The GH-Method

Viscoelastic Medicine Theory (VMT #329): Variations in Cancer Risk Analysis Using Measured and Predicted Body Weight and Glucose Inputs from 2015 to 2023 Applying the Viscoplastic Energy Model of GH-Method: Math-Physical Medicine (No. 929)

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Abstract

Since 2015, the author has focused on developing prediction equations for certain important biomarkers. Specifically, he has created the following three prediction equations for body weight, fasting glucose (FPG), and post-meal glucose (PPG). (1) Body weight prediction: Predicted BW in the early morning = Yesterday's BW in early morning + Yesterday's food quantity (mIa) + Yesterday's H20 drinking (m6) - Yesterday's bowel movement / 5 - Last night's sleeping hours / 10. (2) Statistical glucose prediction: Calculate standard deviations of X (body weight) and Y (FPG or PPG); Calculate sumSX or sunSY is the summation of the squared X or squared Y; Calculate correlation R between X and Y; sdX = sqrt (sumX / number of X), sdY = sqrt (sumY / number of Y), b = R * sdY / sdX, a = avgY - b * avgX, Predicted glucose Y = a + b * weight X. (3) Predicted PPG using linear elastic glucose theory (LEGT): Predicted LEGT PPG = FPG*0.9 + (carbs/sugar grams) * 3.4 - (post-meal walking steps / 1000) * 4. This study focuses on using three significant input factors, body weight, fasting glucose (FPG), and post-meal glucose (PPG), to estimate his cancer risks from January 1, 2015, to September 20, 2023. He performs two quantitative analyses using the viscoplastic energy model (VMT) with two different input datasets, both measured and predicted. He also utilized his VMT-based prediction model to calculate another cancer risk for comparative analysis. The purpose is to assess the differences between using these two datasets. If the disparities of results are minimal, indicating a close alignment, it then demonstrates the high accuracy and practical applicability of the author's predicted biomarker equations in real-life patient scenarios. In summary, this analysis reveals four observations: 1. Time-domain analysis: The measured and predicted waveforms for body weight and FPG show nearly identical results, with a prediction accuracy of around 100% and correlation coefficients of approximately 98%. However, for PPG waveforms, while the prediction accuracy remains high at around 100%, the correlation coefficient is slightly lower at 91%. 2. Space-domain Viscoplasticity energy (SD-VMT) analysis: The energy ratios for body weight, FPG, and PPG are almost identical, with body weight accounting for 32.3%, FPG accounting for 36.3%-36.4%, and PPG accounting for 31.3%-31.4%. Similarly, the distribution of energy in the time zones is identical, with Y15-Y19 accounting for 87% and Y20-Y23 accounting for 13%. 3. VMT-based cancer risk curves: The cancer risk curves generated using VMT for both measured and predicted data closely match each other. These two curves exhibit correlation coefficients of 85% (measured) and 81% (predicted) when compared to the MI-based cancer risk. 4. LEGT-based prediction for PPG: It yields a better correlation of 91%, compared to the statistical-based prediction method of 86%. Both methods, however, demonstrate near 100% prediction accuracy.

Keywords: Viscoelastic; Viscoplastic; Cancer; Body weight; Diabetes; Exercise

Abbreviations: MI: metabolism index; CVD: cardiovascular diseases; CKD: chronic kidney diseases; T2D: type 2 diabetes; PPG: postprandial plasma glucose; FPG: fasting plasma glucose

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1. INTRODUCTION

Since 2015, the author has focused on developing prediction equations for certain important biomarkers. Specifically, he has created the following three prediction equations for body weight, fasting glucose (FPG), and post-meal glucose (PPG).

