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The GH-Method

# Viscoplastic Medicine Theory (VMT #202): An Investigation of Cancer Risk versus 5 Metabolic Biomarkers Over 14 Years from 1/1/2010 to 2/2/2023 Using Two Time-Domain Energy Models and the Space-Domain Energy Model with Viscoplastic Medicine Theory Based on GH-Method: Math-Physical Medicine (No. 797)

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## Abstract

For the past 14 years, the author conducted his medical research work on diseases related to internal organs, including soft tissues, blood, nerves, and hormones. Based on the theory of metabolism and immunity, he started with learning and researching various metabolic disorders, including obesity, diabetes, hypertension, hyperlipidemia, insulin resistance, fatty liver, etc. He has then extended his research effort into mortality diseases induced by metabolic disorders, such as cardiovascular diseases, strokes, chronic kidney diseases, and dementia. Since 2019, he initiated his research work on relationships between cancers and metabolism. Basic metabolic biomarkers include blood sugar, blood pressure, body weight, and cholesterol or triglycerides. Metabolic syndrome can indeed put a person at high risk of several cancers and diseases that can lead to cancer. In this article, the author has chosen 5 metabolic biomarkers: waist-to-hip ratio (WHR) to measure the fat around the waist area, daily estimated average glucose (eAG) to measure diabetes, blood pressure (BP) of normalized SBP, DBP, and HR values, blood lipids of normalized LDL, HDL, triglycerides values, and TyG. Here, the TyG biomarker is chosen for measuring both his insulin resistance condition (TyG > 4.49) and nonalcoholic fatty liver disease condition (TyG > 8.5) with the following definition: TyG = (ln (fasting triglycerides mg/dL) + ln (fasting glucose mg/dL)) / 2. He has collected data on his health conditions and lifestyle details, including those 5 basic metabolic biomarkers since 2010. However, the collected data in earlier years of 2010 and 2011 were incomplete and the 2023 data only has one month (January of 2023). His cancer risk probability % is calculated using a sophisticated mathematical and engineering model which is based on 4 metabolism conditions and 6 lifestyle details. He developed this model in 2014 and then continuously enhance it since then. The cancer risk estimation includes genetic conditions, such as a family history of cancers and long-term bad habits, and other negative environmental factors, such as toxic chemicals, air and water pollution, food pollution or poison, hormonal therapy, etc. The total data collected and involved in this particular study are around 3 million. After data organization, he then applies the theory of wave and energy of physics to process his time-domain data. He also uses the viscoplastic medicine theory of advanced engineering to calculate the associated energies of each biomarker. This study aims to determine the energy ratio (i.e. ratio of the degree of influence or ratio of the degree of contribution) among those 5 metabolic biomarkers on cancer risk. A detailed description of his research methods can be found in his full-text article, but not included in this abstract. It should be noted that the normalization factor for TyG is 4.49, the breakeven line for insulin resistance. In summary, there are 3 observations from this research work: (1) From the time-domain analysis, the energy ratios are: TD1 energy (square of averaged values): WHR = 18%; eAG = 27%; BP = 20%; Lipids = 11%; TyG = 24%. TD2 energy (summation of values): WHR = 19%; eAG = 23%; BP = 20%; Lipids = 15%; TyG = 22%. In short, the TD energy levels are ranked in the order of "eAG > TyG > BP > WHR > lipids". (2) From the SD-VMT analysis, the energy ratios are: WHR = 21%; eAG = 23%; BP = 20%; Lipids = 13%; TyG = 23%. In short, the SD energy levels are ranked in the order of "eAG = TyG > WHR > BP > lipids". (3) SD time-zone analysis results are: Y2010-Y2014 = 44%; Y2015-Y2019 = 53%; Y2020-Y2023 = 3%. This observation shows that the highest contribution period is during the middle 5 years period from Y2015 to Y2019. The second highest contribution period is the earlier 5 years

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from Y2010 to Y2014. The most recent COVID period from Y2020 to Y2023 has contributed the least to his cancer risk. For the author's case of cancer risk with 5 metabolic biomarkers, the highest influential biomarkers on his cancer risk are glucose and TyG. They are followed by waistline and blood pressure. The blood lipids, cholesterol, and triglyceride, contribute the least to his cancer risk. The same analysis method can be applied to other patients provided their biomarker data are available for analysis.

