ISSN: 2639-0108

Research Article

Advances in Theoretical & Computational Physics

A summarized report on relationships of six mortality disease risks and three glycemic intensities of type 2 diabetes using viscoplastic energy model of GH- Method: math-physical medicine

Gerald C Hsu*

EclaireMD Foundation, USA

***Corresponding Author**
Gerald C Hsu, EclaireMD Foundation, USA

Submitted: 2023, Dec 04; **Accepted:** 2024, Jan 08; **Published:** 2024, Jan 24

Citation: Hsu, G. C. (2024). A summarized report on relationships of six mortality disease risks and three glycemic intensities of type 2 diabetes using viscoplastic energy model of GH- Method: math-physical medicine, *Adv Theo Comp Phy, 7*(1), 01- 05.

Abstract

Numerous medical research papers have established the interconnections of diabetes control and ***six mortality diseases, including CVD, CKD, Cancer, AD, PD, and DN. The general trajectory starts from*** *unhealthy diet and a sedentary lifestyle, leading to the development of multiple metabolic disorders especially diabetes in addition to obesity, hypertension, and dyslipidemia. Ultimately, these combined metabolic disorders eventually progress into different mortality diseases, like aforementioned six health issues. This article compiles findings from the author's six previously written papers, specifically focusing on the relationships between those six mortality diseases and three diabetic glycemic intensities (GI), TAR-GI (above 180 mg/dL), TBR-GI (below 70 mg/dL), TIR-GI (within the range from 70 to 180mg/dL). Here,* ***the author introduces a novel concept known as "glycemic intensities (GI)" as new biomarkers to examine various diabetic complications.***

These GI values are calculated as the averaged glucose levels multiplying with their frequency of occurrence. *GI values can shed light on the impact of diabetes glucose management on the development of aforementioned six mortality diseases.*

By analyzing data spanning from 8/1/2018 to 12/2/2023, the author synthesizes more than 500,000 collected data during the past 7 years and explores insights from his six previously written papers to produce this summarized paper. This article focuses on the findings from using the research method of space-domain Viscoplastic energy method (SD- VMT).

In summary, *his averaged risks over the past 7 years have shown the following order in comparison with his actual personal history:*
CKD = 68% (during 2009-2013)
CVD = 54% (during 1995-2004)
DN = 45% (during 2013-2015)
AD = 45% (no sign yet)
PD = 40% (no sign yet) Cancers = 39% (no sign yet)

The space-domain viscoplastic medicine energy (SD-VMT) analysis reveals hidden relationships and averaged energy contributions as follows:

Energy from TAR = 5.6% Energy from TBR = 1.9% Energy from TIR = 92.5%

TAR / TBR = 5.6 / 1.9 = 2.95

Key Message

The author's TIR-GI contributed 92.5% of the total energy associated with these six mortality diseases, indicating that ***his overall glucose has been under pretty good control.*** His highest TAR-GI influence is on CKD, and the lowest is on CVD. His highest TBR-GI influence is on Cancers, and the lowest is on CVD & CKD.

His TIR-GI energy rankings are as follows:
CVD at 94% > AD at 93% > CKD,
Cancers, PD, DN at 92%

The author's TAR-GI energy (5.6%) is 2.95 times higher than his TBR- GI energy (1.9%), suggesting that his hyperglycemia situations occur more frequently than hypoglycemia. Overall, while there is still room for further improvement, the author has done a satisfactory job (not perfect yet) in his overall glycemic control, leading to noticeable reductions in the risks of these 6 diseases over the past 7 years.

The Author's Note

Detailed discussions on the pathophysiological explanations related to specific diseases and the three diabetic glycemic intensity inputs are presented in the Introduction Section of the following six papers:

No. 983: Cardiovascular Diseases (CVD)
No. 984: Chronic Kidney Diseases (CKD)
No. 985: Cancers
No. 986: Alzheimer's Disease (AD) No. 987: Parkinson's Disease (PD) No. 988: Diabetic Neuropathy (DN)

Introduction

Numerous medical research papers have established the interconnections of diabetes control and ***six mortality diseases, including CVD, CKD, Cancer, AD, PD, and DN. The general trajectory starts from unhealthy diet and a sedentary lifestyle, leading to the development of multiple metabolic disorders especially diabetes in addition to obesity, hypertension, and dyslipidemia. Ultimately, these combined metabolic disorders eventually progress into different mortality diseases, like aforementioned six health issues.***

This article compiles findings from the author's six previously written papers, specifically focusing on the relationships between those six mortality diseases and three diabetic glycemic intensities (GI), TAR-GI (above 180 mg/dL), TBR-GI (below 70 mg/dL), TIR-GI (within the range from 70 to 180mg/dL). Here, ***the author introduces a novel concept known as "glycemic intensities (GI)" as new biomarkers to examine various diabetic complications.***

These GI values are calculated as the averaged glucose levels multiplying with their frequency of occurrence.

