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Relationships between cancer 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 GH-Method: math-physical medicine (No. 959)

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Abstract

Combination of diet quality and food portion control play a crucial role in influencing human's body weight which is a primary factor in the progression of type 2 diabetes (T2D) conditions. Furthermore, T2D is characterized by four key biomarkers: insulin resistance (via morning fasting glucose - FPG levels), glycemic control status (via daily averaged glucose - eAG), quarterly glycemic control status (via HbA1c levels), and hyperglycemia control (via hyperglycemia intensity - HyGI). Here, HyGI is defined as the product of averaged glucose above 180 mg/dL multiplied by frequency counts of glucose above 180 mg/dL). This article delves into the author's investigation of his own cancer risks related to the aforementioned four T2D biomarkers. The author's collected personal data spans six years, from 5/1/2018 through 11/19/2023. Traditional statistical correlations revealed four low correlations (ranging between 14% and 41%) between the author's cancer risk waveform and the four influential input waveforms. Subsequently, the author employed the space-domain viscoplastic energy (SD-VMT) method from advanced engineering to unveil hidden relationships and dynamics (i.e., energies) among these four T2D biomarker inputs and the author's output of his annual cancer risks. In summary, traditional statistical correlations offer limited insights into the relationships between the author's cancer risks and his four T2D biomarkers: - Cancer vs. HbA1c: 18%; - Cancer vs. FPG: 23%; - Cancer vs. eAG: 14%; - Cancer vs. HyGI: 41%. However, utilizing SD-VMT energy results from advanced engineering reveals four energy contribution margins on his cancer risks from these T2D biomarkers: - Energy from HbA1c: 23.6%; - Energy from FPG: 28.0%; - Energy from eAG: 23.5%; - Energy from HyGI: 24.8%

Key message: Indeed, his T2D conditions are connected to his cancer risks. His insulin resistance status via FPG contributes the most energy to his cancer risks (28.0%), followed by hyperglycemia intensity (24.8%), and his other two glucose status indicators: quarterly HbA1c at 23.6% and daily eAG at 23.5%. Interestingly, despite hyperglycemia frequency accounting for only 2% of his total glucose dataset, it contributes 25% of the total impact or energy on his overall cancer risks.

Keywords: Viscoelastic; Viscoplastic; Diabetes; Glucose; cancer

Abbreviations: CGM: continuous glucose monitoring; T2D: type 2 diabetes; PPG: postprandial plasma glucose; FPG: fasting plasma glucose; MI: metabolism index; CVD: cardiovascular diseases;

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1. INTRODUCTION

Combination of diet quality and food portion control play a crucial role in influencing human's body weight which is a primary factor in the progression of type 2 diabetes (T2D) conditions. Furthermore, T2D is characterized by four key biomarkers: insulin resistance (via morning fasting glucose - FPG levels), glycemic control status (via daily averaged glucose - eAG), quarterly glycemic control status (via HbA1c levels), and hyperglycemia control (via hyperglycemia intensity - HyGI). Here, HyGI is defined as the product of averaged glucose above 180 mg/dL multiplied by frequency counts of glucose above 180 mg/dL).

This article delves into the author's investigation of his own cancer risks related to the aforementioned four T2D biomarkers. The author's collected personal data spans six years, from 5/1/2018 through 11/19/2023.

Traditional statistical correlations revealed four low correlations (ranging between 14% and 41%) between the author's cancer risk waveform and the four influential input waveforms. Subsequently, the author employed the space-domain viscoplastic energy (SD-VMT) method from advanced engineering to unveil hidden relationships and dynamics (i.e., energies) among these four T2D biomarker inputs and the author's output of his annual cancer risks.

1.1 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.

Statistical data regarding Cancers and Diabetes:

The relationship between cancer and diabetes is a complex and multifaceted one. Studies have suggested that individuals with diabetes may have an increased risk of developing certain types of cancer.

According to the American Cancer Society, people with diabetes are more likely to be diagnosed with certain types of cancer, including liver, pancreatic, endometrial, colorectal, breast, and bladder cancer. The exact percentage of cancer patients who also have diabetes can vary depending on the specific cancer type and the population studied.

For example, a review published in the journal Current Diabetes Reports in 2019 noted that the prevalence of diabetes in cancer patients varies widely depending on the type of cancer. The review highlighted that the prevalence of diabetes in individuals with breast cancer ranged from 8% to 20%, while in individuals with colorectal cancer, the prevalence of diabetes ranged from 16% to 31%. In individuals with pancreatic cancer, the prevalence of diabetes was found to be particularly high, ranging from 27% to 88%.

It is important to note that the relationship between cancer and diabetes is influenced by various factors, including shared risk factors such as obesity, age, lifestyle factors, genetic predisposition, and environmental factors, such as toxic, radiation, pollution, hormonal therapy, etc. Additionally, the impact of diabetes on cancer risk and prognosis can be influenced by factors such as the duration of diabetes, glycemic control, and the presence of other comorbidities.

Overall, the prevalence of diabetes in cancer patients can vary depending on the type of cancer and the specific characteristics of the population being studied, but there is evidence to suggest that individuals with diabetes may have an increased risk of certain types of cancer.

