone energy analysis from the SD-VGT model has shown that the earlier 4 years from Y2013 to Y2016 contribute 95% of total energy or influences while the later 6 years from Y2017 to Y2022 contribute 5% only. This proves that the majority of influences (or damage) on his longevity from these 5 input diseases has been done during the earlier 4 years. After that, he has maintained a healthy level during the recent 6 years; therefore, they have little influence (or damage) to his longevity concern and even help to increase his lifespan.

2. METHODS

2.1 TyG index

The "triglyceride and glucose index (TyG)" is a screening method for insulin resistance, which is simple to use, and only requires two laboratory determinations: serum triglycerides and serum glucose. According to a study by Salazar et al., the insulin resistance cut-off level is placed at the TyG index value of 4.49, with a sensitivity of 82.6% and specificity of 82.1% (AUC=0.889, 95% CI: 0.854-0.924). Subjects with an index of 4.49 or greater are likely to suffer from

insulin resistance (References 1, 2, 3, 4, and 5).

The TyG equation is:

$$\text{TyG} = \ln [\text{Fasting triglyceride (mg / dl)} * \text{Fasting glucose (mg / dl)}] / 2$$

or,

$$\text{TyG} = (\ln[\text{Fasting triglyceride (mg / dl)}] + \ln[\text{Fasting glucose (mg / dl)}]) / 2$$

Furthermore, let us re-express it with an abbreviated format as follows:

$$\text{TyG} = (\ln(\text{TG}) + \ln(\text{FPG})) / 2$$

The TyG is considered a screening tool for large-scale medical studies. Its accuracy and simplicity can be calculated with data obtained from medical records.

According to Fedchuk et al., the TyG values above 8.38 indicates a positive predictive value (PPV) of 99% in predicting steatosis (infiltration of liver cells with fat, associated with a disturbance of the metabolism by alcoholism, malnutrition, pregnancy, or drug therapy) equal to or greater than 5%. A recent cross-sectional study by Zhang et al. aimed to determine whether TyG has any predictive value for non-alcoholic fatty liver disease (NAFLD) by comparing the predictive value of TyG with the determinations of ALT (alanine aminotransferase) in a cohort of 10,761 patients.

The association between a screening method using triglycerides and glucose should not come as a surprise as NAFLD is considered the liver manifestation of metabolic syndrome, while triglycerides and serum glucose are key components of this process.

The following table summarizes the two cut-off points identified for insulin resistance and NAFLD positive diagnosis likelihood:

Condition	Cut-off value	Values below cut-off	Values above cut-off
Insulin resistance	4.49	Insulin resistance unlikely	Suggestive of insulin resistance
Nonalcoholic fatty liver disease	8.5	NAFLD diagnosis is unlikely	High likelihood of NAFLD

2.2 The author's case of diabetes and complications

The author has been a severe T2D patient since 1996. He weighed 220 lb. (100 kg, BMI 32.5) at that time with a one-time glucose reading of 380 mg/dL. By 2010, he still weighed 198 lb. (BMI 29.2) with average daily glucose of 250 mg/dL (HbA1C of 10%). During that year, his triglycerides reached 1161b (hyperlipidemia) and albumin-creatinine ratio (ACR) at 116 (kidney issues). He also suffered from five cardiac episodes within a decade from 1993 through 2003 caused by work stress and diabetes. In 2010, three independent physicians warned him about his urgent need for kidney dialysis treatment and the risk of his life-threatening health situation such as dying from his severe diabetic complications. Other than the cerebrovascular disease (stroke), he has suffered most of the known diabetic complications, including both macro-vascular & micro-vascular complications, nerve damage as in retinopathy and foot ulcer, as well as a hormonal disturbance, e.g. hypothyroidism.

In 2010, he decided to launch his self-study on endocrinology, diabetes, and food nutrition to save his own life. After developing the metabolism model in 2024, during 2015 and 2016, he developed four prediction models related to diabetes conditions: weight, PPG, fasting plasma glucose (FPG), and A1C. As a result, from using his developed mathematical metabolism index (MI) model in 2014 and those 4 prediction tools, by end of 2016, his weight was reduced from 220 lbs. (100 kg, BMI 32.5) to 176 lbs. (89 kg, BMI 26.0), waistline from 44 inches (112 cm) to 33 inches (84 cm), average finger glucose reading from 250 mg/dL to 120 mg/dL, and lab-tested A1C from 10% to ~6.5%. One of his major accomplishments is that he no longer takes any diabetes medications as of 12/8/2015.

