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Research Article

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Relationships of Chronic Kidney Disease Risks and Four Biomarkers of type 2 Diabetes Disease, Insulin Resistance via FPG, Glycemic Control via HbA1c and eAG, Hyperglycemia Intensity using Viscoplastic Energy Model of GHMethod: Math-Physical Medicine (No. 962, VMT #361, 11/22-23/2023)

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Abstract

The interaction between diet quality and portion control significantly influences body weight, a crucial factor in the progression of type 2 diabetes (T2D). T2D is characterized by four key biomarkers: insulin resistance (measured via morning fasting glucose - FPG), daily glycemic control (averaged glucose - eAG), quarterly glycemic control (HbA1c levels), and hyperglycemia situation control (hyperglycemia intensity - HyGI). HbA1c and eAG are similar biomarkers. But, both of them lack representation of insulin resistance influences and damage caused by hyperglycemia.

HyGI is calculated as averaged glucose above 180 mg/dL multiplied by the occurrence frequency of glucose above 180 mg/dL.

*This study explores the author's **chronic kidney diseases (CKD) risks** associated with these four T2D biomarkers, drawing from personal data collected over the past six years (5/1/2018 to 11/20/2023). Traditional statistical analysis reveals strong correlations (90% to 94%) between the author's CKD risk and the four T2D biomarkers. Additionally, the author employs the space-domain viscoplastic energy (SD-VMT) method to unveil hidden relationships and dynamics (i.e. energies) between these four T2D biomarkers and his annual CKD risk output.*

***In summary,** traditional statistical correlations uncovered significant associations between the author's CVD risks and his four T2D biomarkers:*

- ***CKD vs. HbA1c: 92%***
- ***CKD vs. FPG: 92%***
- ***CKD vs. eAG: 90%***
- ***CKD vs. HyGI: 94%***

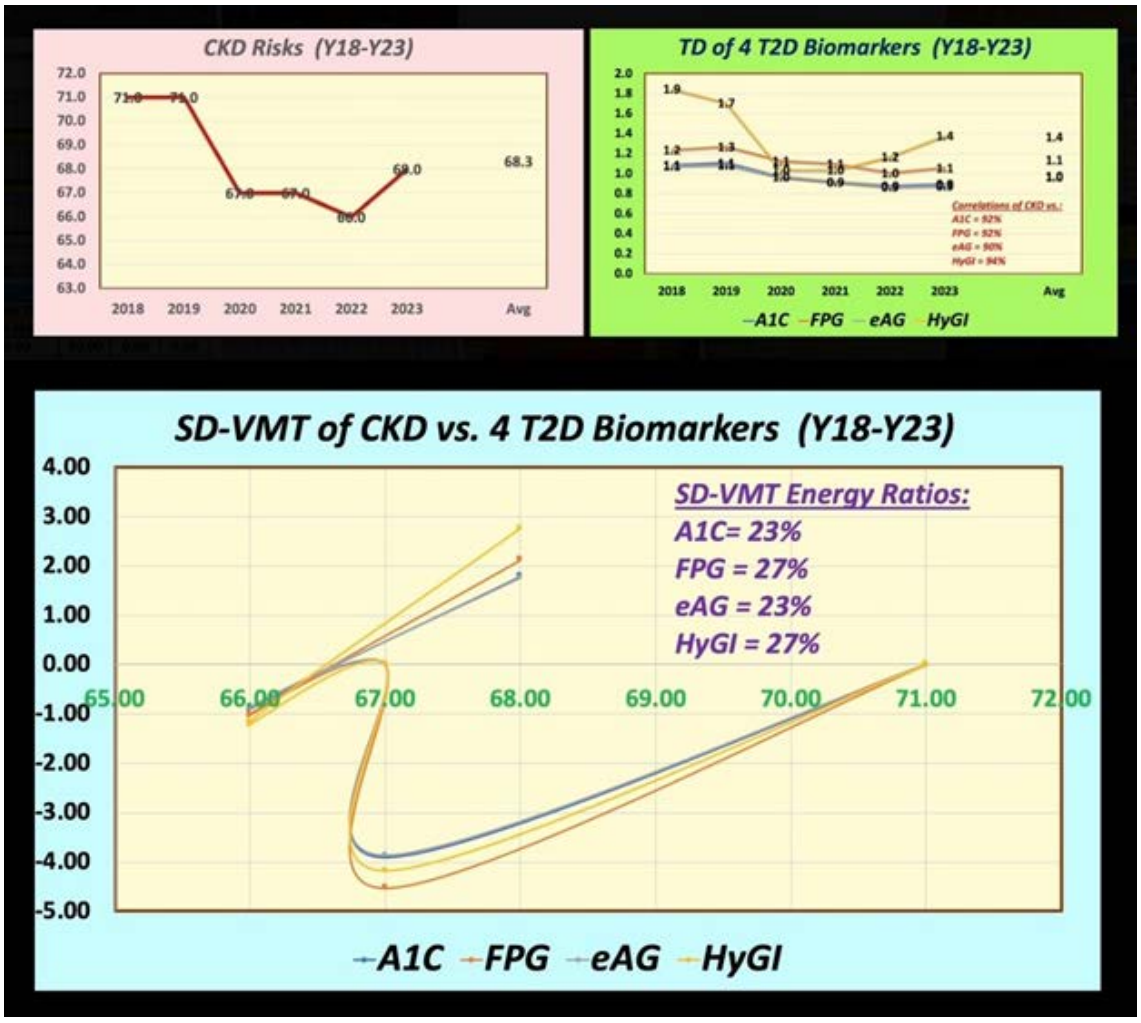
These differ from low positive correlations (14% to 41%) between his cancer risks and the same four T2D biomarkers, reflecting distinct characteristics in the risk waveforms of these two diseases. Using SD-VMT energy results, four energy contribution margins on CVD risks from T2D biomarkers were identified:

- ***Energy from HbA1c: 23%***
- ***Energy from FPG: 27%***
- ***Energy from eAG: 23%***
- ***Energy from HyGI: 27%***

Both insulin resistance via FPG and hyperglycemia intensity are two strongest influential factors for his CKD risks

Key message

The author's T2D conditions are indeed linked to his risks of developing CKD. Insulin resistance, indicated by FPG and hyperglycemia intensity contribute the most energy to CVD risks (27% each), followed by 23% each from HbA1c and eAG. ***Despite representing only 2% occurrence of the total glucose dataset, hyperglycemia intensity contributes 27% of the total impact or energy on his overall CKD risks.***



1. Introduction

The interaction between diet quality and portion control significantly influences body weight, a crucial factor in the progression of type 2 diabetes (T2D). T2D is characterized by four key biomarkers: insulin resistance (measured via morning fasting glucose - FPG), daily glycemic control (averaged glucose - eAG), quarterly glycemic control (HbA1c levels), and hyperglycemia situation control (hyperglycemia intensity - HyGI). HbA1c and eAG are similar biomarkers. But, both of them lack representation of insulin resistance influences and damage caused by hyperglycemia. ***HyGI is calculated as averaged glucose above 180 mg/dL multiplied by the occurrence frequency of glucose above 180 mg/dL.***

This study explores the author's ***chronic kidney diseases (CKD) risks*** associated with these four T2D biomarkers, drawing from personal data collected over the past six years (5/1/2018 to 11/20/2023). Traditional statistical analysis reveals strong correlations (90% to 94%) between the author's CKD risk and the four T2D biomarkers. Additionally, the author employs the space-domain viscoplastic energy (SD-VMT) method to unveil hidden relationships and dynamics (i.e. energies) between these four T2D biomarkers and his annual CKD risk output.

2. 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.

3. Pathophysiological Explanations of Chronic Kidney Diseases and Four Biomarkers of type 2 Diabetes, such as Insulin Resistance via FPG, Diabetic Control via HbA1C and eAG, and hyperglycemia Intensity

Chronic kidney disease (CKD) often results from prolonged conditions such as diabetes and hypertension. ***The pathophysiology involves damage to the kidneys' filtering units (nephrons), leading to impaired filtration and waste elimination. Persistent inflammation and oxidative stress further contribute to kidney damage, progressing through stages marked by declining kidney function.*** Regarding type 2 diabetes biomarkers:

3.1 Insulin Resistance (via Fasting Plasma Glucose - FPG)

Insulin resistance, a common feature in type 2 diabetes, contributes to elevated FPG levels. Over time, this can lead to microvascular damage, affecting the microcells of kidneys and promoting the development of CKD.

3.2 Diabetic Control (via quarterly HbA1C and daily eAG)
Consistent high blood glucose levels, reflected in elevated quarterly HbA1C values and daily estimated Average Glucose (eAG) values, play a significant role in the progression of CKD. Prolonged hyperglycemia contributes to kidney damage and dysfunction.

