

**Research Article** 

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A Preventive Medicine and Public Health Study of Close Relationship Between Cancers Versus Obesity, Diabetes, and Diet Based on One T2d Patient's Collected Data Using The Viscoplastic Energy Model of GH-Method: Math-Physical Medicine (No. 1036, viscoelastic medicine Theory #435)

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# Category: Cancers & Disbetes Abstract

Article 1034 by the author, titled "The Relationship Between Cancer and Type 2 Diabetes Based on a UK Study," was selected as the keynote address for the upcoming Preventive Medicine and Public Health Annual Conference in Prague this September. This invitation inspired the author to expand his previous research to explore more connections between food portion sizes, body weight, fasting plasma glucose, carbohydrate and sugar intake, postprandial glucose, and hemoglobin A1c, and their links to cancers risk. To conduct this analysis, he analyzed his 3 million data points collected over past 15 years, from 2010 to 2024. He then compared ratios of these biomarkers by averaging data from 2010 to 2011, a period during which he suffered from obesity and diabetes, with data from 2023 to 2024, when he achieved significantly better health conditions.

The results of this study offer some sort of guidelines for patients to lower their cancers risk, incorporating insights from both preventive medicine and public health.

In summary, this analysis reveals a conclusive view of his reduced cancer risk through health improvement:

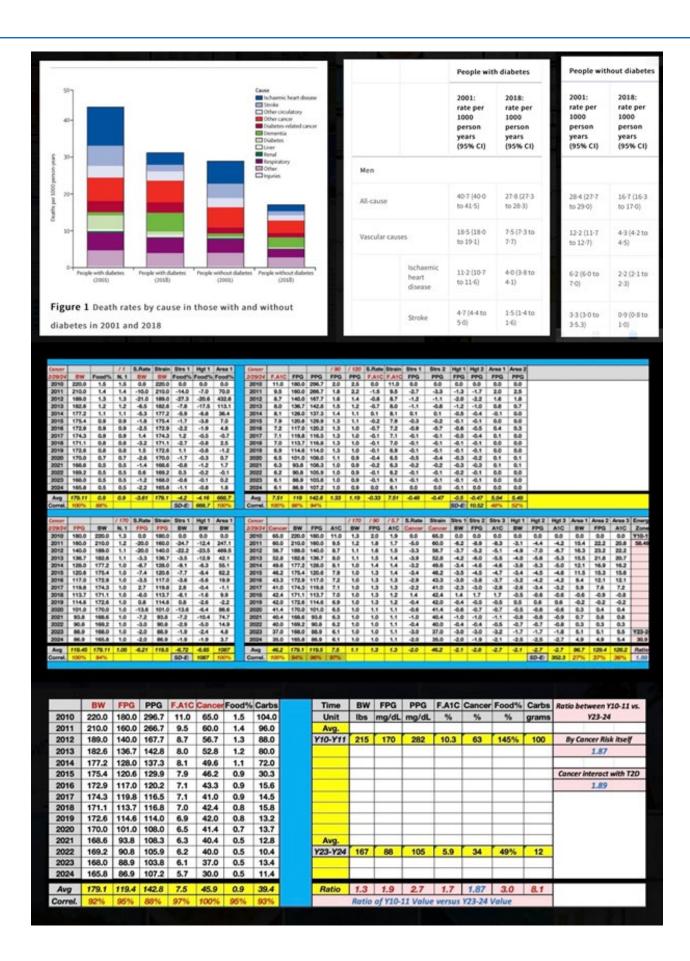
- Food portion per meal decreased from 145% in the initial period to 49% in the current period, with a ratio of 3.0.
- Body weight was reduced from 215 lbs to 167 lbs through food portion control, resulting in a ratio of 1.3.
- FPG dropped from 170 mg/dL to 88 mg/dL, with a ratio of 1.9.
- Carbohydrate/sugar intake went from 100 grams to 12 grams, with a ratio of 8.3.
- PPG decreased from 282 mg/dL to 105 mg/dL, with a ratio of 2.7.
- HbA1C levels fell from 10.3% to 5.9%, with a ratio of 1.7.
- Cancer risk reduced from 63% to 34%, with a ratio of 1.87.

Furthermore, all of correlations between any set of two variables are very high, within the range of 88% to 98%.

By applying the viscoplastic energy method, he also calculated the energy ratio resulting from the interplay between cancer risk and health indicators such as obesity, pancreatic insulin resistance situation from FPG, and the severity of type 2 diabetes through HbA1C values, finding a ratio of 1.89 between the initial and present periods. These two ratios, 1.87 and 1.89, derived from the author's math-physical medicine research methodology, align similarly with the UK study's finding of 1.58 (diabetes averaged 13.0 versus non-diabetes averaged 8.25) based on traditional statistical methods involving hundreds of thousands of patients.