Around that time (2014-2017), he started to focus on preventive medicine instead of blindly trusting and depending on medication treatments only. He also gambled on his belief that most human organs have strong inherent abilities to self-repair themselves through lifestyle improvements by taking good care of them - even though it can only accomplish a certain degree of repairing or healing dependent on certain organ cells and

their status of damage, such as pancreatic beta cells.

In 2017, he has achieved excellent results on all fronts, especially glucose control. However, during the pre-COVID period of 2018 and 2019, he traveled to approximately 50+ international cities to attend 65+ medical conferences and made ~120 oral presentations. This hectic schedule inflicted damage to his diabetes control, through dining out frequently, post-meal exercise disruption, jet lag, and along with the overall metabolic impact due to his irregular life patterns through a busy travel schedule; therefore, his glucose control and overall metabolism state were somewhat affected during this two-year heavy traveling period.

Since 1/19/2020, living in a COVID-19 quarantined lifestyle, not only has he written and published ~500 medical papers in 100+ journals, but he has also reached his best health conditions in the past 26 years. By the beginning of 2022, his weight was further reduced to 168 lbs. (BMI 24.8) along with a 5.8% A1C value (beginning level of pre-diabetes), without having any medication interventions or insulin injections. During the period from 1/1/2022 to 8/20/2022, his average FPG is 93 mg/dL, PPG is 113 mg/dL, and daily glucose is 106 mg/dL. These good results are due to his non-traveling, low-stress, and regular daily life routines. Of course, the accumulated knowledge of chronic diseases, various complications, practical lifestyle management experiences, and development of many high-tech tools along with his medical research academic findings have contributed to his excellent health status since 1/19/2020, the beginning date of his self-quarantined life.

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. He has maintained the same measurement pattern to the present day. In his research work, he uses his CGM sensor glucose at a time interval of 15 minutes (96 data per day). Incidentally, the average sensor glucoses between 5-minute intervals and 15-minute intervals has only a 0.6% difference (average glucose of 111.86 mg/dL for 5 minutes and average glucose of 111.18 mg/dL for 15 minutes with a correlation of 94% between these two sensor glucose

curves) during the period from 2/19/20 to 7/22/22.

Therefore, over the past 13 years, he could study and analyze his collected 3+ 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 research work has a goal of achieving both “high precision” and “quantitative proof” in the medical findings for the ultimate objectives of “preventive medicine”.

The following timetable provides a rough sketch of the emphasis in his medical research during each stage:

2000-2013: Self-study diabetes and food nutrition, developing a data collection and analysis software.

2014: Develop a mathematical model of metabolism, using engineering modeling and advanced mathematics.

2015: Weight & FPG prediction models, using neuroscience.

2016: PPG & HbA1C prediction models, using optical physics, artificial intelligence (AI), and neuroscience.

2017: Complications due to macro-vascular research, such as cardiovascular disease (CVD), coronary heart diseases (CHD), and stroke, using pattern analysis and segmentation analysis.

2018: Complications due to micro-vascular research such as kidney (CKD), bladder, foot, and eye issues (DR).

2019: CGM big data analysis, using wave theory, energy theory, frequency domain analysis, quantum mechanics, and AI.

2020: Cancer, dementia, longevity, geriatrics, DR, hypothyroidism, diabetic foot, diabetic fungal infection, and linkage between metabolism and immunity, learning about certain infectious diseases, such as COVID-19.

2021: Applications of linear elastic glucose theory (LEGT) and perturbation theory from

quantum mechanics on medical research subjects, such as chronic diseases and their complications, cancer, and dementia.

2022: Applications of viscoelastic/viscoplastic glucose theory (LEGT) on 142 biomedical research cases and 5 economics research cases.

Again, to date, he has spent ~40,000 hours self-studying and researching medicine and he has read 4,000+ published medical papers online. He has collected and calculated more than 3+ million pieces of data regarding his own medical conditions and lifestyle details. In addition, he has written and published 700+ medical research papers in 100+ various medicine, physics, mathematics, and engineering journals. Moreover, he has also given 120+ presentations at 70+ international medical conferences. He has continuously dedicated his time (11-12 hours per day and work each day of a year, without rest during the past 13 years) and efforts to his medical research work and shared his findings and learnings with other patients worldwide. In addition, he has also spent the past 12 years developing and maintaining a medicine and health software APP on his iPhone which functions as his private numerical laboratory to process the various experimental datasets of his medical conditions and lifestyle details.