Pathophysiological explanations of relationships between cancers and ; diabetes biomarkers, HbA1C, insulin resistance (FPG), daily averaged glucose (eAG), hyperglycemia intensity methods:

The relationship between cancer and diabetes biomarkers such as HbA1C, insulin resistance (via FPG), daily averaged glucose (eAG), and hyperglycemia intensity (HyGI) is complex and involves various

pathophysiological mechanisms. Here are some explanations for the potential connections:

HbA1c:
HbA1c reflects average blood glucose levels over a period of time and is used to monitor long-term glycemic control in individuals with diabetes. Elevated HbA1c levels are indicative of chronic hyperglycemia and may contribute to cancer development and progression through several mechanisms.

Chronic hyperglycemia can lead to increased oxidative stress, chronic inflammation, and alterations in cellular metabolism, which can promote cancer growth and progression.

Additionally, high HbA1c levels have been associated with insulin resistance and increased levels of insulin-like growth factor-1 (IGF-1), which are implicated in promoting cell proliferation and are linked to cancer development.

Insulin Resistance (via FPG):
Insulin resistance is a condition in which the body's cells become less responsive to insulin, leading to elevated blood glucose levels. The overall insulin resistance situation can be indicated by the level of fasting plasma glucose in the early morning (FPG). Insulin resistance is often associated with obesity and type 2 diabetes, and it has been linked to an increased risk of certain cancers, including breast, colon, and pancreatic cancer.

Insulin resistance can result in compensatory hyperinsulinemia, which may promote cancer development through its mitogenic and anti-apoptotic effects.

Insulin resistance is also associated with alterations in insulin-like growth factor (IGF) signaling, which can influence cancer cell growth and survival.

Daily Averaged Glucose (eAG) and Hyperglycemia Intensity:
Daily averaged glucose (eAG) reflects an estimation of average glucose levels over a 24-hour period. For example, the author utilized a continuous glucose monitoring (CGM) device, Libre 3, and automatically recorded his glucose values every 15 minutes interval, a total of 96 glucose data each day.

Persistent hyperglycemia, reflected in elevated eAG levels, can contribute to cancer development by promoting chronic inflammation, increased oxidative stress, and alterations in cell signaling pathways. Hyperglycemia can also directly influence the tumor microenvironment, providing a favorable energy source for cancer cells and promoting tumor growth.

Overall, the relationships between cancer and diabetes biomarkers are multifaceted and involve various interconnected pathways, including alterations in glucose metabolism, insulin signaling, inflammation, and oxidative stress. Managing diabetes and glycemic control may have implications for cancer risk and prognosis, as well as potential therapeutic implications for cancer patients with concurrent diabetes. Further research is needed to elucidate the specific mechanisms underlying these relationships and to identify potential targets for intervention.

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 (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.

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).

3. RESULTS

Figure 1 shows data table, Time-domain curves and SD-VMT energies.

4. CONCLUSION

In summary, traditional statistical correlations offer limited insights into the relationships between the author's cancer risks and his four T2D biomarkers:
- Cancer vs. HbA1c: 18%
- Cancer vs. FPG: 23%
- Cancer vs. eAG: 14%
- Cancer vs. HyGI: 41%

However, utilizing SD-VMT energy results from advanced engineering reveals four energy contribution margins on his cancer risks from these T2D biomarkers:
- Energy from HbA1c: 23.6%
- Energy from FPG: 28.0%
- Energy from eAG: 23.5%
- Energy from HyGI: 24.8%

5. KEY MESSAGE

Indeed, his T2D conditions are connected to his cancer risks. His insulin resistance status via FPG contributes the most energy to his cancer risks (28.0%), followed by hyperglycemia intensity (24.8%), and his other two glucose status indicators: quarterly HbA1c at 23.6% and daily eAG at 23.5%. Interestingly, despite hyperglycemia frequency accounting for only 2% of his total glucose dataset, it contributes 25% of the total impact or energy on his overall cancer risks.