**Keywords:** Viscoelastic; Viscoplastic; Cancer; Metabolism; Diabetes

**Abbreviations:** PPG: postprandial plasma glucose; FPG: fasting plasma glucose; WHR: waist-to-hip ratio; BP: blood pressure; TD: time-domain; SD: space-domain; FD: frequency-domain

## 1. INTRODUCTION

For the past 14 years, the author conducted his medical research work on diseases related to internal organs, including soft tissues, blood, nerves, and hormones. Based on the theory of metabolism and immunity, he started with learning and researching various metabolic disorders, including obesity, diabetes, hypertension, hyperlipidemia, insulin resistance, fatty liver, etc. He has then extended his research effort into mortality diseases induced by metabolic disorders, such as cardiovascular diseases, strokes, chronic kidney diseases, and dementia. Since 2019, he initiated his research work on relationships between cancers and metabolism.

Basic metabolic biomarkers include blood sugar, blood pressure, body weight, and cholesterol or triglycerides. Metabolic syndrome can indeed put a person at high risk of several cancers and diseases that can lead to cancer. In this article, the author has chosen 5 metabolic biomarkers: waist-to-hip ratio (WHR) to measure the fat around the waist area, daily estimated average glucose (eAG) to measure diabetes, blood pressure (BP) of normalized SBP, DBP, and HR values, blood lipids of normalized LDL, HDL, triglycerides values, and TyG. Here, the TyG biomarker is chosen for measuring both his insulin resistance condition (TyG > 4.49) and nonalcoholic fatty liver disease condition (TyG > 8.5) with the following definition:

TyG = (ln (fasting triglycerides mg/dL) + ln (fasting glucose mg/dL)) / 2

He has collected data on his health conditions and lifestyle details, including those 5 basic metabolic biomarkers since 2010. However, the collected data in earlier years of 2010 and 2011 were incomplete and the 2023 data only has one month (January of 2023).

His cancer risk probability % is calculated using a sophisticated mathematical and engineering model which is based on 4 metabolism conditions and 6 lifestyle details. He developed this model in 2014 and then continuously enhance it since then. The cancer risk estimation includes genetic conditions, such as a family history of cancers and long-term bad habits, and other negative environmental factors, such as toxic chemicals, air and water pollution, food pollution or poison, hormonal therapy, etc. The total data collected and involved in this particular study are around 3 million.

After data organization, he then applies the theory of wave and energy of physics to process his time-domain data. He also uses the viscoplastic medicine theory of advanced engineering to calculate the associated energies of each biomarker. This study aims to determine the energy ratio (i.e. ratio of the degree of influence or ratio of the degree of contribution) among those 5 metabolic biomarkers on cancer risk. A detailed description of his research methods can be found in his full-text article, but not included in this abstract. It should be noted that the normalization factor for TyG is 4.49, the breakeven line for insulin resistance.

## 2. METHODS

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

### 2.2 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.

### 2.3 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.

### 2.4 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).

**Note:** For a more detailed description, please refer to the “consolidated method” section which is given at the beginning of the special issue.

## 3. RESULTS

Figure 1 shows time-domain analysis results.

Figure 2 shows SD-VMT analysis results and data table.

## 4. CONCLUSION

In summary, there are 3 observations from this research work:

(1) From the time-domain analysis, the energy ratios are: TD1 energy (square of averaged values): WHR = 18%; eAG = 27%; BP = 20%; Lipids = 11%; TyG = 24%. TD2 energy (summation of values): WHR = 19%; eAG = 23%; BP = 20%; Lipids = 15%; TyG = 22%. In short, the TD energy levels are ranked in the order of “eAG > TyG > BP > WHR > lipids”.