2.3 Brief introduction of math-physical medicine (MPM) research

The author has collected 3+ million data regarding his health condition and lifestyle details over the past 13 years. He spent the entire year of 2014 developing a metabolism index (MI) model using a topology concept, nonlinear algebra, algebraic geometry, and finite element method. This MI model contains various measured biomarkers and recorded lifestyle details along with their induced new biomedical variables for an additional ~1.5 million data. Detailed data of his body weight, glucose, blood pressure, heart rate, blood lipids, body temperature, and blood oxygen level, along with important lifestyle details, including diet, exercise, sleep, stress, water intake, and daily life routines are included in the MI database. In addition, these lifestyle details also include some lifetime bad habits and certain environmental exposures. Fortunately, the author has none of these lifetime bad habits

and an extremely low degree of exposure to environmental factors. The developed MI model has a total of 10 categories covering approximately 500 detailed elements that constitute his defined “metabolism index model” which are the building blocks or root causes for diabetes and other chronic disease-induced complications, including but not limited to cardiovascular disease (CVD), chronic heart disease (CHD), stroke, chronic kidney disease (CKD), diabetic retinopathy (DR), neuropathy, foot ulcer, hypothyroidism, dementia, and various cancers. The end result of the MI development work is a combined MI value within any selected period with 73.5% as its dividing line between a healthy and unhealthy state. The MI serves as the foundation for many of his follow-up medical research work.

During the period from 2015 to 2017, he focused his research on type 2 diabetes (T2D), especially glucose, including fasting plasma glucose (FPG), PPG, estimated average glucose (eAG), and hemoglobin A1C (HbA1C). During the following period from 2018 to 2022, he concentrated on researching medical complications resulting from diabetes, chronic diseases, and metabolic disorders which include heart problems, stroke, kidney problems, retinopathy, neuropathy, foot ulcer, diabetic skin fungal infection, hypothyroidism, diabetic constipation, dementia, and various cancers. He also developed a few mathematical risk models to calculate the probability percentages of developing various diabetic complications based on this MI model. From his previous medical research work with 700+ published papers, he has identified and learned that the associated energy of hyperglycemic conditions is the primary source of causing many diabetic complications which lead to death. Therefore, a thorough knowledge of these energies is important for achieving a better understanding of the dangerous complications.

2.4 TD, SD, and FD analysis tools

This section has brief descriptions of TD correlation analysis with other observational results, SD VGT analysis with hysteresis loop area's energy results, and FD analysis with frequency curve area's energy results.

First of all, by using a TD analysis tool, we can examine the curves' moving trend and

pattern visually along with their correlation numerically. We can also study the extremely high or low data values in the dataset. The visual observation or calculation-derived interpretations are a part of statistical analysis results which can indeed provide some useful hints or even derive some accurate conclusions. However, we must be aware of the limitations of the selected data size and time window and also be cautious of the appropriate statistics tool we choose.

Regarding the TD energy, we can apply the rudimentary definition of physics that “the wave carried energy is directly proportional to the square of wave’s amplitude”. However, the data quantity % of each wave category should be considered and included in order to obtain a more accurate TD energy value.

The author would like to describe the essence of his developed “hybrid model” that combines both the SD viscoelastic/plastic VGT analysis method and FD FFT analysis method with a comparison against the traditional time-domain statistical correlation analysis.

It is described in 10 steps in the English language instead of using mathematical equations to explain it. In this article, he has applied both the SD-VGT operations (steps 1-7) and the FD-FFT operations (steps 8-10). As a result, it is aimed at readers who do not have an extensive background in the academic subjects of engineering, physics & mathematics.

The first step is to collect the output data or symptom (strain or ϵ) on a time scale. The second step is to calculate the output change rate with time ($d\epsilon/dt$), i.e. the change rate of strain or symptom over each period. The third step is to gather the input data or cause (viscosity or η) on a time scale. The fourth step is to calculate the time-dependent input or cause (time-dependent stress or σ) by multiplying $d\epsilon/dt$ and η together. The “time-dependent input or cause equation” of “stress $\sigma = \text{strain change rate of } d\epsilon/dt * \text{viscosity } \eta$ ” is the essential part of this “time dependency”. The fifth step is to plot the input-output (i.e. stress-strain or cause-symptom) curve in a two-dimensional space-domain or SD (x-axis versus y-axis) with strain (output or symptom) on the x-axis and stresses (time-dependent inputs, causes, or stresses) on the y-axis.