3.3 Hyperglycemia Intensity
The intensity of hyperglycemia, measured through fasting and postprandial glucose levels, is linked to the severity of kidney complications in diabetes. Persistent high glucose levels can damage micro-blood vessels in the kidneys, impairing their function over time.

3.4 **Albuminuria**
Albumin, a protein, should be retained in the bloodstream. ***In chronic kidney disease (CKD), impaired kidneys may permit albumin leakage into urine, a condition known as albuminuria. This signals compromised filtration function and serves as an early indicator of kidney damage. Another informative biomarker is the albumin-creatinine ratio (ACR), which assesses the protein level in urine, providing insights into the extent of kidney impairment.***

Understanding and managing these biomarkers are crucial for preventing and managing both type 2 diabetes and the associated risk of chronic kidney disease. Regular monitoring and interventions to control glucose levels and blood pressure are essential components of comprehensive care.

4. 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.

5. 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 fingerpiercing 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 preCOVID 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 selfquarantined 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 indepth 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 5minute intervals from every 15minute 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 wellbalanced 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.

6. 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 laborwork 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. timedependent. *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 ksteps * 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.

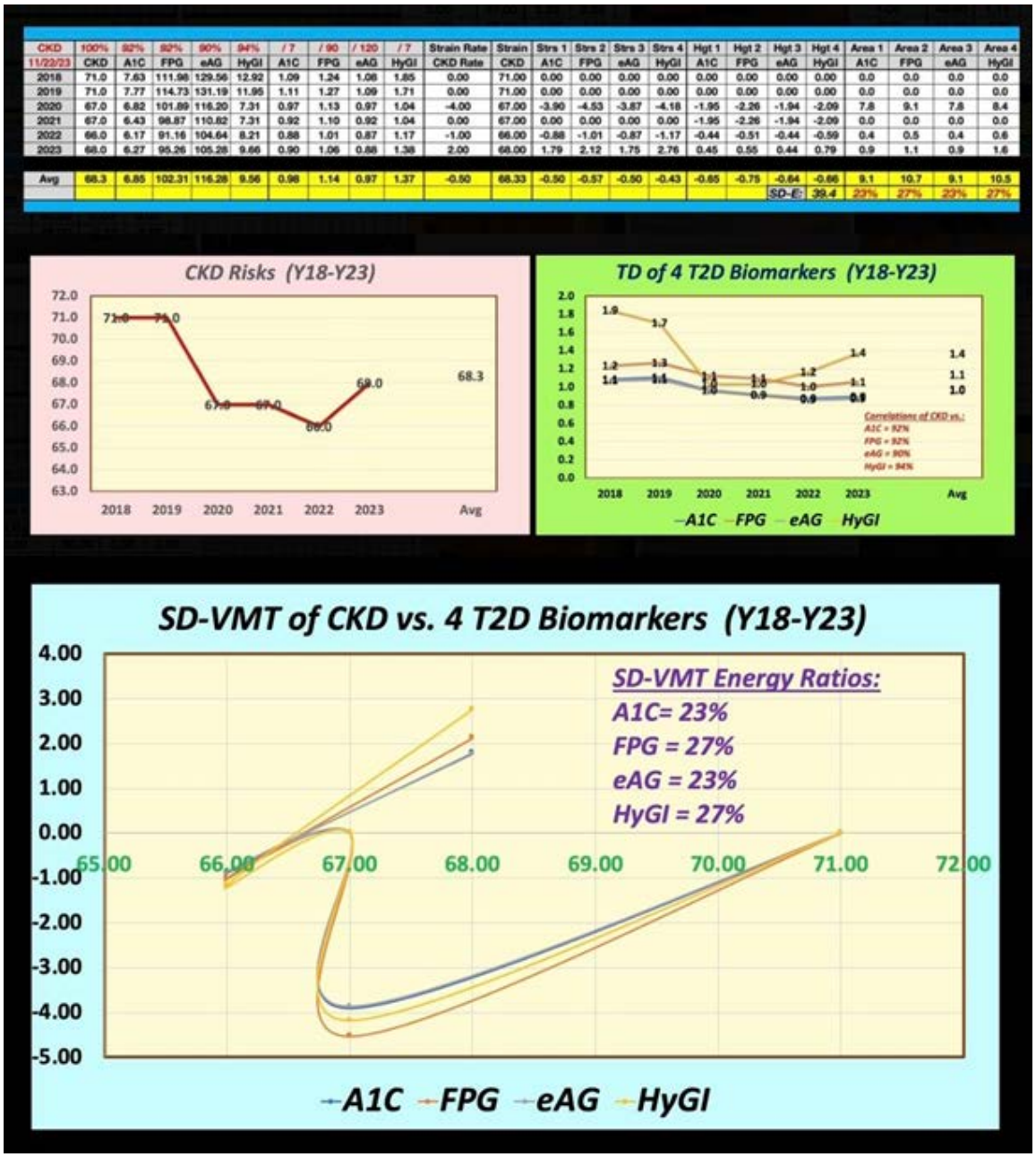
In this article, in order to construct an "ellipse-like" diagram in a stressstrain space domain (e.g. "hysteresis loop") covering both the positive side and negative side of space, he has modified the definition of strain as follows:
Strain
= (body weight at certain specific time instant)

