ISSN: 2689-1204

Research Article

Journal of Applied Material Science & Engineering Research

An Re-Examination of CVD Risk Versus Both Metabolic Conditions and Lifestyle Details Using Signal Processing Techniques and Viscoplastic Energy Model of Gh-Method: Math-Physical Medicine (No. 1017, Viscoelastic Medicine Theory #415)

Gerald C. Hsu

EclaireMD Foundation, USA

[*]Corresponding Author
Gerald C. Hsu, EclaireMD Foundation, USA

Submitted: 2024, Feb 26; **Accepted:** 2024, Mar 14; **Published:** 2024, Mar 19

Citation: Hsu, G. C. (2024). A partial view of the gut-brain axis study from lifestyle details through metabolic disorders to dementia using viscoplastic energy model of GH-Method: Math-Physical Medicine (No. 1015, VMT #413). *J App Mat Sci & Engg Res, 8*(1), 01-09.

Category: Dementia

Abstract

The author has recently studied his risks of having cardiovascular diseases (CVD) or strokes stemming from various influential factors. In this article, he aims to leverage both signal processing techniques and the viscoplastic energy method to reassess his CVD risks based on both metabolic conditions (MC) and lifestyle details (LD).

This article introduces two new formulas for combined MC and combined LD.
T.MC = body weight (BW)* 0.3 + glucose (T2D)* 0.3 + hypertension (BP) * 0.2 * 0.7 + dyslipidemia (Lipid) * 0.2 * 0.3
This formula suggests that the CVD risk is more often caused by blockages in the arteries than by ruptures of the arteries.

T.LD = food portion and quality (Food) * 0.3 + walking steps (Exercise) * 0.3 + sleep * 0.2 + Stress * 0.2

Initially, the author used signal processing techniques to decompose his CVD risk curve into two sets of influential factors - five from MC and five from LD. Subsequently, he compared the averaged amplitudes of each of these five influential curves and then calculated five energy ratios of these two analysis sets using the viscoplastic energy method.

***In summary,** the author found that **his MC energy area (530) is higher than his LD energy area (379), suggesting that his lifestyle management has been more effective than his metabolic condition over the past 11 years.** He also observed the higher input amplitudes of BW and T2D compared to BP and Lipid, as well as the higher input amplitudes of Food, Exercise, and Sleep compared to Stress. Those higher amplitudes usually leading into elevated relative energies (stress-strain curve area). Please noting that the strain change rate of CVD risk is identical for both MC and LD cases.*

SD-VMT energy ratios of his CVD risk curve versus Metabolic inputs
Combined MC = 21.1%;
Obesity = 22.5%;
Diabetes = 22.6%;
Hypertension = 19.6%;
Dyslipidemia = 14.2%.

SD-VMT energy ratios of his CVD risk curve versus Lifestyle inputs
Combined LD = 24.0%;
Food = 20.8%;
Exercise = 20.7%;
Sleep = 19.2%;
Stress = 15.3%.

The time-zone energy distributions are:
Y2014-Y2019 = 96%
Y2020-Y2024 = 4%

The previous 6 years contribute the majority, 96% of the total energy associated with his CVD risk curve, while the recent 5 years contribute only 4% of the total PPG energy.

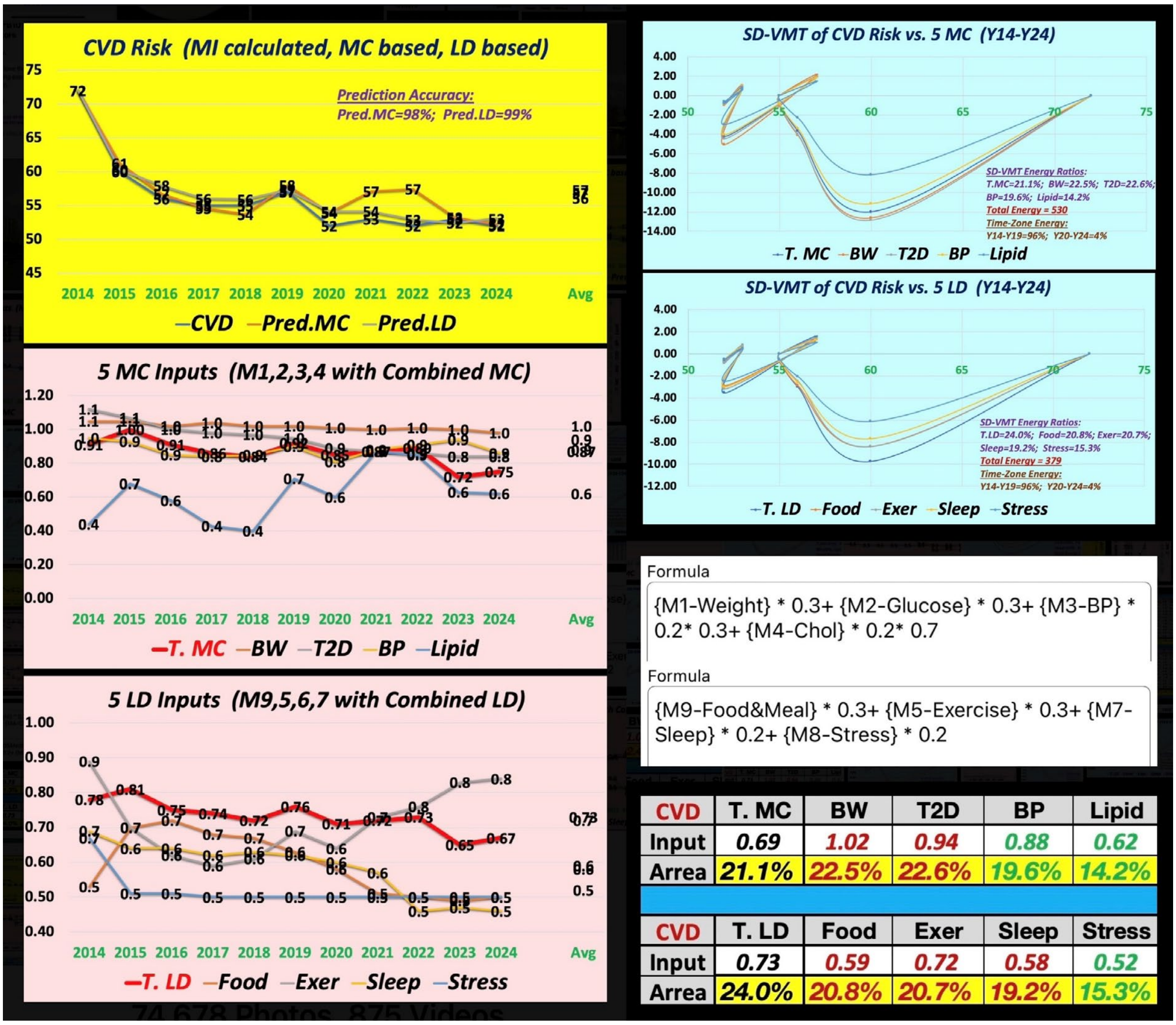
During this selected period of 11 years (from 1/1/2014 to 1/8/2024), the average CVD risk values are:

MI-based calculation: 56%
MC-based Prediction: 57%
LD-based prediction: 57%

MC Prediction accuracy = 98%
LD Prediction accuracy = 99%

Key Message

His four lifestyle management effort is proving more effective in reducing his CVD risk (lowering viscoplastic energy) than his four metabolic management effort. In a more detailed analysis, the control of his diabetes and body weight are identified as higher-priority factors compared to managing his blood pressures and blood lipids. Additionally, his diet, exercise, and sleep play a more crucial role than his stress (the lowest energy). This decomposed signal processing and viscoplastic energy analysis offers a clear understanding of overall health profile of his heart and brain, supported by quantitative data and scientific evidence.



Category: Diabetes

1. Introduction

The author has recently studied his risks of having cardiovascular diseases (CVD) or strokes stemming from various influential factors. In this article, he aims to leverage both signal processing techniques and the viscoplastic energy method to reassess his CVD risks based on both metabolic conditions (MC) and lifestyle details (LD).

This article introduces two new formulas for combined MC and combined LD.

T.MC = body weight (BW)* 0.3 + glucose (T2D)* 0.3 + hypertension (BP) * 0.2 * 0.7 + dyslipidemia (Lipid) * 0.2 * 0.3

This formula suggests that the CVD risk is more often caused by blockages in the arteries than by ruptures of the arteries.

T.LD = food portion and quality (Food) * 0.3 + walking steps (Exercise) * 0.3 + sleep * 0.2 + Stress * 0.2

Initially, the author used signal processing techniques to decompose his CVD risk curve into two sets of influential factors - five from MC and five from LD. Subsequently, he compared the averaged amplitudes of each of these five influential curves and then calculated five energy ratios of these two analysis sets using the viscoplastic energy method.

1.1Engineering and Biomedical information

The following sections contain excerpts and concise information drawn from multiple medical articles, which have been meticulously reviewed by the author of this paper. The author has adopted this approach as an alternative to including a conventional reference list at the end of this document, with the intention of optimizing his valuable research time. It is essential to clarify that these sections do not constitute part of the author's original contribution but have been included to aid the author in his future reviews and offer valuable insights to other readers with an interest in these subjects.

2. What Are Common Signal Processing Techniques?

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

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

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

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

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

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

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

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

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

3. How To Decompose One Signal Waveform Into Multiple Constitute Waveforms?

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

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

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

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

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

4. How To Decompose A Combined Signal Into Several Component Waveforms Using Signal Processing Techniques?

It is possible to decompose a combined signal wave into several component waveforms using signal processing techniques. This process is known as ***signal decomposition or signal***

demodulation, and it is a common practice in fields such as communications, audio processing, and biomedical signal analysis.

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

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

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

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

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

5. Pathophysiological Explanations of CVD Risk versus Obesity, Diabetes, Hypertension and Dyslipidemia

Cardiovascular disease (CVD) risk is influenced by several factors including obesity, diabetes, hypertension, and dyslipidemia. Here are some pathophysiological explanations for how these conditions can contribute to CVD risk:

Obesity: Excess body weight, particularly visceral adiposity (fat around the abdomen or belly fat), can lead to a state of chronic low-grade inflammation. This inflammatory state is associated with the release of inflammatory cytokines and adipokines, disrupting metabolic homeostasis and promoting atherosclerosis, a major underlying cause of CVD. ***(Note: Staring from November if 2923, the author launched his effort of belly fat reduction through resistance training in addition to his 15,000 steps of daily walking. His goal is to further reduce his waist line by 2 to 3 inches in order to reduce his visceral fat from 16% to 13%).***

Diabetes: Both type 1 and type 2 diabetes are associated with an increased risk of CVD. Hyperglycemia, insulin resistance, and associated abnormalities in lipid metabolism contribute to the development of atherosclerosis and endothelial dysfunction, increasing the likelihood of developing CVD.