(1) Body weight prediction:

Predicted BW in the early morning
= Yesterday's BW in early morning
+ Yesterday's food quantity (mIa)
+ Yesterday's H20 drinking (m6)
- Yesterday's bowel movement / 5
- Last night's sleeping hours / 10

(2) Statistical glucose prediction:

Calculate standard deviations of X (body weight) and Y (FPG or PPG);
Calculate sumSX or sunSY is the summation of the squared X or squared Y;
Calculate correlation R between X and Y;
sdX = sqrt (sumX / number of X)
sdY = sqrt (sumY / number of Y)
b = R * sdY / sdX
a = avgY - b * avgX
Predicted glucose Y
= a + b * weight X

(3) Predicted PPG using linear elastic glucose theory (LEGT):

Predicted LEGT PPG
= FPG*0.9 + (carbs/sugar grams) * 3.4 - (post-meal walking steps / 1000) * 4

This study focuses on using three significant input factors, body weight, fasting glucose (FPG), and post-meal glucose (PPG), to estimate his cancer risks from January 1, 2015, to September 20, 2023. He performs two quantitative analyses using the viscoplastic energy model (VMT) with two different input datasets, both measured and predicted. He also utilized his VMT-based prediction model to calculate another cancer risk for comparative analysis.

The purpose is to assess the differences between using these two datasets. If the disparities of results are minimal, indicating a close alignment, it then demonstrates the high accuracy and practical applicability of the author's predicted biomarker equations in real-life patient scenarios.

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.

Notes from the author of this paper:

Upon reviewing the upcoming excerpts from other published articles, it becomes evident that these findings are predominantly conveyed using qualitative statements. On occasion, these statements include a limited number of numerical values, typically sourced from statistical data within epidemiological studies. However, a recurring deficiency among them is the lack of robust quantitative findings to underpin their qualitative conclusions. Consequently, the author of this paper has deliberately opted to leverage his familiar methodologies from mathematics, physics, and engineering fields in his medical research pursuits. This strategic choice is intended to yield substantial conclusions supported by sound proofs via quantitative data, effectively bridging the current gap in the realm of biomedical research.

Pathophysiological explanations and statistical data regarding relationships between cancers versus both body weight and glucoses:

Pathophysiological mechanisms and statistical data provide valuable insights into the relationships between cancers and body weight, as well as glucose levels such as fasting plasma glucose (FPG) and postprandial plasma glucose (PPG).

Various studies have shown that obesity is strongly associated with an increased risk of several types of cancers. Excess body weight can lead to chronic inflammation, insulin resistance, and hormonal imbalances, creating an environment that promotes cancer development and progression. The adipose tissue itself releases pro-inflammatory molecules and hormones that can contribute to cancer initiation and growth. Additionally, obesity is linked to changes in adipokines, which are involved in regulating cell growth and differentiation.

Regarding glucose levels, elevated FPG and PPG levels have also been associated with an increased risk of cancer. Prolonged exposure to high glucose levels can lead to oxidative stress and the production of advanced glycation end-products (AGEs), which can damage cells and DNA. This, in turn, can promote cancer formation and growth.

Statistical data supports these pathophysiological explanations. Research studies have consistently shown a positive correlation between obesity and the incidence of various cancers, including breast, colorectal, endometrial, kidney, liver, pancreatic, and ovarian cancer, among others. Similarly, studies have found that individuals with higher FPG and PPG levels are more likely to develop certain types of cancer, such as colorectal, pancreatic, and liver cancer.

Taken together, pathophysiological mechanisms and statistical data emphasize the importance of maintaining a healthy body weight and managing glucose levels to reduce the risk of cancer development and progression. These findings highlight the significance of lifestyle modifications, including regular exercise, balanced diet, and glucose control, in cancer prevention and management.

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 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 supporting curves and a data table.

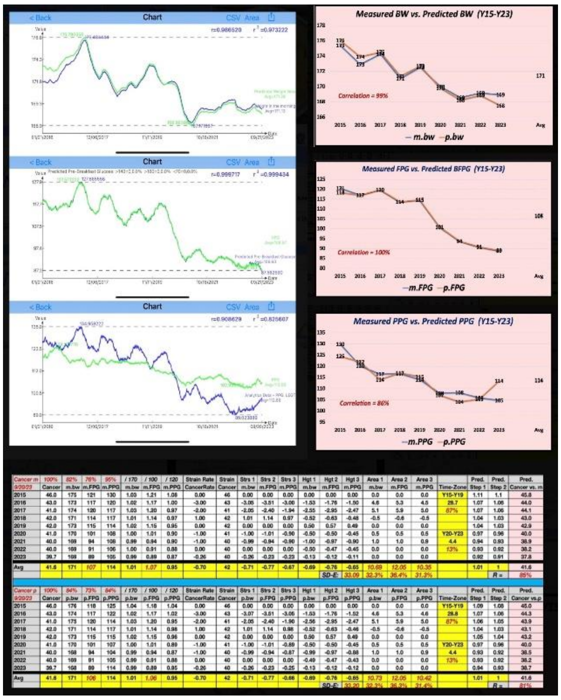

Figure 1: Supporting curves and data table.

