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The GH-Method

Viscoelastic or Viscoplastic Glucose Theory (VGT #152): Two Case Studies of Risk Probability in Having Cardiovascular Diseases and Strokes versus Body Weight, Glucose, and the Average Value of Blood Pressure and Blood Lipids Using 3 Different Energy Analysis Models of Time Domain, Space Domain, and Frequency Domain Based on the GH-Method: Math-Physical Medicine (No. 745)

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Keywords: Viscoelastic; Viscoplastic; Cardiovascular diseases; Stroke; Body weight; Blood pressure; Blood lipids; Postprandial plasma glucose; Fasting plasma glucose; Type 2 diabetes; Fast Fourier transform

Abbreviations: CVD: cardiovascular disease; FFT: fast Fourier transform; T2D: type 2 diabetes; PPG: postprandial plasma glucose; FPG: fasting 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:

“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 amount of US deaths was 2,506,540 (100%) which includes a new category of 350,831 (14%) from COVID. The subtotal death cases that directly or indirectly resulted from a variety of metabolic disorders are 1,748,553 (70%). This subtotal category includes 34% of both heart attacks (28%) and strokes (6%).

A note from WHO: An estimated 17.9 million people died from CVDs in 2019, representing 32% of all global deaths. Of these deaths, 85% were due to heart attack and stroke.”

The main path of having many deadly diseases and medical complications is due to a poor lifestyle leading to body weight problems such as being overweight and having obesity, then developing diabetes, hypertension, and hyperlipidemia. As a result, a variety of metabolic disorder-induced complications such as heart issues, stroke, kidney problems, even cancers and Alzheimer’s can occur, and finally leading to death or shortening a person’s lifespan/longevity. This article particularly focuses on investigating the risk % of having

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CVD or stroke (CVD) versus body weight (m1), glucose (m2), and the average value of blood pressure (m3) and blood lipids (m4). Obesity and diabetes are two of the strongest influential diseases which would develop into many different deadly complications, particularly CVD or stroke when they are combined with the conditions of hypertension and hyperlipidemia. It should be noted that m1, m2, m3, and m4 values have already been normalized based on each individual healthy/unhealthy dividing line value.

This article's data preparation and data processing work is 100% dependent on the author's recently developed and enhanced VGT software tool which has reduced his data work time from 5-6 hours to less than 1 minute. Therefore, he can spend this saved time on results investigation and biophysical phenomenon interpretation.

The specific program enhancements for this particular study have included the following 4 newly defined variables for fast Fourier transformed (FFT) frequency-domain (FD) analysis results:

(1) strain * stress (stress = strain rate * normalized viscosity)

(2) strain * normalized viscosity change rate

(3) strain * squared normalized viscosity change rate

(4) normalized viscosity change rate

However, after examining the energy results using FD Models 2, 3, and 4 in 24 studies, the author has discovered that about 5 studies (about 20% of his total examined results thus far) have derived somewhat unsatisfactory results or results he could not interpret properly. Therefore, the author has decided to stop using his developed FD Models 2, 3, and 4, and return to using the following three original energy models.

The first time-domain (TD) model using a rudimentary physics definition of energy is proportional to the squared wave amplitude. The second space-domain (SD) model utilizes the strain-stress curve's hysteresis loop area of viscoelastic and viscoplastic engineering material behaviors. The third FD model uses the author-defined variable of strain multiplying with stress (i.e. strain change rate multiplying with normalized viscosity) and FFT operation of wave theory in physics.

In conclusion, there are two case studies in this research article regarding the output symptom of CVD risk versus three input causes of m1, m2, and the average value of m3 and m4. In addition, there are a few summarized findings regarding energies:

(1) The First Case of Y2010-Y2015: He has calculated 6 CVD % annual data using the metabolism index approach as the output strain, and corresponding measured m1, m2, and average m3&m4 as three input causes (viscosities) from 1/1/2010 to 12/31/2015. In this First Case, due to a lack of a stringent lifestyle management effort (even taking 3 different diabetes medications), his average values are CVD risk % = 96%, m1 = 1.13, m2 = 1.46, m3&m4 = 0.61. In the following section of Methods concerning the author's medical history, he had suffered multiple cardiac episodes before and during the earlier period of Y10-Y15 (CVD risk at 96%). It is also quite clear that he was very "unhealthy" in terms of both overweight (13% higher) and diabetic glucose (46% higher).