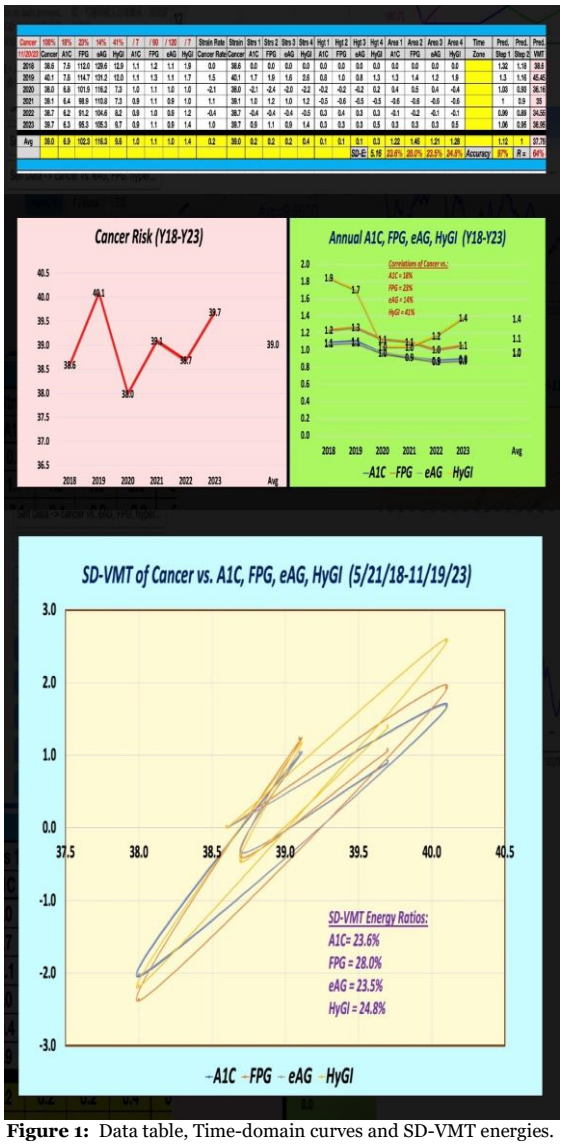

Figure 1: Data table, Time-domain curves and SD-VMT energies.

6. 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.

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.

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Viscoelastic and Viscoplastic Glucose Theory Application in Medicine

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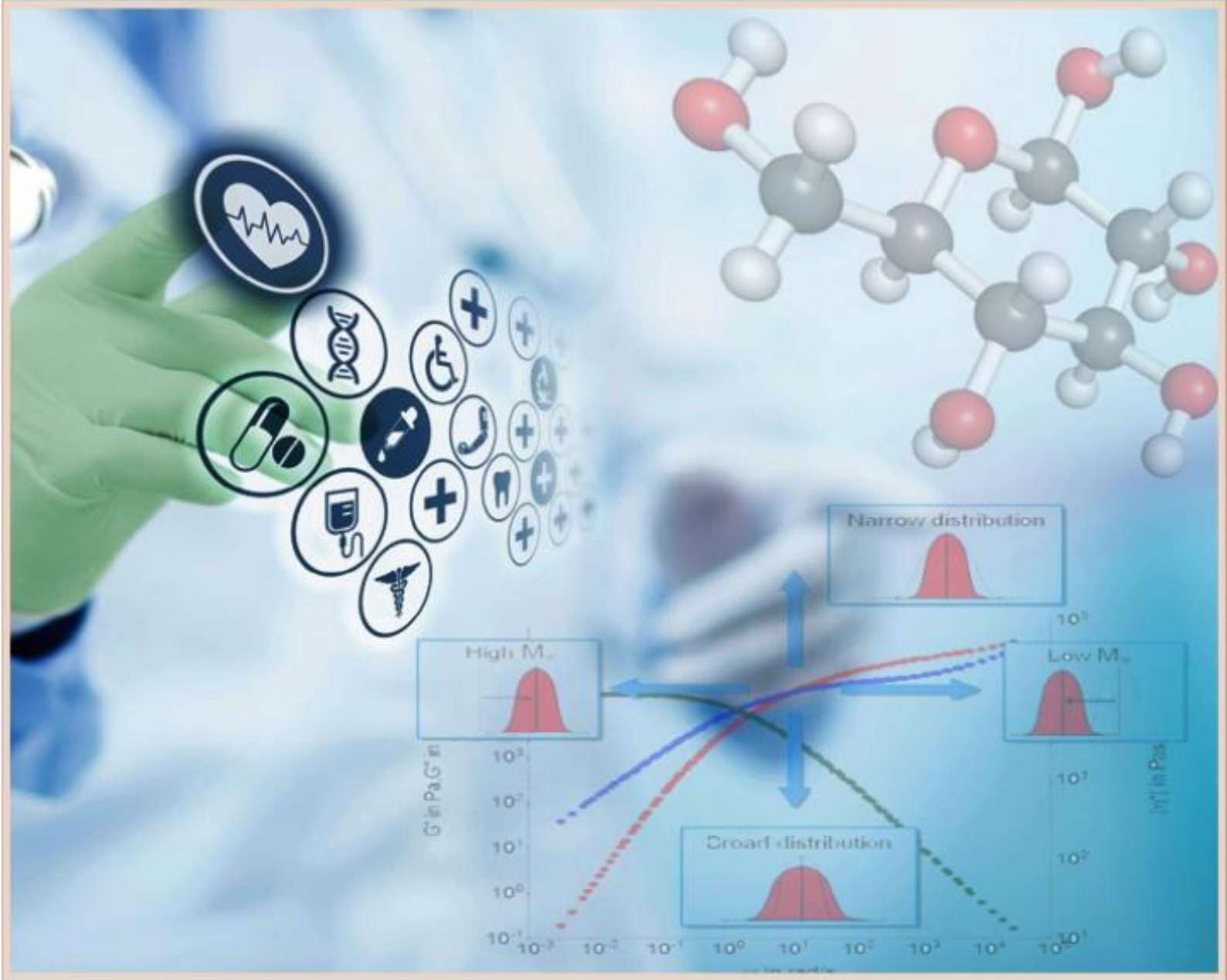

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