(2) From the SD-VMT analysis, the energy ratios are: WHR = 21%; eAG = 23%; BP = 20%; Lipids = 13%; TyG = 23%. In short, the SD energy levels are ranked in the order of “eAG = TyG > WHR > BP > lipids”.

(3) SD time-zone analysis results are: Y2010-Y2014 = 44%; Y2015-Y2019 = 53%; Y2020-Y2023 = 3%. This observation shows that the highest contribution period is during the middle 5 years period from Y2015 to Y2019. The second highest contribution period is the earlier 5 years from Y2010 to Y2014. The most recent COVID period from Y2020 to Y2023 has contributed the least to his cancer risk.

For the author’s case of cancer risk with 5 metabolic biomarkers, the highest influential biomarkers on his cancer risk are glucose and TyG. They are followed by waistline and blood pressure. The blood lipids, cholesterol, and triglyceride, contribute the least to his cancer risk. The same analysis method can be applied to other patients provided their biomarker data are available for analysis.

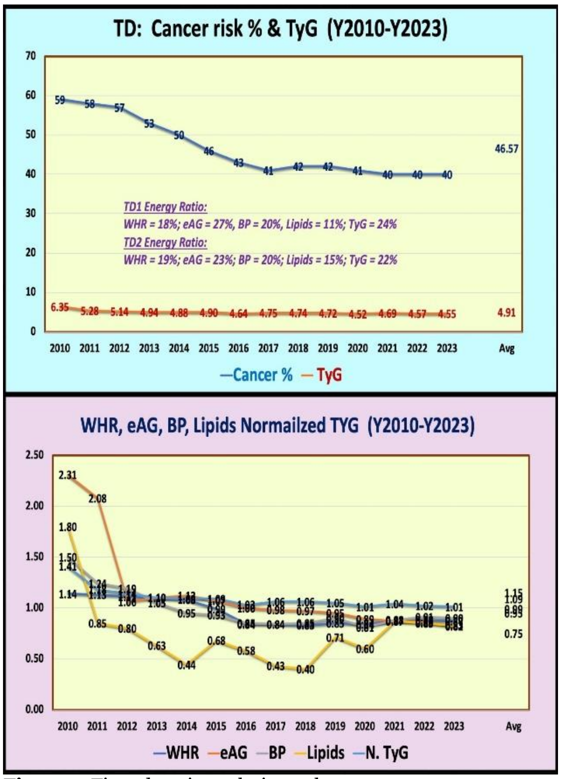
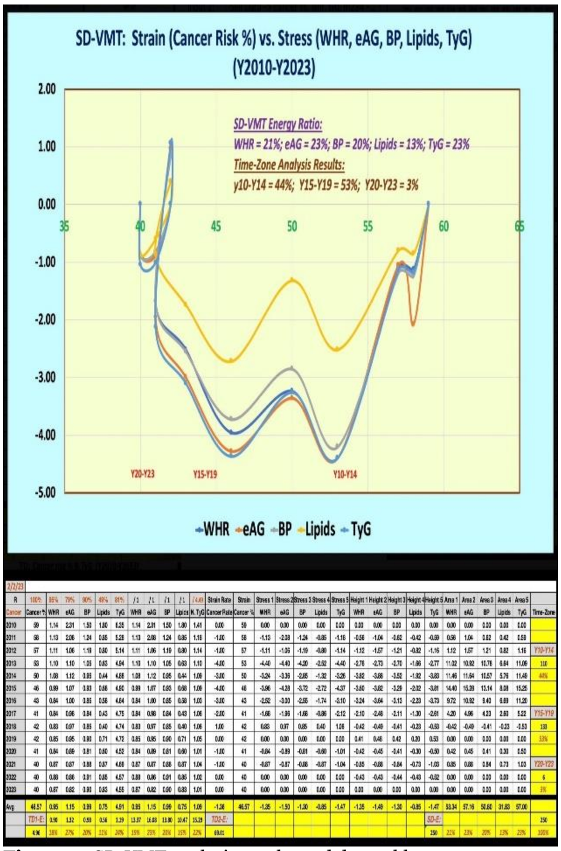