(2) The Second Case of Y2016-Y2021: He has calculated 6 CVD % annual data using the metabolism index approach as the output strain, and corresponding measured m1, m2, and average m3&m4 as three input causes (viscosities) from 1/1/2016 to 12/31/2021. In this Second Case, due to a better lifestyle management effort (without taking any diabetes medications), his average values are CVD risk % = 55%, m1 = 1.02 (170 lbs. and BMI 25 as 1.0), m2 = 0.94 (120 mg/dL as 1.0), m3&m4 = 0.66 (which is similar to the First Case of 0.61). It is evident that, during the second period of Y16-Y21, he has become "healthier" (CVD risk at 55%) in terms of both body weight (100% at BMI 25) and glucose control (6% lower than 120 mg/dL).

(3) The total SD-VGT energy area calculations have shown a 300 times difference between the earlier First Case versus the recent Second Case. However, the total FD-FFT energy area calculations have shown a 776 times difference between the First Case versus the Second Case. This means that the First Case of Y10-Y15 still has an extremely high probability of having CVD or stroke due to obesity/overweight and hyperglycemia. The Second Case of Y16-Y21

has significantly reduced his risk of having CVD/stroke (however, he should continuously make effort on reducing his body weight). This higher ~2X area ratio (766 FD energy versus 300 SD energy) is expected since the author has chosen his defined FD variable as the strain*stress (i.e. strain change rate * normalized viscosity). Therefore, an amplification effect is expected. Nevertheless, a similar energy distribution pattern is preserved.

(4) These 2-case studies have clearly demonstrated the energy-shift pattern among m1, m2, and the average m3 and m4. Using the average values of these three energy percentages, the most prominent finding of the First Case of Y10-Y15 is that m2 glucose has made the most contribution or influence on CVD, 60%. Body Weight m1 contributes or influences 30% and m3&m4 contributes or influences the remaining 9%. However, the most prominent finding of the Second Case of Y16-Y21 is that Body Weight m1 has made the most contribution or influence on CVD, 43%. Glucose m2 contributes or influences 37% and m3&m4 contributes or influences the remaining 20%.

(5) In the second period of Y16-Y21, the author had a better effort in controlling his glucose situation compared to his weight control. This has caused the energy shift from m1 weight being the number 1 contribution factor in the first period to m2 glucose being the number 1 contribution factor in the second period. Comparing the first case versus the second case, glucose m2 contribution has been reduced by 23% from 60% to 37%, and weight m1 contribution has been increased by 13% from 31% to 43%, while m3&m4 contribution has also gained 11% from 9% to 20%. This clear picture of energy shifting illustrates the importance of the roles of both glucose in the earlier period of Case 1 and body weight in the recent period of Case 2.

2. METHODS

2.1 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.

2.2 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 CVD, CHD, stroke, CKD, 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.

2.3 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 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 (dε/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 dε/dt and η together. The "time-dependent input or cause equation" of "stress σ = strain change rate of dε/dt * viscosity η" 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 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
= ε (time-dependency characteristics of individual strain value at the present time duration)

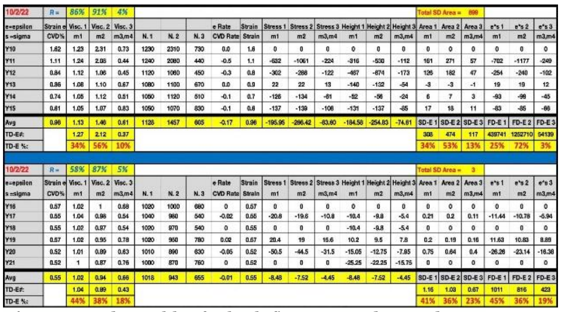
Stress
= σ (based on the change rate of strain multiplying with a chosen viscosity factor η)
= η * (dε/dt)
= η * (d-strain/d-time)
= (viscosity factor η using individual viscosity factor at present time duration) * (strain at present quarter - strain at previous time duration)

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 2 data tables for both First Case and Second Case.