GI values can shed light ***on the impact of diabetes glucose management on the development of aforementioned six mortality diseases.***

By analyzing data spanning from 8/1/2018 to 12/2/2023, the author synthesizes more than 500,000 collected data during the past 7 years and explores insights from his six previously written papers to produce this summarized paper. This article focuses on the findings from using the research method of space-domain Viscoplastic energy method (SD- VMT).

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.

The Author's Note

Detailed discussions on the pathophysiological explanations related to specific diseases and the three diabetic glycemic intensity inputs are presented in the Introduction Section of the following six papers:

No. 983: Cardiovascular Diseases (CVD)
No. 984: Chronic Kidney Diseases (CKD)
No. 985: Cancers
No. 986: Alzheimer's Disease (AD) No. 987: Parkinson's Disease (PD) No. 988: Diabetic Neuropathy (DN)

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.

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.

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 causes 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:

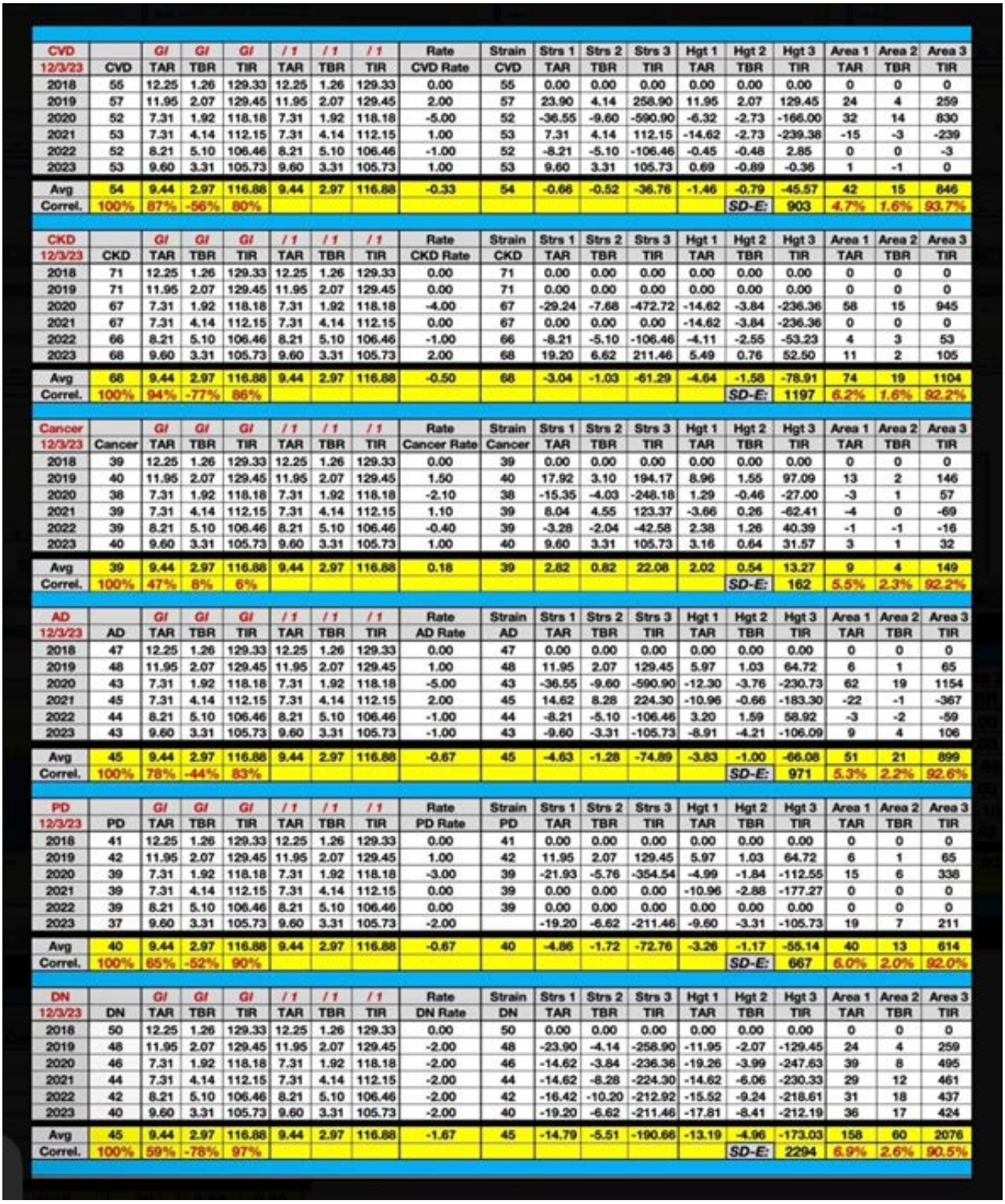
Strain rate
= (body weight at next time instant)
- (body weight at present time instant)