Hypertension: High blood pressure causes chronic stress on the arterial walls, leading to endothelial injury and impaired vasodilation, which contributes to the development of atherosclerosis. Additionally, hypertension increases the workload on the heart, leading to structural changes that can predispose individuals to heart failure, coronary artery disease, and other CVDs.

Dyslipidemia: Abnormal lipid levels, particularly elevated LDL cholesterol and decreased HDL cholesterol, play a significant role in the development of atherosclerosis. High LDL levels promote the deposition of cholesterol in the arterial walls, leading to plaque formation, while low HDL levels impair reverse cholesterol transport, further exacerbating the risk of CVD.

By understanding the pathophysiological mechanisms underlying the association between these meteoric conditions and CVD, healthcare providers can better tailor interventions and treatments to reduce the overall risk of developing cardiovascular disease.

6. Pathophysiological Explanations of CVD Risk versus Diet, Exercise, Sleep and Stress

Diet: Poor dietary choices, including large meal portion and particularly those high in saturated fats, trans fats, and simple sugars, can lead to dyslipidemia, insulin resistance, and obesity. These factors contribute to atherosclerosis, inflammation, and endothelial dysfunction, increasing the risk of developing cardiovascular disease (CVD).

Exercise: Regular physical activity has a protective effect on the cardiovascular system by improving vascular function, reducing inflammation, and promoting favorable lipid profiles. Exercise also helps to maintain a healthy body weight, reduce blood pressure, and improve insulin sensitivity, all of which are beneficial for lowering the risk of CVD.

Sleep: Inadequate or poor-quality sleep is associated with an increased risk of developing CVD. Sleep disturbances can lead to disruptions in hormonal regulation, including increased levels of stress hormones, such as cortisol, and decreased levels of growth hormone and sex hormones. These changes can contribute to inflammation, insulin resistance, and dyslipidemia, all of which are risk factors for CVD.

Stress: Chronic stress can lead to dysregulation of the hypothalamic-pituitary-adrenal (HPA) axis and sympathetic nervous system, resulting in sustained elevations in cortisol and catecholamines. These hormonal imbalances can contribute to elevated blood pressure, inflammation, and endothelial dysfunction, increasing the risk of developing CVD.

Understanding the pathophysiological impact of diet, exercise, sleep, and stress on cardiovascular health is essential for developing comprehensive strategies to mitigate CVD risk. Lifestyle modifications that target these factors can play a crucial role in preventing and managing cardiovascular disease.

7. MPM Background

To learn more about his developed GH-Method: math-physical medicine (MPM) methodology, readers can read the following three papers selected from his published 760+ papers.

The first paper, No. 386 (Reference 1) describes his MPM methodology in a general conceptual format. The second paper, No. 387 (Reference 2) outlines the history of his personalized diabetes research, various application tools, and the differences between biochemical medicine (BCM) approach versus the MPM approach. The third paper, No. 397 (Reference 3) depicts a general flow diagram containing ~10 key MPM research methods and different tools.

8. The Author'S Diabetes History

The author was a severe T2D patient since 1995. He weighed 220 lb. (100 kg) at that time. By 2010, he still weighed 198 lb. with an average daily glucose of 250 mg/dL (HbA1C at 10%). During that year, his triglycerides reached 1161 (high risk for CVD and stroke) and his albumin-creatinine ratio (ACR) at 116 (high risk for chronic kidney disease). He also suffered from five cardiac episodes within a decade. In 2010, three independent physicians warned him regarding the need for kidney dialysis treatment and the future high risk of dying from his severe diabetic complications.

In 2010, he decided to self-study endocrinology with an emphasis on diabetes and food nutrition. He spent the entire year of 2014 to develop a metabolism index (MI) mathematical model. During 2015 and 2016, he developed four mathematical prediction models related to diabetes conditions: weight, PPG, fasting plasma glucose (FPG), and HbA1C (A1C). Through using his developed mathematical metabolism index (MI) model and the other four glucose prediction tools, by the end of 2016, his weight was reduced from 220 lbs. (100 kg) to 176 lbs. (89 kg), waistline from 44 inches (112 cm) to 33 inches (84 cm), average finger-piercing glucose from 250 mg/dL to 120 mg/dL, and A1C from 10% to ~6.5%. One of his major accomplishments is that he no longer takes any diabetes-related medications since 12/8/2015.

In 2017, he achieved excellent results on all fronts, especially his glucose control. However, during the pre-COVID period, including both 2018 and 2019, he traveled to ~50 international cities to attend 65+ medical conferences and made ~120 oral presentations. This hectic schedule inflicted damage to his diabetes control caused by stress, dining out frequently, post-meal exercise disruption, and jet lag, along with the overall negative metabolic impact from the irregular life patterns; therefore, his glucose control was somewhat affected during the two-year traveling period of 2018-2019.