10/2/22	R =	86%	91%	4%												Total SD Area =	899				
e=epsilon	Strain e	Visc. 1	Visc. 2	Visc. 3				e Rate	Strain	Stress 1	Stress 2	Stress 3	Height 1	Height 2	Height 3	Area 1	Area 2	Area 3	e*s 1	e*s 2	e*s 3
s =sigma	CVD%	m1	m2	m3,m4	N. 1	N. 2	N. 3	CVD Rate	Strain	m1	m2	m3,m4	m1	m2	m3,m4	m1	m2	m3,m4	m1	m2	m3,m4
Y10	1.62	1.23	2.31	0.73	1230	2310	730	0.0	1.6	0	0	0	0	0	0	0	0	0	0	0	0
Y11	1.11	1.24	2.08	0.44	1240	2080	440	-0.5	1.1	-632	-1061	-224	-316	-530	-112	161	271	57	-702	-1177	-249
Y12	0.84	1.12	1.06	0.45	1120	1060	450	-0.3	0.8	-302	-288	-122	-467	-674	-173	126	182	47	-254	-240	-102
Y13	0.86	1.08	1.10	0.67	1080	1100	670	0.0	0.9	22	22	13	-140	-132	-54	-3	-3	-1	19	19	12
Y14	0.74	1.05	1.12	0.51	1050	1120	510	-0.1	0.7	-126	-134	-61	-82	-56	-24	6	7	3	-93	-99	-45
Y15	0.61	1.05	1.07	0.83	1050	1070	830	-0.1	0.6	-137	-139	-106	-131	-137	-65	17	18	11	-83	-85	-66
Avg	0.96	1.13	1.46	0.61	1128	1457	605	-0.17	0.96	-195.95	-286.42	-83.60	-184.58	-254.83	-74.61	SD-E 1	SD-E 2	SD-E 3	FD-E 1	FD-E 2	FD-E 3
TD-E#:		1.27	2.12	0.37												308	474	117	439741	1252710	54139
TD-E %:		34%	56%	10%												34%	53%	13%	25%	72%	3%

10/2/22	R =	58%	87%	5%												Total SD Area =	3				
e=epsilon	Strain e	Visc. 1	Visc. 2	Visc. 3				e Rate	Strain	Stress 1	Stress 2	Stress 3	Height 1	Height 2	Height 3	Area 1	Area 2	Area 3	e*s 1	e*s 2	e*s 3
s =sigma	CVD%	m1	m2	m3,m4	N. 1	N. 2	N. 3	CVD Rate	Strain	m1	m2	m3,m4	m1	m2	m3,m4	m1	m2	m3,m4	m1	m2	m3,m4
Y16	0.57	1.02	1	0.68	1020	1000	680	0	0.57	0	0	0	0	0	0	0	0	0	0	0	0
Y17	0.55	1.04	0.98	0.54	1040	980	540	-0.02	0.55	-20.8	-19.6	-10.8	-10.4	-9.8	-5.4	0.21	0.2	0.11	-11.44	-10.78	-5.94
Y18	0.55	1.02	0.97	0.54	1020	970	540	0	0.55	0	0	0	-10.4	-9.8	-5.4	0	0	0	0	0	0
Y19	0.57	1.02	0.95	0.78	1020	950	780	0.02	0.57	20.4	19	15.6	10.2	9.5	7.8	0.2	0.19	0.16	11.63	10.83	8.89
Y20	0.52	1.01	0.89	0.63	1010	890	630	-0.05	0.52	-50.5	-44.5	-31.5	-15.05	-12.75	-7.85	0.75	0.64	0.4	-26.26	-23.14	-16.38
Y21	0.52	1	0.87	0.76	1000	870	760	0	0.52	0	0	0	-25.25	-22.25	-15.75	0	0	0	0	0	0
Avg	0.55	1.02	0.94	0.66	1018	943	655	-0.01	0.55	-8.48	-7.52	-4.45	-8.48	-7.52	-4.45	SD-E 1	SD-E 2	SD-E 3	FD-E 1	FD-E 2	FD-E 3
TD-E#:		1.04	0.89	0.43												1.16	1.03	0.67	1011	816	423
TD-E %:		44%	38%	18%												41%	36%	23%	45%	36%	19%

Figure 1: 2 data tables for both first case and second case.