The sixth step is to calculate the total enclosed area within these stress-strain curves or input-output curves (i.e. the hysteresis loops), which is also an indicator of associated energies (either created energy or dissipated energy) of this input and output dataset. These energy values can also be considered as the degrees of influence on output by inputs. The seventh step is the assembly of the area values of the selected periods to compare the “historical progression and contribution of medical condition” over certain time periods. For the frequency domain, the eighth step is to define a “hybrid input variable” by using “strain*stress” which yields another accurate estimation of the energy ratio similar to the SD-VGT energy ratio associated with the hysteresis loop. The ninth step is to present these hybrid models’ results of (strain*stress) in TD and then perform the FFT operation to convert them into FD. The enclosed area of the frequency curve (where the x-axis is the frequency and the y-axis is the amplitude of energy) can be used to estimate the total FD-FFT energy. The tenth step is to compare these FD energy results against the SD-VGT energy results, or even TD energy results.

After providing the above 10-step description, the author would still like to use the following set of VGT stress-strain mathematical equations in a two-dimensional SD to address the selected medical variables:

Strain
 $= \epsilon$ (time-dependency characteristics of individual strain value at the present time duration)

Stress
 $= \sigma$ (based on the change rate of strain multiplying with a chosen viscosity factor η)
 $= \eta * (d\epsilon/dt)$
 $= \eta * (d\text{-strain}/d\text{-time})$
 $= (\text{viscosity factor } \eta \text{ using individual viscosity factor at present time duration}) * (\text{strain at present quarter} - \text{strain at previous time duration})$

Some of these inputs (causes or viscosity factors) are further normalized by dividing them or being divided by a normalization factor using certain established health standards or medical pieces of knowledge. Some examples of normalization factors are 6.0 for HbA1C, 120 mg/dL for glucose, 25 for body mass index (BMI), 4,000 steps after each

meal, 10,000 or 12,000 steps for daily walking exercise depending on time-period selection, 13 grams to 20 grams of carbs/sugar intake amount per meal depends on time-period selection. If using the originally collected data, i.e. the non-normalized data, it would distort the numerical comparison of the hysteresis loop areas. Using this “normalization process”, we can remove the dependency of the individual unit or certain unique characteristics associated with each viscosity factor. This process allows us to convert the originally collected variables into a set of “dimensionless variables” for easier numerical comparison and result interpretation.

Note: For a more detailed description, please refer to the “consolidated method” section which is given at the beginning of the special issue.

3. RESULTS

Figure 1 displays waveforms of BMI, PPG, FPG, and TyG.

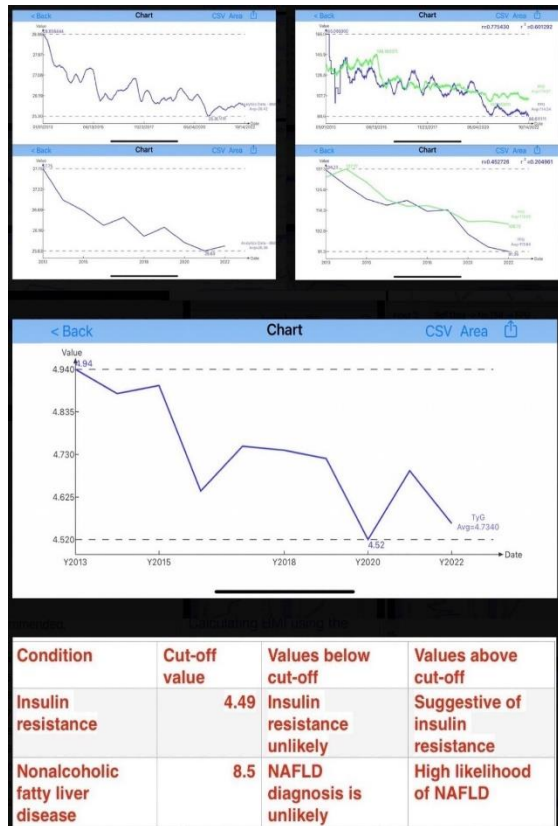


Figure 1: Waveforms of BMI, PPG, FPG, and TyG.

Figure 2 shows the SD-VGT data.