He started his COVID-19 self-quarantined life on 1/19/2020. By 10/16/2022, his weight was further reduced to ~164 lbs. (BMI 24.22) and his A1C was at 6.0% without any medication intervention or insulin injection. In fact, with the special COVID-19 quarantine lifestyle since early 2020, not only has he written and published ~500 new research articles in various medical and engineering journals, but he has also achieved his best health conditions for the past 27 years. These achievements have resulted from his non-traveling, low-stress, and regular daily life routines. Of course, his in-depth knowledge of chronic diseases, sufficient practical lifestyle management experiences, and his own developed high-tech tools have also contributed to his excellent health improvements.

On 5/5/2018, he applied a continuous glucose monitoring (CGM) sensor device on his upper arm and checks his glucose measurements every 5 minutes for a total of 288 times each day. Furthermore, he extracted the 5-minute intervals from every 15-minute interval for a total of 96 glucose data each day stored in his computer software.

Through the author's medical research work over 40,000 hours and read over 4,000 published medical papers online in the past 13 years, he discovered and became convinced that good life habits of not smoking, moderate or no alcohol intake, avoiding illicit drugs; along with eating the right food with well-balanced nutrition, persistent exercise, having a sufficient and good quality of sleep, reducing all kinds of unnecessary stress, maintaining a regular daily life routine contribute to the risk reduction of having many diseases, including CVD, stroke, kidney problems, micro blood vessels issues, peripheral nervous system problems, and even cancers and dementia. In addition, a long-term healthy lifestyle can even "repair" some damaged internal organs, with different required time-length depending on the particular organ's cell lifespan. For example, he has "self-repaired" about 35% of his damaged pancreatic beta cells during the past 10 years.

9. Energy Theory

The human body and organs have around 37 trillion live cells which are composed of different organic cells that require energy infusion from glucose carried by red blood cells; and energy consumption from labor-work or exercise. When the residual energy (resulting from the plastic glucose scenario) is stored inside our bodies, it will cause different degrees of damage or influence to many of our internal organs.

According to physics, energies associated with the glucose waves are proportional to the square of the glucose amplitude. The residual energies from elevated glucoses are circulating inside the body via blood vessels which then impact all of the internal organs to cause different degrees of damage or influence, e.g. diabetic complications. Elevated glucose (hyperglycemia) causes damage to the structural integrity of blood vessels. When it combines with both hypertension (rupture of arteries) and hyperlipidemia (blockage of arteries), CVD or Stroke happens. Similarly, many other deadly diseases could result from these excessive energies which would finally shorten our lifespan. For an example, the combination of hyperglycemia and hypertension would cause micro-blood vessel's leakage in kidney systems which is one of the major cause of CKD.

The author then applied Fast Fourier Transform (FFT) operations to convert the input wave from a time domain into a frequency domain. The y-axis amplitude values in the frequency domain indicate the proportional energy levels associated with each different frequency component of input occurrence. ***Both output symptom value (i.e. strain amplitude in the time domain) and output symptom fluctuation rate (i.e. the strain rate and strain frequency) are influencing the energy level (i.e. the Y-amplitude in the frequency domain).***

Currently, many people live a sedentary lifestyle and lack sufficient exercise to burn off the energy influx which causes them to become overweight or obese. Being overweight and having obesity leads to a variety of chronic diseases, particularly diabetes. In addition, many types of processed food add unnecessary ingredients and harmful chemicals that are toxic to the bodies, which lead to the development of many other deadly diseases, such as cancers. For example, ~85% of worldwide diabetes patients are overweight, and ~75% of patients with cardiac illnesses or surgeries have diabetes conditions.

In engineering analysis, when the load is applied to the structure, it bends or twists, i.e. deform; however, when the load is removed, it will either be restored to its original shape (i.e, elastic case) or remain in a deformed shape (i.e. plastic case). In a biomedical system, the glucose level will increase after eating carbohydrates or sugar from food; therefore, the carbohydrates and sugar function as the energy supply. After having labor work or exercise, the glucose level will decrease. As a result, the exercise burns off the energy, which is similar to load removal in the engineering case. In the biomedical case, both processes of energy influx and energy dissipation take some time which is not as simple and quick as the structural load removal in the engineering case. Therefore, the age difference and 3 input behaviors are "dynamic" in nature, i.e. time-dependent. This time-dependent nature leads to *a "viscoelastic or viscoplastic" situation.* ***For the author's case, it is "viscoplastic" since most of his biomarkers are continuously improved during the past 13-year time window.***

Time-dependent output strain and stress of (viscous input*output rate)

Hooke's law of linear elasticity is expressed as:

Strain (ε: epsilon)
= Stress (σ: sigma) / Young's modulus (E)

For biomedical glucose application, his developed linear elastic glucose theory (LEGT) is expressed as:

PPG (strain) = carbs/sugar (stress) * GH.p-Modulus (a positive number) + post-meal walking k-steps * GH.w-Modulus (a negative number)

Where GH.p-Modulus is reciprocal of Young's modulus E.

However, in viscoelasticity or viscoplasticity theory, the stress is expressed as:

Stress
= viscosity factor (η: eta) * strain rate (dε/dt)

Where strain is expressed as Greek epsilon or ε.