Figure 2 reflects 2 TD curves for both First Case and Second Case.

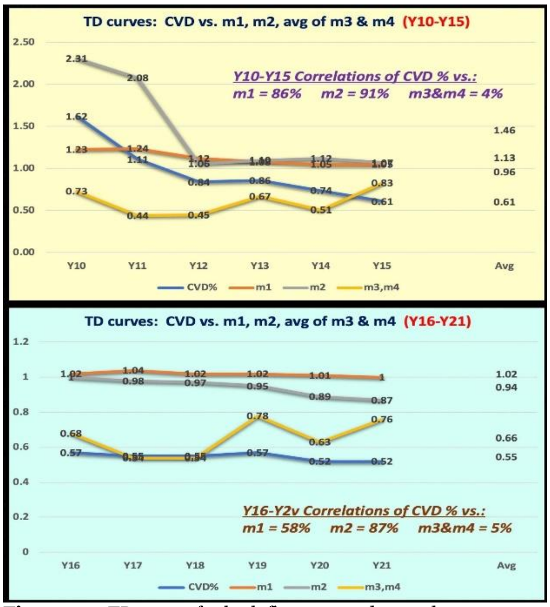


Figure 2: 2 TD curves for both first case and second case.

Figure 3 shows 2 SD-VGT analysis results for both First Case and Second Case.

Figure 4 depicts 2 FD-FFT analysis results for both First Case and Second Case.

Figure 5 reveals the energy contribution percentages of 3 different models (TD, SD, and FD).

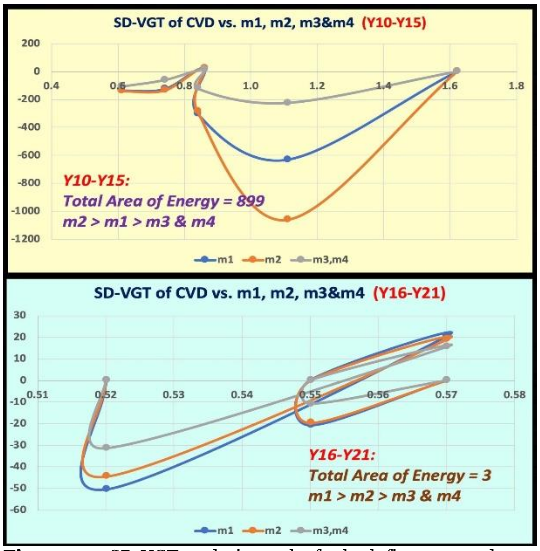


Figure 3: 2 SD-VGT analysis results for both first case and second case.

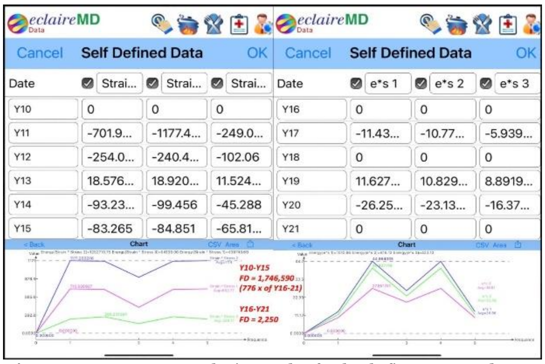


Figure 4: 2 FD-FFT analysis results for both first case and second case.