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).***

Results

Figure 1 shows data tables.



CVD		GI	GI	GI	/ 1	/ 1	/ 1	Rate	Strain	Strs 1	Strs 2	Strs 3	Hgt 1	Hgt 2	Hgt 3	Area 1	Area 2	Area 3
12/3/23	CVD	TAR	TBR	TIR	TAR	TBR	TIR	CVD Rate	CVD	TAR	TBR	TIR	TAR	TBR	TIR	TAR	TBR	TIR
2018	55	12.25	1.26	129.33	12.25	1.26	129.33	0.00	55	0.00	0.00	0.00	0.00	0.00	0.00	0	0	0
2019	57	11.95	2.07	129.45	11.95	2.07	129.45	2.00	57	23.90	4.14	258.90	11.95	2.07	129.45	24	4	259
2020	52	7.31	1.92	118.18	7.31	1.92	118.18	-5.00	52	-36.55	-9.60	-590.90	-6.32	-2.73	-166.00	32	14	830
2021	53	7.31	4.14	112.15	7.31	4.14	112.15	1.00	53	7.31	4.14	112.15	-14.62	-2.73	-239.38	-15	-3	-239
2022	52	8.21	5.10	106.46	8.21	5.10	106.46	-1.00	52	-8.21	-5.10	-106.46	-0.45	-0.48	2.85	0	0	-3
2023	53	9.60	3.31	105.73	9.60	3.31	105.73	1.00	53	9.60	3.31	105.73	0.69	-0.89	-0.36	1	-1	0
Avg	54	9.44	2.97	116.88	9.44	2.97	116.88	-0.33	54	-0.66	-0.52	-36.76	-1.46	-0.79	-45.57	42	15	846
Correl.	100%	87%	-56%	80%										SD-E:	903	4.7%	1.6%	93.7%

CKD		GI	GI	GI	/ 1	/ 1	/ 1	Rate	Strain	Strs 1	Strs 2	Strs 3	Hgt 1	Hgt 2	Hgt 3	Area 1	Area 2	Area 3
12/3/23	CKD	TAR	TBR	TIR	TAR	TBR	TIR	CKD Rate	CKD	TAR	TBR	TIR	TAR	TBR	TIR	TAR	TBR	TIR
2018	71	12.25	1.26	129.33	12.25	1.26	129.33	0.00	71	0.00	0.00	0.00	0.00	0.00	0.00	0	0	0
2019	71	11.95	2.07	129.45	11.95	2.07	129.45	0.00	71	0.00	0.00	0.00	0.00	0.00	0.00	0	0	0
2020	67	7.31	1.92	118.18	7.31	1.92	118.18	-4.00	67	-29.24	-7.68	-472.72	-14.62	-3.84	-236.36	58	15	945
2021	67	7.31	4.14	112.15	7.31	4.14	112.15	0.00	67	0.00	0.00	0.00	-14.62	-3.84	-236.36	0	0	0
2022	66	8.21	5.10	106.46	8.21	5.10	106.46	-1.00	66	-8.21	-5.10	-106.46	-4.11	-2.55	-53.23	4	3	53
2023	68	9.60	3.31	105.73	9.60	3.31	105.73	2.00	68	19.20	6.62	211.46	5.49	0.76	52.50	11	2	105
Avg	68	9.44	2.97	116.88	9.44	2.97	116.88	-0.50	68	-3.04	-1.03	-61.29	-4.64	-1.58	-78.91	74	19	1104
Correl.	100%	94%	-77%	86%										SD-E:	1197	6.2%	1.6%	92.2%