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 disorderinduced 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).***

7. Results



CKD	100%	92%	92%	90%	94%	/ 7	/ 90	/ 120	/ 7	Strain Rate	Strain	Strs 1	Strs 2	Strs 3	Strs 4	Hgt 1	Hgt 2	Hgt 3	Hgt 4	Area 1	Area 2	Area 3	Area 4
11/22/23	CKD	A1C	FPG	eAG	HyGI	A1C	FPG	eAG	HyGI	CKD Rate	CKD	A1C	FPG	eAG	HyGI	A1C	FPG	eAG	HyGI	A1C	FPG	eAG	HyGI
2018	71.0	7.63	111.98	129.56	12.92	1.09	1.24	1.08	1.85	0.00	71.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.0	0.0	0.0	0.0
2019	71.0	7.77	114.73	131.19	11.95	1.11	1.27	1.09	1.71	0.00	71.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.0	0.0	0.0	0.0
2020	67.0	6.82	101.89	116.20	7.31	0.97	1.13	0.97	1.04	-4.00	67.00	-3.90	-4.53	-3.87	-4.18	-1.95	-2.26	-1.94	-2.09	7.8	9.1	7.8	8.4
2021	67.0	6.43	98.87	110.82	7.31	0.92	1.10	0.92	1.04	0.00	67.00	0.00	0.00	0.00	0.00	-1.95	-2.26	-1.94	-2.09	0.0	0.0	0.0	0.0
2022	66.0	6.17	91.16	104.64	8.21	0.88	1.01	0.87	1.17	-1.00	66.00	-0.88	-1.01	-0.87	-1.17	-0.44	-0.51	-0.44	-0.59	0.4	0.5	0.4	0.6
2023	68.0	6.27	95.26	105.28	9.66	0.90	1.06	0.88	1.38	2.00	68.00	1.79	2.12	1.75	2.76	0.45	0.55	0.44	0.79	0.9	1.1	0.9	1.6
Avg	68.3	6.85	102.31	116.28	9.56	0.98	1.14	0.97	1.37	-0.50	68.33	-0.50	-0.57	-0.50	-0.43	-0.65	-0.75	-0.64	-0.66	9.1	10.7	9.1	10.5
																		SD-E:	39.4	23%	27%	23%	27%

Figure 1: Data table, Time-domain curves and SD-VMT energies.

8. Conclusions

In summary, traditional statistical correlations uncovered significant associations between the author's CVD risks and his four T2D biomarkers:

- ***CKD vs. HbA1c: 92%***
- ***CKD vs. FPG: 92%***
- ***CKD vs. eAG: 90%***
- ***CKD vs. HyGI: 94%***

These differ from low positive correlations (14% to 41%) between his cancer risks and the same four T2D biomarkers, reflecting distinct characteristics in the risk waveforms of these two diseases.

Using SD-VMT energy results, four energy contribution margins on CVD risks from T2D biomarkers were identified:

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9. Key Message

The author's T2D conditions are indeed linked to his risks of developing CKD. Insulin resistance, indicated by FPG and hyperglycemia intensity contribute the most energy to CVD risks (27% each), followed by 23% each from HbA1c and eAG. ***Despite representing only 2% occurrence of the total glucose dataset, hyperglycemia intensity contributes 27% of the total impact or energy on his overall CKD risks.***

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.

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