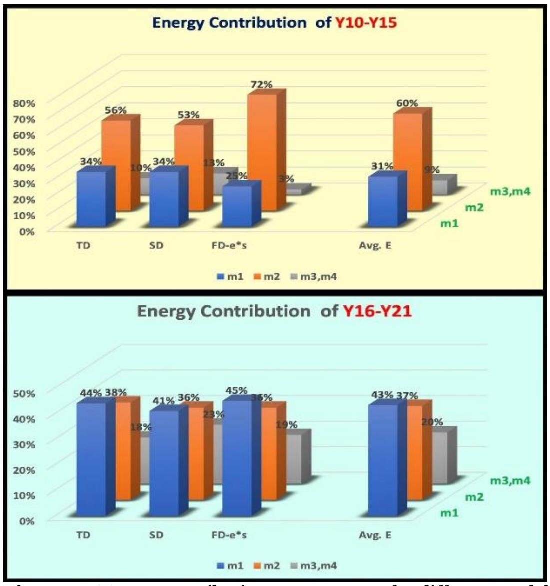


Figure 5: Energy contribution percentages of 3 different models (TD, SD, FD).

4. CONCLUSION

In conclusion, there are two case studies in this research article regarding the output symptom of CVD risk versus three input causes of m1, m2, and the average value of m3 and m4. In additions, there are a few summarized findings regarding energies:

(1) The First Case of Y2010-Y2015: He has calculated 6 CVD % annual data using the metabolism index approach as the output strain, and corresponding measured m1, m2, and average m3&m4 as three input causes (viscosities) from 1/1/2010 to 12/31/2015. In this First Case, due to a lack of a stringent lifestyle management effort (even taking 3 different diabetes medications), his average values are CVD risk % = 96%, m1 = 1.13, m2 = 1.46, m3&m4 = 0.61. In the following section of Methods concerning the author's medical history, he had suffered multiple cardiac episodes before and during the earlier period of Y10-Y15 (CVD risk at 96%). It is also quite clear that he was very "unhealthy" in terms of both overweight (13% higher) and diabetic glucose (46% higher).

(2) The Second Case of Y2016-Y2021: He has calculated 6 CVD % annual data using metabolism index approach as the output strain, and corresponding measured m1, m2, and average m3&m4 as three input causes (viscosities) from 1/1/2016 to 12/31/2021. In this Second Case, due to a better lifestyle management effort (without taking any diabetes medications), his average values are CVD risk % = 55%, m1 = 1.02 (170 lbs. and BMI 25 as 1.0), m2 = 0.94 (120 mg/dL as 1.0), m3&m4 = 0.66 (which is similar to the First Case of 0.61). It is evident that, during the second period of Y16-Y21, he has become "healthier" (CVD risk at 55%) in terms of both body weight (100% at BMI 25) and glucose control (6% lower than 120 mg/dL).

(3) The total SD-VGT energy area calculations have shown a 300 times difference between the earlier First Case versus the recent Second Case. However, the total FD-FFT energy area calculations have shown a 776 times difference between the First Case versus the Second Case. This means that the First Case of Y10-Y15 still has an extremely high probability of having CVD or stroke due to obesity/overweight and hyperglycemia. The Second Case of Y16-Y21 has significantly reduced his risk of having CVD/stroke (however, he should continuously make effort on reducing his body weight). This higher ~2X area ratio (766 FD energy versus 300 SD energy) is expected since the author has chosen his defined FD variable as the strain*stress (i.e. strain change rate * normalized viscosity). Therefore, an amplification effect is expected. Nevertheless, a similar energy distribution pattern is preserved.

(4) These 2-case studies have clearly demonstrated the energy-shift pattern among m1, m2, and the average m3 and m4. Using the average values of these three energy percentages, the most prominent finding of the First Case of Y10-Y15 is that m2 glucose has made the most contribution or influence on CVD, 60%. Body Weight m1 contributes or influences 30% and m3&m4 contributes or influences the remaining 9%. However, the most prominent finding of the Second Case of Y16-Y21 is that Body Weight m1 has made the most contribution or influence on CVD, 43%. Glucose m2 contributes or influences 37% and m3&m4 contributes or influences the remaining 20%.

(5) In the second period of Y16-Y21, the author had a better effort on controlling his glucose situation compared to his weight control. This has caused the energy shift from m1 weight being the number 1 contribution factor in the first period to m2 glucose being the number 1 contribution factor in the second period. Comparing the first case versus the second case, glucose m2 contribution has been reduced by 23% from 60% to 37%, and weight m1 contribution has been increased by 13% from 31% to 43%, while m3&m4 contribution has also gained 11% from 9% to 20%. This clear picture of energy shifting illustrates the importance of the roles of both glucose in the earlier period of Case 1 and body weight in the recent period of Case 2.