Cancer		GI	GI	GI	/ 1	/ 1	/ 1	Rate	Strain	Strs 1	Strs 2	Strs 3	Hgt 1	Hgt 2	Hgt 3	Area 1	Area 2	Area 3
12/3/23	Cancer	TAR	TBR	TIR	TAR	TBR	TIR	Cancer Rate	Cancer	TAR	TBR	TIR	TAR	TBR	TIR	TAR	TBR	TIR
2018	39	12.25	1.26	129.33	12.25	1.26	129.33	0.00	39	0.00	0.00	0.00	0.00	0.00	0.00	0	0	0
2019	40	11.95	2.07	129.45	11.95	2.07	129.45	1.50	40	17.92	3.10	194.17	8.96	1.55	97.09	13	2	146
2020	38	7.31	1.92	118.18	7.31	1.92	118.18	-2.10	38	-15.35	-4.03	-248.18	1.29	-0.46	-27.00	-3	1	57
2021	39	7.31	4.14	112.15	7.31	4.14	112.15	1.10	39	8.04	4.55	123.37	-3.66	0.26	-62.41	-4	0	-69
2022	39	8.21	5.10	106.46	8.21	5.10	106.46	-0.40	39	-3.28	-2.04	-42.58	2.38	1.26	40.39	-1	-1	-16
2023	40	9.60	3.31	105.73	9.60	3.31	105.73	1.00	40	9.60	3.31	105.73	3.16	0.64	31.57	3	1	32
Avg	39	9.44	2.97	116.88	9.44	2.97	116.88	0.18	39	2.82	0.82	22.08	2.02	0.54	13.27	9	4	149
Correl.	100%	47%	8%	6%										SD-E:	162	5.5%	2.3%	92.2%

AD		GI	GI	GI	/ 1	/ 1	/ 1	Rate	Strain	Strs 1	Strs 2	Strs 3	Hgt 1	Hgt 2	Hgt 3	Area 1	Area 2	Area 3
12/3/23	AD	TAR	TBR	TIR	TAR	TBR	TIR	AD Rate	AD	TAR	TBR	TIR	TAR	TBR	TIR	TAR	TBR	TIR
2018	47	12.25	1.26	129.33	12.25	1.26	129.33	0.00	47	0.00	0.00	0.00	0.00	0.00	0.00	0	0	0
2019	48	11.95	2.07	129.45	11.95	2.07	129.45	1.00	48	11.95	2.07	129.45	5.97	1.03	64.72	6	1	65
2020	43	7.31	1.92	118.18	7.31	1.92	118.18	-5.00	43	-36.55	-9.60	-590.90	-12.30	-3.76	-230.73	62	19	1154
2021	45	7.31	4.14	112.15	7.31	4.14	112.15	2.00	45	14.62	8.28	224.30	-10.96	-0.66	-183.30	-22	-1	-367
2022	44	8.21	5.10	106.46	8.21	5.10	106.46	-1.00	44	-8.21	-5.10	-106.46	3.20	1.59	58.92	-3	-2	-59
2023	43	9.60	3.31	105.73	9.60	3.31	105.73	-1.00	43	-9.60	-3.31	-105.73	-8.91	-4.21	-106.09	9	4	106
Avg	45	9.44	2.97	116.88	9.44	2.97	116.88	-0.67	45	-4.63	-1.28	-74.89	-3.83	-1.00	-66.08	51	21	899
Correl.	100%	78%	-44%	83%										SD-E:	971	5.3%	2.2%	92.6%