**Figure 1:** Time-domain analysis results.




| R | 100% | 85% | 79% | 90% | 49% | 81% | /1 | /1 | /1 | /1 | /4.49 | Strain Rate | Strain | Stress 1 | Stress 2 | Stress 3 | Stress 4 | Stress 5 | Height 1 | Height 2 | Height 3 | Height 4 | Height 5 | Area 1 | Area 2 | Area 3 | Area 4 | Area 5 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Cancer | Cancer % | WHR | eAG | BP | Lipids | TyG | WHR | eAG | BP | Lipids | N. TyG | Cancer Rate | Cancer % | WHR | eAG | BP | Lipids | TyG | WHR | eAG | BP | Lipids | TyG | WHR | eAG | BP | Lipids | TyG | Time-Zone |
| 2010 | 59 | 1.14 | 2.31 | 1.50 | 1.80 | 6.35 | 1.14 | 2.31 | 1.50 | 1.80 | 1.41 | 0.00 | 59 | 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 | |
| 2011 | 58 | 1.13 | 2.08 | 1.24 | 0.85 | 5.28 | 1.13 | 2.08 | 1.24 | 0.85 | 1.18 | -1.00 | 58 | -1.13 | -2.08 | -1.24 | -0.85 | -1.18 | -0.56 | -1.04 | -0.62 | -0.42 | -0.59 | 0.56 | 1.04 | 0.62 | 0.42 | 0.59 | |
| 2012 | 57 | 1.11 | 1.06 | 1.19 | 0.80 | 5.14 | 1.11 | 1.06 | 1.19 | 0.80 | 1.14 | -1.00 | 57 | -1.11 | -1.06 | -1.19 | -0.80 | -1.14 | -1.12 | -1.57 | -1.21 | -0.82 | -1.16 | 1.12 | 1.57 | 1.21 | 0.82 | 1.16 | Y10-Y14 |
| 2013 | 53 | 1.10 | 1.10 | 1.05 | 0.63 | 4.94 | 1.10 | 1.10 | 1.05 | 0.63 | 1.10 | -4.00 | 53 | -4.40 | -4.40 | -4.20 | -2.52 | -4.40 | -2.76 | -2.73 | -2.70 | -1.66 | -2.77 | 11.02 | 10.92 | 10.76 | 6.64 | 11.09 | 110 |
| 2014 | 50 | 1.08 | 1.12 | 0.95 | 0.44 | 4.88 | 1.08 | 1.12 | 0.95 | 0.44 | 1.09 | -3.00 | 50 | -3.24 | -3.36 | -2.85 | -1.32 | -3.26 | -3.82 | -3.86 | -3.52 | -1.92 | -3.83 | 11.46 | 11.64 | 10.57 | 5.76 | 11.49 | 44% |
| 2015 | 46 | 0.99 | 1.07 | 0.93 | 0.68 | 4.90 | 0.99 | 1.07 | 0.93 | 0.68 | 1.09 | -4.00 | 46 | -3.96 | -4.28 | -3.72 | -2.72 | -4.37 | -3.60 | -3.82 | -3.29 | -2.02 | -3.81 | 14.40 | 15.28 | 13.14 | 8.08 | 15.25 | |
| 2016 | 43 | 0.84 | 1.00 | 0.85 | 0.58 | 4.64 | 0.84 | 1.00 | 0.85 | 0.58 | 1.03 | -3.00 | 43 | -2.52 | -3.00 | -2.55 | -1.74 | -3.10 | -3.24 | -3.64 | -3.13 | -2.23 | -3.73 | 9.72 | 10.92 | 9.40 | 6.69 | 11.20 | |
| 2017 | 41 | 0.84 | 0.98 | 0.84 | 0.43 | 4.75 | 0.84 | 0.98 | 0.84 | 0.43 | 1.06 | -2.00 | 41 | -1.68 | -1.96 | -1.68 | -0.86 | -2.12 | -2.10 | -2.48 | -2.11 | -1.30 | -2.61 | 4.20 | 4.96 | 4.23 | 2.60 | 5.22 | Y15-Y19 |