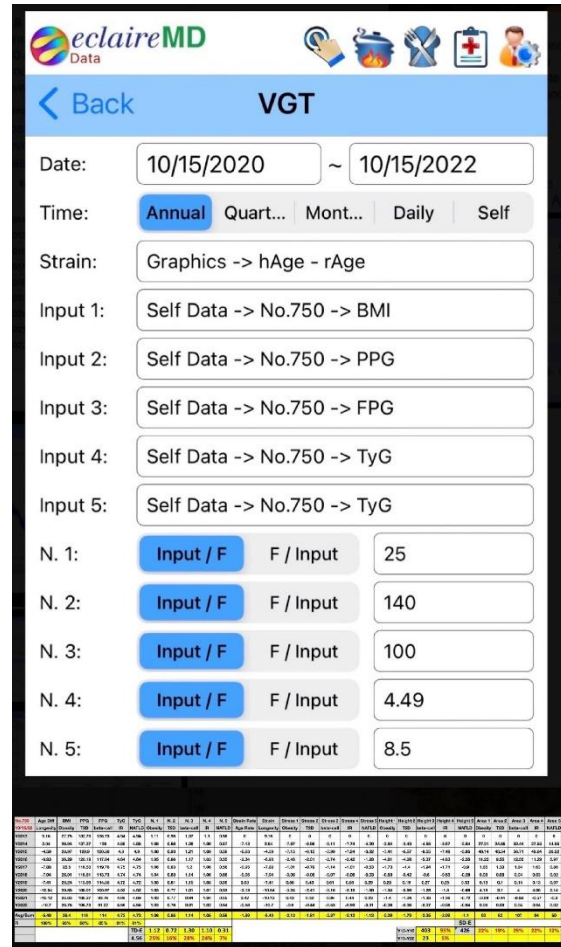


Figure 2: SD-VGT data.

Figure 3 reveals both TD and SD-VGT analysis results for longevity versus 5 input diseases.

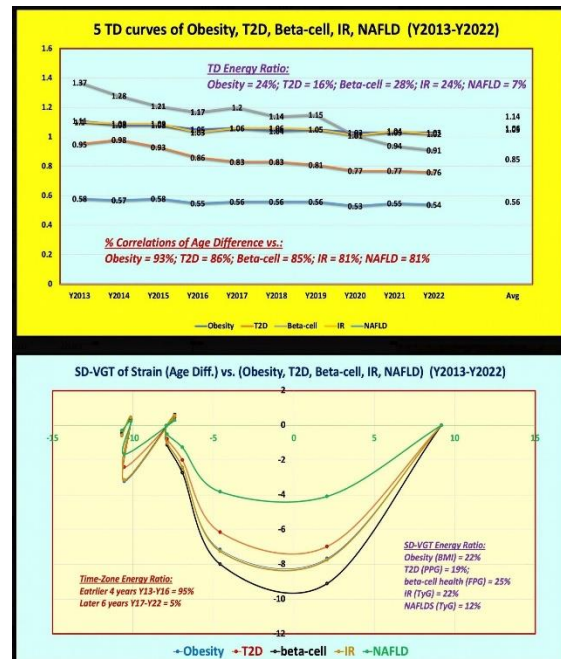


Figure 3: TD and SD-VGT analysis results for longevity versus 5 input diseases.

4. CONCLUSION

In summary, there are 5 noticeable findings regarding the energy study regarding the output of longevity via age difference versus 5 selected input diseases, obesity, T2D, pancreatic beta cell damage, insulin resistance, and NAFLD.

(1) From the collected data and waveforms of age difference output versus 5 selected inputs, his average age difference is 19.84 years (~20 years of life extension). The age difference here is defined as the maximum health age minus the minimum health age. The calculated correlation coefficients between age difference versus 5 inputs are: Obesity = 93%; T2D = 86%; Beta-cell = 85%; IR = 81%, NAFLD = 81%. All 5 correlations are above 80%.

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recent years because he needs more muscle strength in his old-age life. His triglyceride (TG) values have been kept around the borderline between healthy/unhealthy conditions; therefore, TG is not the main cause for IR being in the second-ranking position. His T2D via PPG is ranked as the number 4 energy contributor due to the higher normalization factor of 140 mg/dL as the Normalization factor or the dividing line between diabetes and normal condition by the existing medical community. However, the author's personal goal has always been 120 mg/dL. He does not have a fatty liver condition; therefore, NAFLD in the bottom-ranking position (the smallest hysteresis loop area) is understandable which also matches his routine medical checkup results.

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The conclusive statements of this article are, "The author only prepares the data for the numerical calculations according to math-physical theorems or energy methods. Then, he only interpreted his observed result findings and certain biophysical phenomena. But, those observed analysis results have totally matched with biomedical judgments made by his clinical doctors."

5. REFERENCES

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

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

For reading more of the author's published VGT or FD analysis results on medical applications, please locate them through three published special editions from the following three specific journals:

(1) Special Issue. The GH-Method. (<https://www.theghmethod.com>).

(2) Journal of Applied Material Science & Engineering Research (contact: Catherine).

(3) Advances in Bioengineering and Biomedical Science Research (contact: Sony Hazi).

Viscoelastic and Viscoplastic Glucose Theory Application in Medicine

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