In this article, in order to construct an "ellipse-like" diagram in a stress-strain space domain (e.g. "hysteresis loop") covering both the positive side and negative side of space, he has modified the definition of strain as follows:

Strain
= (body weight at certain specific time instant)

He also calculates his strain rate using the following formula:

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

The risk probability % of developing into CVD, CKD, Cancer is calculated based on his developed metabolism index model (MI) in 2014. His MI value is calculated using inputs of 4 chronic conditions, i.e. weight, glucose, blood pressure, and lipids; and 6 lifestyle details, i.e. diet, drinking water, exercise, sleep, stress, and daily routines. These 10 metabolism categories further contain ~500 elements with millions of input data collected and processed since 2010. For individual deadly disease risk probability %, his mathematical model contains certain specific weighting factors for simulating certain risk percentages associated with different deadly diseases, such as metabolic disorder-induced CVD, stroke, kidney failure, cancers, dementia; artery damage in heart and brain, micro-vessel damage in kidney, and immunity-related infectious diseases, such as COVID death.

Some of explored deadly diseases and longevity characteristics using the ***viscoplastic medicine theory (VMT)*** include stress relaxation, creep, hysteresis loop, and material stiffness, damping effect ***based on time-dependent stress and strain*** which are different from his previous research findings using ***linear elastic glucose theory (LEGT) and nonlinear plastic glucose theory (NPGT).***

10. Results

							/ 0.8	/ 1	/ 1	/ 1	/ 1	S. Rate	Strain
	CVD	T. MC	BW	T2D	BP	Lipid	T. MC	BW	T2D	BP	Lipid	CVD	CVD
2014	72	0.73	1.05	1.12	0.95	0.44	0.91	1.05	1.12	0.95	0.44	0.00	72
2015	60	0.80	1.05	1.07	0.93	0.68	1.00	1.05	1.07	0.93	0.68	-12.00	60
2016	56	0.73	1.02	1.00	0.85	0.58	0.91	1.02	1.00	0.85	0.58	-4.00	56
2017	55	0.69	1.04	0.98	0.84	0.43	0.86	1.04	0.98	0.84	0.43	-1.00	55
2018	55	0.67	1.02	0.97	0.85	0.40	0.84	1.02	0.97	0.85	0.40	0.00	55
2019	57	0.74	1.02	0.95	0.90	0.71	0.92	1.02	0.95	0.90	0.71	2.00	57
2020	52	0.68	1.01	0.89	0.81	0.60	0.85	1.01	0.89	0.81	0.60	-5.00	52
2021	53	0.70	1.00	0.87	0.88	0.87	0.87	1.00	0.87	0.88	0.87	1.00	53
2022	52	0.71	1.01	0.86	0.91	0.85	0.89	1.01	0.86	0.91	0.85	-1.00	52
2023	53	0.58	1.00	0.84	0.94	0.63	0.72	1.00	0.84	0.94	0.63	1.00	53
2024	52	0.60	0.98	0.84	0.86	0.62	0.75	0.98	0.84	0.86	0.62	-1.00	52
Avg	56	0.69	1.02	0.94	0.88	0.62	0.87	1.02	0.94	0.88	0.62	-1.82	56
Correl.	100%	49%	74%	86%	55%	-41%							

	Strs 1	Strs 2	Strs 3	Strs 4	Strs 5	Hgt 1	Hgt 2	Hgt 3	Hgt 4	Hgt 5	Area 1	Area 2	Area 3	Area 4	Area 5	Time	Pred.	Pred.	Pred.
	T. MC	BW	T2D	BP	Lipid	T. MC	BW	T2D	BP	Lipid	T. MC	BW	T2D	BP	Lipid	Zone	Step 1	Step 2	CVD
2014	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.0	0.0	0.0	0.0	0.0	Y14-Y19	0.93	1.05	72
2015	-12.00	-12.60	-12.84	-11.16	-8.16	-6.00	-6.30	-6.42	-5.58	-4.08	72.0	75.6	77.0	67.0	49.0	509	0.97	1.09	61
2016	-3.65	-4.08	-4.00	-3.40	-2.32	-7.83	-8.34	-8.42	-7.28	-5.24	31.3	33.4	33.7	29.1	21.0	96%	0.9	1.01	57
2017	-0.86	-1.04	-0.98	-0.84	-0.43	-2.26	-2.56	-2.49	-2.12	-1.38	2.3	2.6	2.5	2.1	1.4		0.86	0.97	55
2018	0.00	0.00	0.00	0.00	0.00	-0.43	-0.52	-0.49	-0.42	-0.21	0.0	0.0	0.0	0.0	0.0		0.85	0.96	54
2019	1.85	2.04	1.90	1.80	1.42	0.92	1.02	0.95	0.90	0.71	1.9	2.0	1.9	1.8	1.4		0.92	1.03	58
2020	-4.25	-5.05	-4.45	-4.05	-3.00	-1.20	-1.50	-1.28	-1.13	-0.79	6.0	7.5	6.4	5.6	4.0	Y20-Y24	0.85	0.96	54
2021	0.87	1.00	0.87	0.88	0.87	-1.69	-2.02	-1.79	-1.59	-1.06	-1.7	-2.0	-1.8	-1.6	-1.1	21	0.9	1.02	57
2022	-0.89	-1.01	-0.86	-0.91	-0.85	-0.01	-0.01	0.01	-0.02	0.01	0.0	0.0	0.0	0.0	0.0	4%	0.91	1.02	57
2023	0.72	1.00	0.84	0.94	0.63	-0.08	-0.01	-0.01	0.01	-0.11	-0.1	0.0	0.0	0.0	-0.1		0.84	0.95	53
2024	-0.75	-0.98	-0.84	-0.86	-0.62	-0.01	0.01	0.00	0.04	0.01	0.0	0.0	0.0	0.0	0.0		0.83	0.93	52
Avg	-1.72	-1.88	-1.85	-1.60	-1.13	-1.69	-1.84	-1.81	-1.56	-1.10	111.7	119.1	119.7	104.0	75.5	Pred.	0.89	1.00	57
Correl.									SD-E:	530	21.1%	22.5%	22.6%	19.6%	14.2%	Accu=	98%	R =	94%