| 2018 | 42 | 0.83 | 0.97 | 0.85 | 0.40 | 4.74 | 0.83 | 0.97 | 0.85 | 0.40 | 1.06 | 1.00 | 42 | 0.83 | 0.97 | 0.85 | 0.40 | 1.06 | -0.42 | -0.49 | -0.41 | -0.23 | -0.53 | -0.42 | -0.49 | -0.41 | -0.23 | -0.53 | 130 |
| 2019 | 42 | 0.85 | 0.95 | 0.90 | 0.71 | 4.72 | 0.85 | 0.95 | 0.90 | 0.71 | 1.05 | 0.00 | 42 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.41 | 0.46 | 0.42 | 0.20 | 0.53 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 53% |
| 2020 | 41 | 0.84 | 0.89 | 0.81 | 0.60 | 4.52 | 0.84 | 0.89 | 0.81 | 0.60 | 1.01 | -1.00 | 41 | -0.84 | -0.89 | -0.81 | -0.60 | -1.01 | -0.42 | -0.45 | -0.41 | -0.30 | -0.50 | 0.42 | 0.45 | 0.41 | 0.30 | 0.50 | |
| 2021 | 40 | 0.87 | 0.87 | 0.88 | 0.87 | 4.68 | 0.87 | 0.87 | 0.88 | 0.87 | 1.04 | -1.00 | 40 | -0.87 | -0.87 | -0.88 | -0.87 | -1.04 | -0.85 | -0.88 | -0.84 | -0.73 | -1.03 | 0.85 | 0.88 | 0.84 | 0.73 | 1.03 | Y20-Y23 |
| 2022 | 40 | 0.88 | 0.86 | 0.91 | 0.86 | 4.57 | 0.88 | 0.86 | 0.91 | 0.86 | 1.02 | 0.00 | 40 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | -0.43 | -0.43 | -0.44 | -0.43 | -0.52 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 6 |
| 2023 | 40 | 0.87 | 0.82 | 0.90 | 0.83 | 4.55 | 0.87 | 0.82 | 0.90 | 0.83 | 1.01 | 0.00 | 40 | 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 | 3% |
| Avg | 46.57 | 0.95 | 1.15 | 0.99 | 0.75 | 4.91 | 0.95 | 1.15 | 0.99 | 0.75 | 1.09 | -1.36 | 46.57 | -1.35 | -1.50 | -1.30 | -0.85 | -1.47 | -1.35 | -1.49 | -1.30 | -0.85 | -1.47 | 53.34 | 57.16 | 50.60 | 31.83 | 57.00 | |
| | TD1-E: | 0.90 | 1.32 | 0.98 | 0.56 | 1.39 | 13.87 | 16.08 | 13.80 | 10.47 | 15.29 | TD2-E: | | | | | | | | | | | SD-E: | | | | | | 250 |
| | 4.96 | 18% | 27% | 20% | 11% | 24% | 19% | 23% | 20% | 15% | 22% | 69.01 | | | | | | | | | | | 250 | 21% | 23% | 20% | 13% | 23% | 100% |

**Figure 2:** SD-VMT analysis results and data table.

## 5. 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 three published special editions from the following three specific journals:

(1) Special Issue. The GH-Method. (https://www.theghmethod.com).

(2) Journal of Applied Material Science & Engineering Research (contact: Catherine).

(3) Advances in Bioengineering and Biomedical Science Research (contact: Sony Hazi).

