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Research Article

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Relationships of Cancers Risks and Three Glycemic Intensities of Type 2 Diabetes Using Viscoplastic Energy Model of Gh-Method: Math- Physical Medicine

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Abstract

In a comprehensive meta-analysis, Pearson-Stuttard et al. found that from 2012 onwards, 6% of all newly diagnosed cancers were linked to the combined effects of diabetes and obesity. It was observed that globally, approximately 26.9% of cancer patients above 65 years of age have diabetes, with 60% of this age group being diagnosed with cancer (source: https://www.nature.com › articles, June 9, 2023). Furthermore, 8 to 18% of cancer patients also have diabetes. For example, up to 80% of pancreatic cancer patients display new-onset type 2 diabetes or impaired glucose tolerance at the time of diagnosis.

Individuals with type 2 diabetes face an increased risk of developing liver cancer, pancreatic cancer, colon cancer, bladder cancer, and postmenopausal breast cancer.

Postmenopausal breast cancer is particularly prevalent as an obesity- associated cancer among women, while colorectal cancer holds this distinction among men.

The American Diabetes Association (ADA) describes three glucose categories:
*• **Hyperglycemia TAR** (time above range for glucose above 180 mg/dL)*
*• **Hypoglycemic TBR** (time below range for glucose below 70 mg/dL)*
*• **Normal Glycemic TIR** (time in range for glucose between 70 and 180 mg/ dL).*

*This paper delves into the author's risks of developing various cancers associated with his type 2 diabetes conditions, introducing three new biomarkers, known as glycemic intensities (GI). **These GI values, calculated as the averaged glucose value of a category multiplied by its occurrence frequency,** aim to uncover the impact of diabetes conditions and controls on the likelihood of developing other mortality-related diseases, including various cancers.*

This study specifically investigates the author's cancer risks associated with three glucose inputs: TAR-GI value (TAR), TBR-GI value (TBR), and TIR-GI value (TIR), drawing insights from his personal data collected between 8/1/2018 and 12/2/2023.

***In summary,** the author utilizes the space-domain viscoplastic energy (SD-VMT) method to explore the underlying connections and dynamics (i.e. energies) between three diabetic glycemic intensity (GI) inputs and the annual cancer risk output:*
*• **Energy from Time Above Range (TAR): 5.5%***
*• **Energy from Time Below Range (TBR): 2.3%***
*• **Energy from Time in Range (TIR): 92.2%***

Key Message

It is expected that the predominant contribution of TIR energy to cancer risk is significant. Notably, the finding indicating that the TAR- GI contribution (5.5%) to various cancers risk is nearly 2.4 times higher than that of TBR-GI (2.3%) is of particular importance. The intensity of hyperglycemia can negatively impact internal organs, while the intensity of hypoglycemia can potentially lead to sudden death due to insulin shock.

Introduction

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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.

Pathophysiological Explanations of Various Cancers and Glycemic Intensity, Including TAR, TBR, TIR:

There is a growing body of research exploring the potential link between glycemic intensity and the risk of various cancers. In the context of Time Above Range (TAR), Time Below Range (TBR), and Time In Range (TIR) as markers of glycemic intensity, the influence of these factors on cancer pathophysiology is an area of active investigation. Time Above Range (TAR) is associated with sustained high blood sugar levels, which can contribute to chronic inflammation and oxidative stress. These conditions create an environment that may promote the growth and spread of certain types of cancer cells. Elevated TAR has been implicated in promoting tumor cell proliferation, angiogenesis (the formation of new blood vessels to support tumor growth), and metastasis.

Conversely, Time Below Range (TBR), representing hypoglycemic episodes, has been linked to conditions that compromise the immune system and increase stress hormone levels. Both of these factors are known to impact the body's ability to detect and destroy cancer cells, potentially impacting cancer progression.

Time In Range (TIR), representing the amount of time spent within the target glucose range, is associated with optimal glycemic control and reduced glycemic variability. This has the potential to reduce inflammation, limit oxidative stress, and promote metabolic stability, which may have a protective effect against the development and progression of certain cancers.

It is important to note that while emerging evidence suggests a potential association between glycemic intensity and cancer pathophysiology, more research is needed to fully understand these complex relationships. The impact of TAR, TBR, and TIR on cancer development and progression likely varies by cancer type and individual factors. Therefore, further studies are needed to elucidate the specific mechanisms by which glycemic intensity may influence cancer risk and progression.

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 table, Time- domain curves and SD-VMT energies.

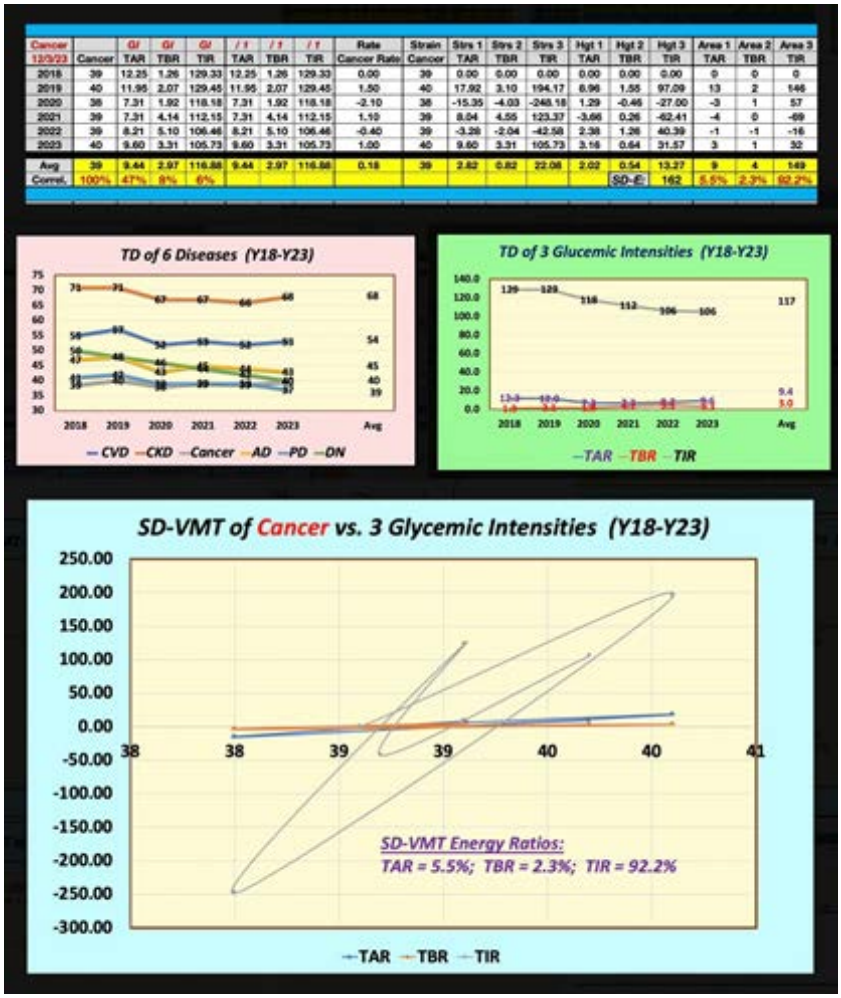

Figure 1: Data table, Time-domain curves and SD-VMT energies

Conclusions

In summary, the author utilizes the space-domain viscoplastic energy (SD-VMT) method to explore the underlying connections and dynamics (i.e. energies) between three diabetic glycemic intensity (GI) inputs and the annual cancer risk output:

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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.

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