							/ 1	/ 1	/ 1	/ 1	/ 1	S. Rate	Strain
	CVD	T. LD	Food	Exer	Sleep	Stress	T. LD	Food	Exer	Sleep	Stress	CVD	CVD
2014	72	0.78	0.53	0.89	0.69	0.67	0.8	0.5	0.9	0.7	0.7	0.00	72
2015	60	0.81	0.70	0.70	0.64	0.51	0.8	0.7	0.7	0.6	0.5	-12.00	60
2016	56	0.75	0.72	0.62	0.64	0.51	0.8	0.7	0.6	0.6	0.5	-4.00	56
2017	55	0.74	0.68	0.59	0.62	0.50	0.7	0.7	0.6	0.6	0.5	-1.00	55
2018	55	0.72	0.67	0.61	0.63	0.50	0.7	0.7	0.6	0.6	0.5	0.00	55
2019	57	0.76	0.63	0.69	0.62	0.50	0.8	0.6	0.7	0.6	0.5	2.00	57
2020	52	0.71	0.58	0.64	0.60	0.50	0.7	0.6	0.6	0.6	0.5	-5.00	52
2021	53	0.72	0.51	0.73	0.57	0.50	0.7	0.5	0.7	0.6	0.5	1.00	53
2022	52	0.73	0.50	0.76	0.46	0.50	0.7	0.5	0.8	0.5	0.5	-1.00	52
2023	53	0.65	0.49	0.83	0.47	0.50	0.7	0.5	0.8	0.5	0.5	1.00	53
2024	52	0.67	0.50	0.84	0.46	0.50	0.7	0.5	0.8	0.5	0.5	-1.00	52
Avg	56	0.73	0.59	0.72	0.58	0.52	0.7	0.6	0.7	0.6	0.5	-1.8	56
Correl.	100%	65%	12%	37%	67%	92%							

	Strs 1	Strs 2	Strs 3	Strs 4	Strs 5	Hgt 1	Hgt 2	Hgt 3	Hgt 4	Hgt 5	Area 1	Area 2	Area 3	Area 4	Area 5	Time	Pred.	Pred.	Pred.
	T. LD	Food	Exer	Sleep	Stress	T. LD	Food	Exer	Sleep	Stress	T. LD	Food	Exer	Sleep	Stress	Zone	Step 1	Step 2	CVD
2014	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	Y14-Y19	0.72	1.12	72
2015	-9.72	-8.40	-8.40	-7.68	-6.12	-4.86	-4.20	-4.20	-3.84	-3.06	58.32	50.40	50.40	46.08	36.72	363	0.69	1.07	60
2016	-3.00	-2.88	-2.48	-2.56	-2.04	-6.36	-5.64	-5.44	-5.12	-4.08	25.44	22.56	21.76	20.48	16.32	96%	0.66	1.03	58
2017	-0.74	-0.68	-0.59	-0.62	-0.50	-1.87	-1.78	-1.53	-1.59	-1.27	1.87	1.78	1.53	1.59	1.27		0.64	1.00	56
2018	0.00	0.00	0.00	0.00	0.00	-0.37	-0.34	-0.29	-0.31	-0.25	0.00	0.00	0.00	0.00	0.00		0.64	1.00	56
2019	1.52	1.26	1.38	1.24	1.00	0.76	0.63	0.69	0.62	0.50	1.52	1.26	1.38	1.24	1.00		0.65	1.02	57
2020	-3.55	-2.90	-3.20	-3.00	-2.50	-1.01	-0.82	-0.91	-0.88	-0.75	5.07	4.10	4.55	4.40	3.75	Y20-Y24	0.62	0.96	54
2021	0.72	0.51	0.73	0.57	0.50	-1.42	-1.19	-1.24	-1.22	-1.00	-1.42	-1.19	-1.24	-1.22	-1.00	16	0.62	0.97	54
2022	-0.73	-0.50	-0.76	-0.46	-0.50	-0.01	0.01	-0.02	0.05	0.00	0.01	-0.01	0.02	-0.05	0.00	4%	0.60	0.94	53
2023	0.65	0.49	0.83	0.47	0.50	-0.04	-0.01	0.03	0.00	0.00	-0.04	-0.01	0.03	0.00	0.00		0.60	0.93	52
2024	-0.67	-0.50	-0.84	-0.46	-0.50	-0.01	-0.01	-0.01	0.00	0.00	0.01	0.01	0.01	0.00	0.00		0.60	0.95	53
Avg	-1.4	-1.2	-1.2	-1.1	-0.9	-1.4	-1.2	-1.2	-1.1	-0.9	90.8	78.9	78.4	72.5	58.1	Pred.	0.64	1.00	57
Correl.									SD-E:	379	24.0%	20.8%	20.7%	19.2%	15.3%	Accu=	99%	R =	99%