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# Viscoelastic and Viscoplastic Glucose Theory Application in Medicine

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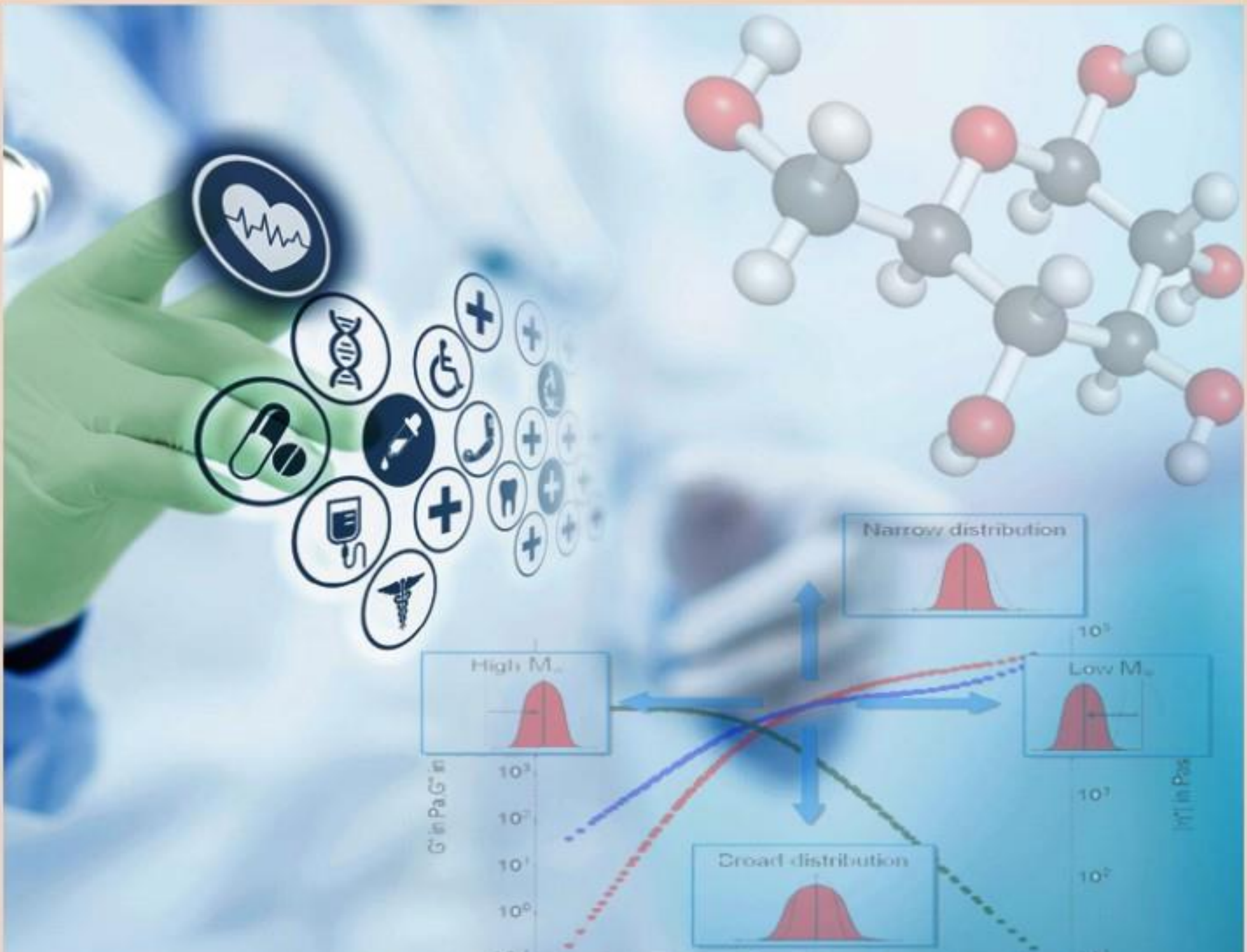


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