## Key Message

Controlling food portions leads to body weight reduction, which can improve pancreatic insulin function via reduced FPG. Lowering carbohydrate and sugar intake results in decreased PPG, which in turn lowers HbA1C levels, the hallmark of type 2 diabetes. Finally, managing diabetes effectively can significantly reduce cancers risk.



#### 1. Introduction

Article 1034 by the author, titled "The Relationship Between Cancer and Type 2 Diabetes Based on a UK Study," was selected as the keynote address for the upcoming Preventive Medicine and Public Health Annual Conference in Prague this September. This invitation inspired the author to expand his previous research to explore more connections between food portion sizes, body weight, fasting plasma glucose, carbohydrate and sugar intake, postprandial glucose, and hemoglobin A1c, and their links to cancers risk. To conduct this analysis, he analyzed his 3 million data points collected over past 15 years, from 2010 to 2024. He then compared ratios of these biomarkers by averaging data from 2010 to 2011, a period during which he suffered from obesity and diabetes, with data from 2023 to 2024, when he achieved significantly better health conditions.

The results of this study offer some sort of guidelines for patients to lower their cancers risk, incorporating insights from both preventive medicine and public health.

#### 1.1 Biomedical or Certain Technical Information

The following sections contain excerpts and concise information on 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. Pathophysiological Explanations of Relationship between Diabetes and Cancers

The relationship between diabetes and cancer is a complex and multifaceted one, and the underlying pathophysiological explanations are still being studied. Here are a few key points that help explain the relationship:

### 2.1 Hyperinsulinemia and Insulin Resistance

Type 2 diabetes is often associated with insulin resistance and hyperinsulinemia, where the body's cells become less responsive to insulin, leading to higher insulin levels in the bloodstream. Elevated insulin levels can promote cell proliferation and growth, which may contribute to the development and progression of cancer.

#### 2.2 Chronic Inflammation

Both diabetes and cancer are associated with chronic inflammation. Inflammatory processes can create a microenvironment that is conducive to cancer development and growth. In diabetes, chronic inflammation is often related to elevated blood sugar levels, which can trigger the release of proinflammatory cytokines.

## 2.3 Hyperglycemia

Diabetes is characterized by elevated blood sugar levels (hyperglycemia). High glucose levels provide a source of energy for cancer cells, potentially promoting tumor growth and progression.

#### 2.4. Shared Risk Factors

Diabetes and cancer share common risk factors such as obesity, physical inactivity, and poor diet. These lifestyle-related risk factors can contribute to the development of both conditions.

#### 2.5 Hormonal Factors

Diabetes can disrupt the balance of various hormones such as insulin, IGF-1 (insulin-like growth factor 1), and sex hormones. These hormonal imbalances can impact cell growth, apoptosis (cell death), and other processes related to cancer development.

## 2.6 Shared Genetic and Molecular Pathways

Some evidence suggests that diabetes and cancer share common genetic and molecular pathways. For example, alterations in genes involved in insulin signaling may be linked to both conditions.

While these points provide a partial understanding of the relationship between diabetes and cancer, it's important to note that ongoing research is continually shedding light on the complex interplay of genetic, metabolic, and environmental factors that underlie this relationship.

#### 3. 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.

## 4. 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  $\sim$ 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, postmeal 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 "selfrepaired" about 35% of his damaged pancreatic beta cells during the past 10 years.

## 5. 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 13year time window.

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

Hooke's law of linear elasticity is expressed as:

Strain ( $\varepsilon$ : epsilon) = Stress ( $\sigma$ : 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  $\varepsilon$ .

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)*.

#### 6. Results



Figure 1: The UK report data of cancer risk

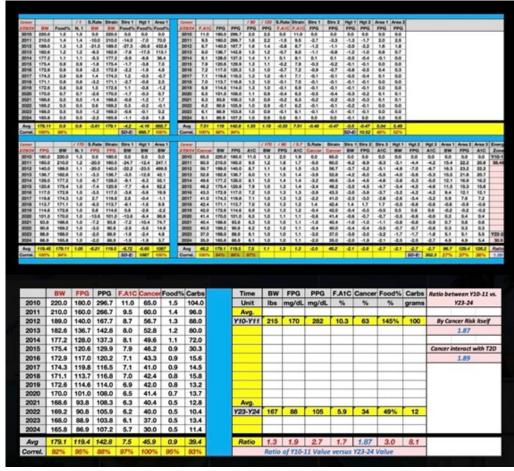


Figure 2: Input Information, TD and SD results of cancer risk

#### **Conclusions**

*In summary,* this analysis reveals a conclusive view of his reduced cancer risk through health improvement:

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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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