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.eclairemd.com.

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).

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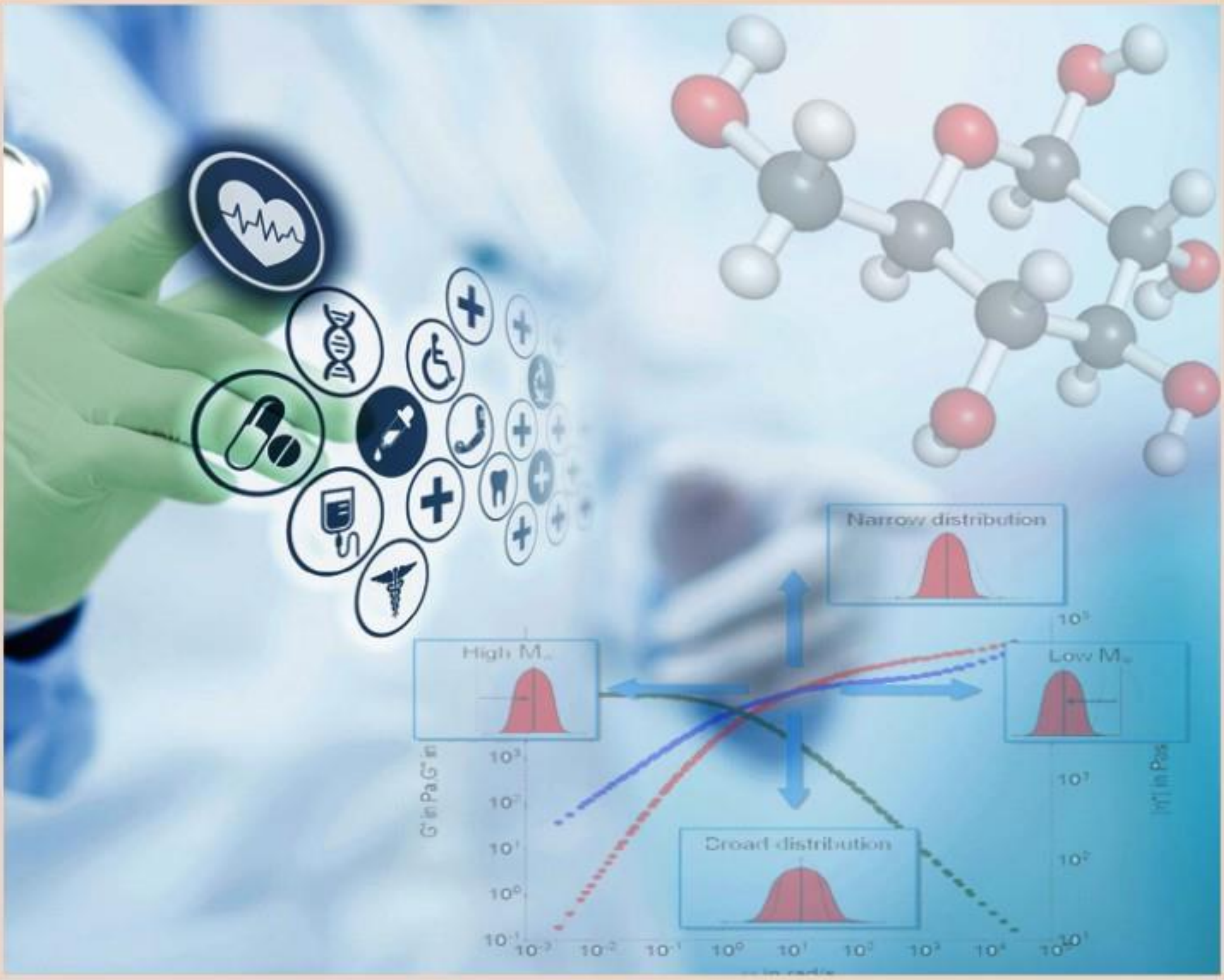

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