Figure 1: Data tables

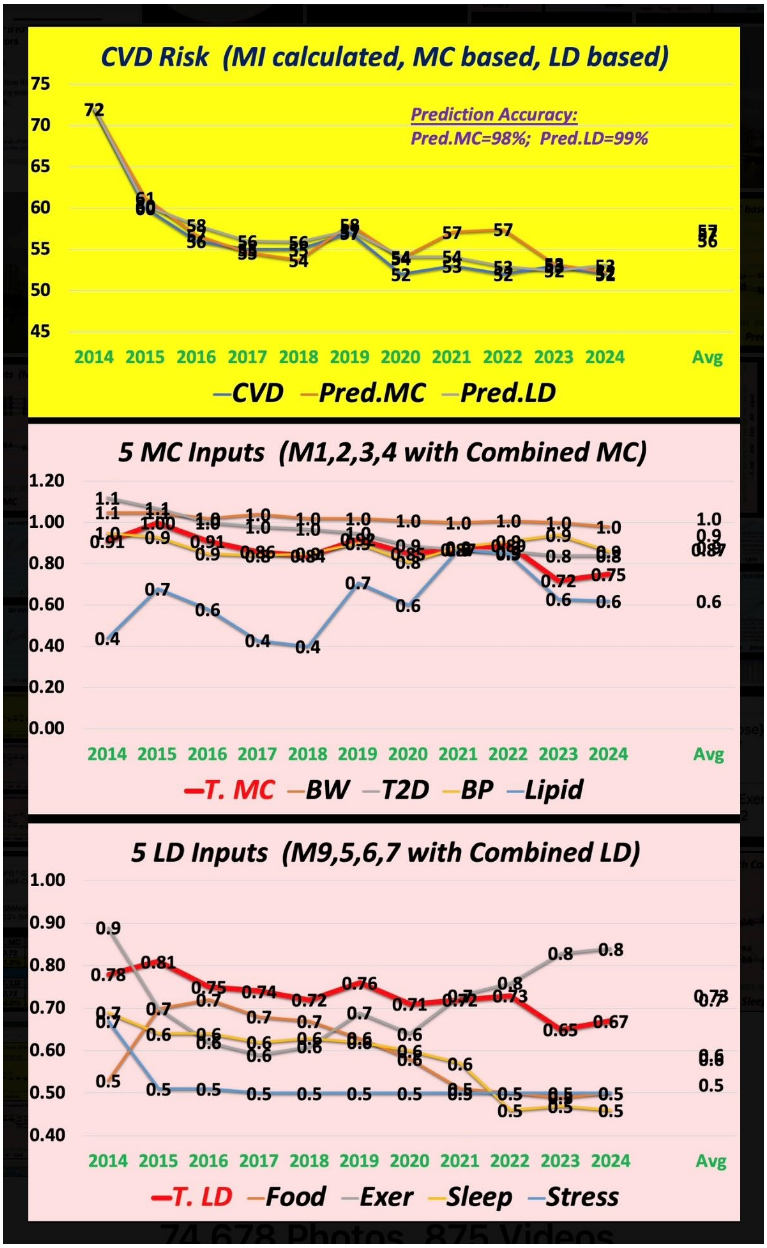
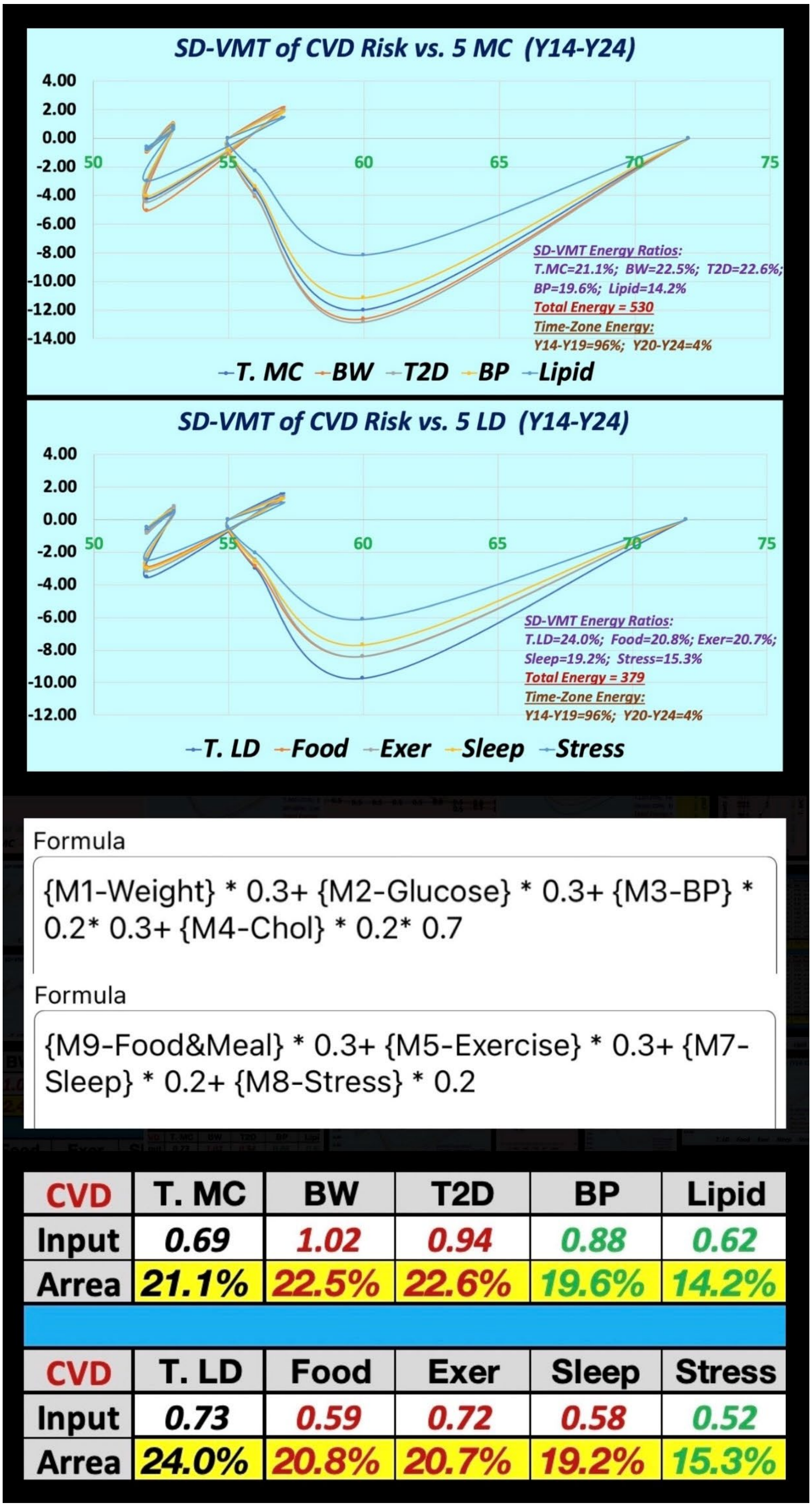