PD		GI	GI	GI	/ 1	/ 1	/ 1	Rate	Strain	Strs 1	Strs 2	Strs 3	Hgt 1	Hgt 2	Hgt 3	Area 1	Area 2	Area 3
12/3/23	PD	TAR	TBR	TIR	TAR	TBR	TIR	PD Rate	PD	TAR	TBR	TIR	TAR	TBR	TIR	TAR	TBR	TIR
2018	41	12.25	1.26	129.33	12.25	1.26	129.33	0.00	41	0.00	0.00	0.00	0.00	0.00	0.00	0	0	0
2019	42	11.95	2.07	129.45	11.95	2.07	129.45	1.00	42	11.95	2.07	129.45	5.97	1.03	64.72	6	1	65
2020	39	7.31	1.92	118.18	7.31	1.92	118.18	-3.00	39	-21.93	-5.76	-354.54	-4.99	-1.84	-112.55	15	6	338
2021	39	7.31	4.14	112.15	7.31	4.14	112.15	0.00	39	0.00	0.00	0.00	-10.96	-2.88	-177.27	0	0	0
2022	39	8.21	5.10	106.46	8.21	5.10	106.46	0.00	39	0.00	0.00	0.00	0.00	0.00	0.00	0	0	0
2023	37	9.60	3.31	105.73	9.60	3.31	105.73	-2.00		-19.20	-6.62	-211.46	-9.60	-3.31	-105.73	19	7	211
Avg	40	9.44	2.97	116.88	9.44	2.97	116.88	-0.67	40	-4.86	-1.72	-72.76	-3.26	-1.17	-55.14	40	13	614
Correl.	100%	65%	-52%	90%										SD-E:	667	6.0%	2.0%	92.0%

DN		GI	GI	GI	/ 1	/ 1	/ 1	Rate	Strain	Strs 1	Strs 2	Strs 3	Hgt 1	Hgt 2	Hgt 3	Area 1	Area 2	Area 3
12/3/23	DN	TAR	TBR	TIR	TAR	TBR	TIR	DN Rate	DN	TAR	TBR	TIR	TAR	TBR	TIR	TAR	TBR	TIR
2018	50	12.25	1.26	129.33	12.25	1.26	129.33	0.00	50	0.00	0.00	0.00	0.00	0.00	0.00	0	0	0
2019	48	11.95	2.07	129.45	11.95	2.07	129.45	-2.00	48	-23.90	-4.14	-258.90	-11.95	-2.07	-129.45	24	4	259
2020	46	7.31	1.92	118.18	7.31	1.92	118.18	-2.00	46	-14.62	-3.84	-236.36	-19.26	-3.99	-247.63	39	8	495
2021	44	7.31	4.14	112.15	7.31	4.14	112.15	-2.00	44	-14.62	-8.28	-224.30	-14.62	-6.06	-230.33	29	12	461
2022	42	8.21	5.10	106.46	8.21	5.10	106.46	-2.00	42	-16.42	-10.20	-212.92	-15.52	-9.24	-218.61	31	18	437
2023	40	9.60	3.31	105.73	9.60	3.31	105.73	-2.00	40	-19.20	-6.62	-211.46	-17.81	-8.41	-212.19	36	17	424
Avg	45	9.44	2.97	116.88	9.44	2.97	116.88	-1.67	45	-14.79	-5.51	-190.66	-13.19	-4.96	-173.03	158	60	2076
Correl.	100%	59%	-78%	97%										SD-E:	2294	6.9%	2.6%	90.5%

Figure 1: Data tables

Figure 2 shows input/output table and charts.