Figure 2: Inputs



CVD	T. MC	BW	T2D	BP	Lipid
Input	0.69	1.02	0.94	0.88	0.62
Arrea	21.1%	22.5%	22.6%	19.6%	14.2%

CVD	T. LD	Food	Exer	Sleep	Stress
Input	0.73	0.59	0.72	0.58	0.52
Arrea	24.0%	20.8%	20.7%	19.2%	15.3%

Figure 3: SD-VMT energy output diagram

11. Conclusions

In summary, the author found that ***his MC energy area (530) is higher than his LD energy area (379), suggesting that his lifestyle management has been more effective than his metabolic condition over the past 11 years.*** He also observed the higher input amplitudes of BW and T2D compared to BP and Lipid, as well as the higher input amplitudes of Food, Exercise, and Sleep compared to Stress. Those higher amplitudes usually leading into elevated relative energies (stress-strain curve area). Please noting that the strain change rate of CVD risk is identical for both MC and LD cases.

SD-VMT energy ratios of his CVD risk curve versus Metabolic inputs

Combined MC = 21.1%;
Obesity = 22.5%;
Diabetes = 22.6%;
Hypertension = 19.6%;
Dyslipidemia = 14.2%.

SD-VMT energy ratios of his CVD risk curve versus Lifestyle inputs
Combined LD = 24.0%;
Food = 20.8%;
Exercise = 20.7%;
Sleep = 19.2%;
Stress = 15.3%.

The time-zone energy distributions are:
Y2014-Y2019 = 96%
Y2020-Y2024 = 4%
The previous 6 years contribute the majority, 96% of the total energy associated with his CVD risk curve, while the recent 5 years contribute only 4% of the total PPG energy.

During this selected period of 11 years (from 1/1/2014 to 1/8/2024), the average CVD risk values are:
MI-based calculation: 56%
MC-based Prediction: 57%
LD-based prediction: 57%

MC Prediction accuracy = 98%
LD Prediction accuracy = 99%

Key message

His four lifestyle management effort is proving more effective in reducing his CVD risk (lowering viscoplastic energy) than his four metabolic management effort. In a more detailed analysis, the control of his diabetes and body weight are identified as higher-priority factors compared to managing his blood pressures and blood lipids. Additionally, his diet, exercise, and sleep play a more crucial role than his stress (the lowest energy). This decomposed signal processing and viscoplastic energy analysis offers a clear understanding of overall health profile of his heart and brain, supported by quantitative data and scientific evidence.

References

For editing purposes, majority of the references in this paper, which are self-references, have been removed for this article. Only references from other authors' published sources remain. The bibliography of the author's original self-references can be viewed at www.eclairemd.com.
Readers may use this article as long as the work is properly cited, and 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 platforms for scientific research publications, such as ResearchGate, Google Scholar, etc.