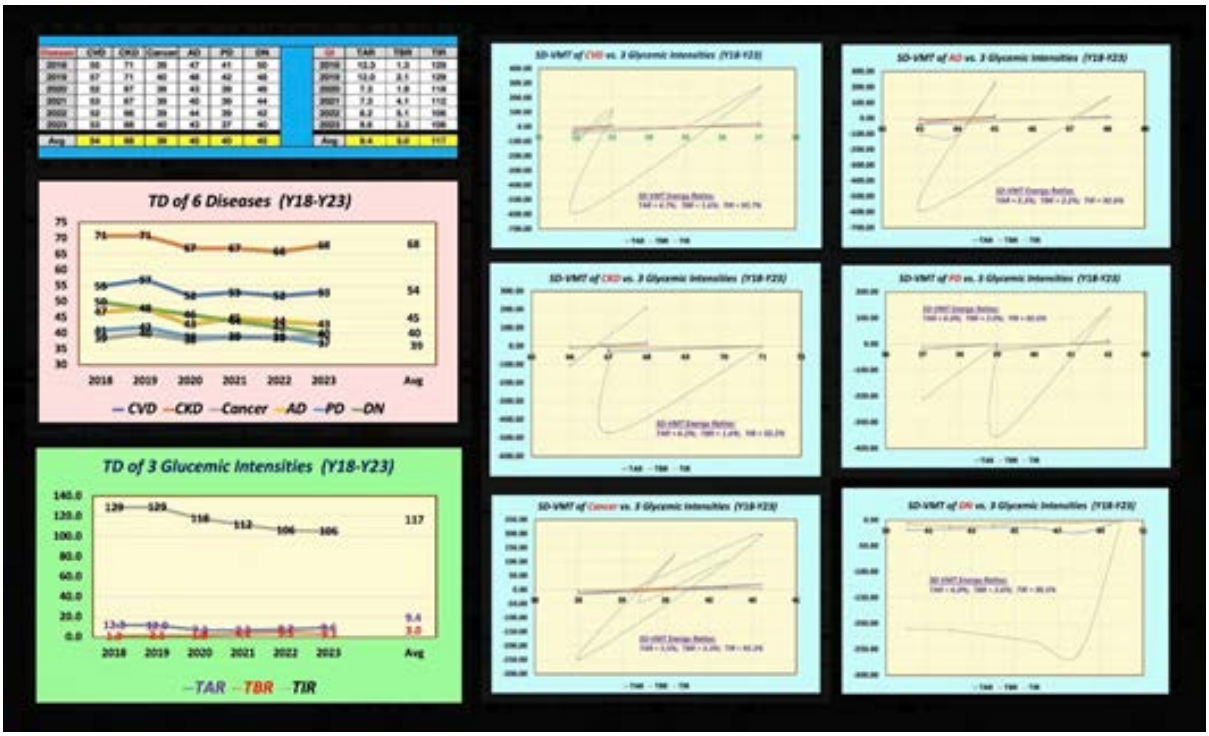


Figure 2: Input/output table & charts

Figure 3 shows summarized table and chart.

GI	TAR	TBR	TIR
CVD	4.7%	1.6%	94%
CKD	6.2%	1.6%	92%
Cancer	5.5%	2.3%	92%
AD	5.3%	2.2%	93%
PD	6.0%	2.0%	92%
DN	6.0%	2.0%	92%
Average	5.6%	1.9%	92%

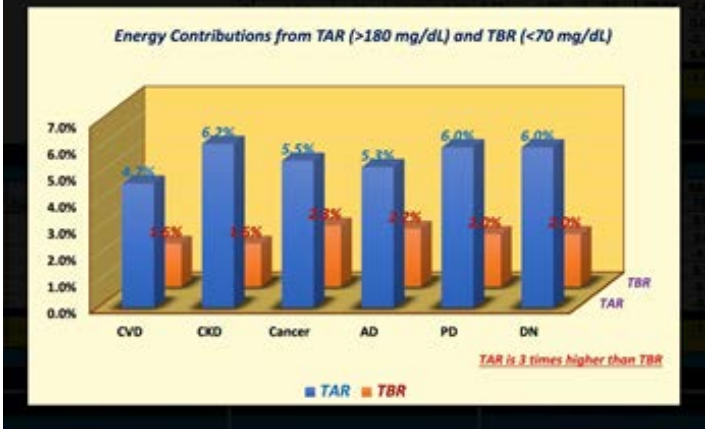


Figure 3: Summarized table and chart

Conclusions

In summary, his averaged risks over the past 7 years have shown the following order in comparison with his actual personal history:

CKD = 68% (during 2009-2013)
CVD = 54% (during 1995-2004)
DN = 45% (during 2013-2015)
AD = 45% (no sign yet) PD = 40% (no sign yet)
Cancers = 39% (no sign yet)

The space-domain viscoplastic medicine energy (SD-VMT) analysis reveals hidden relationships and averaged energy contributions as follows:

Energy from TAR = 5.6% Energy from TBR = 1.9% Energy from TIR = 92.5%

TAR / TBR = 5.6 / 1.9 = 2.95

Key Message

The author's TIR-GI contributed 92.5% of the total energy associated with these six mortality diseases, indicating that ***his overall glucose has been under pretty good control.*** His highest TAR-GI influence is on CKD, and the lowest is on CVD. His highest TBR-GI influence is on Cancers, and the lowest is on CVD & CKD.

His TIR-GI energy rankings are as follows:
CVD at 94% > AD at 93% > CKD,
Cancers, PD, DN at 92%

The author's TAR-GI energy (5.6%) is 2.95 times higher than his TBR- GI energy (1.9%), suggesting that his hyperglycemia situations occur more frequently than hypoglycemia. Overall, while there is still room for further improvement, the author has done a satisfactory job (not perfect yet) in his overall glycemic control, leading to noticeable reductions in the risks of these 6 diseases over the past 7 years.

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.