Figure 2 shows output curves.

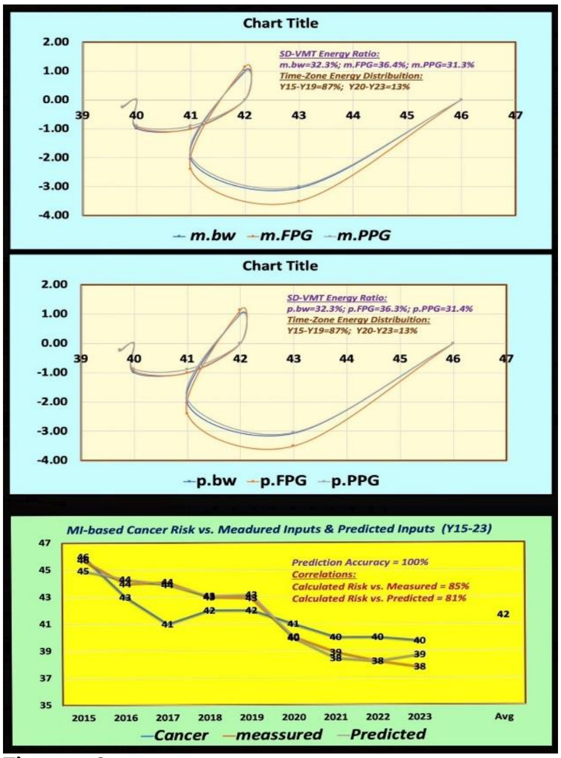

Figure 2: Output curves.

Figure 3 shows comparison between LEGT-based & statistics-based PPG.

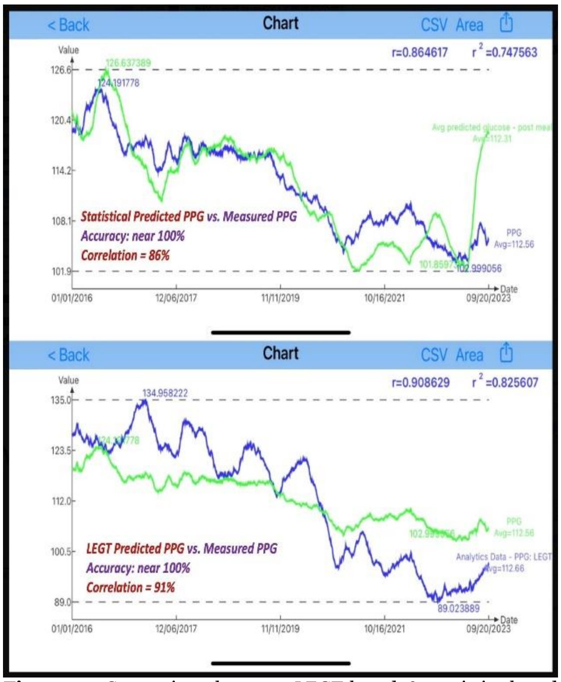

Figure 3: Comparison between LEGT-based & statistics-based PPG.

4. CONCLUSION

In summary, this analysis reveals four observations:

1. Time-domain analysis: The measured and predicted waveforms for body weight and FPG show nearly identical results, with a prediction accuracy of around 100% and correlation coefficients of approximately 98%. However, for PPG waveforms, while the prediction accuracy remains high at around 100%, the correlation coefficient is slightly lower at 91%.

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and 81% (predicted) when compared to the MI-based cancer risk.

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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 platforms for scientific research publications, such as ResearchGate, Google Scholar, etc.

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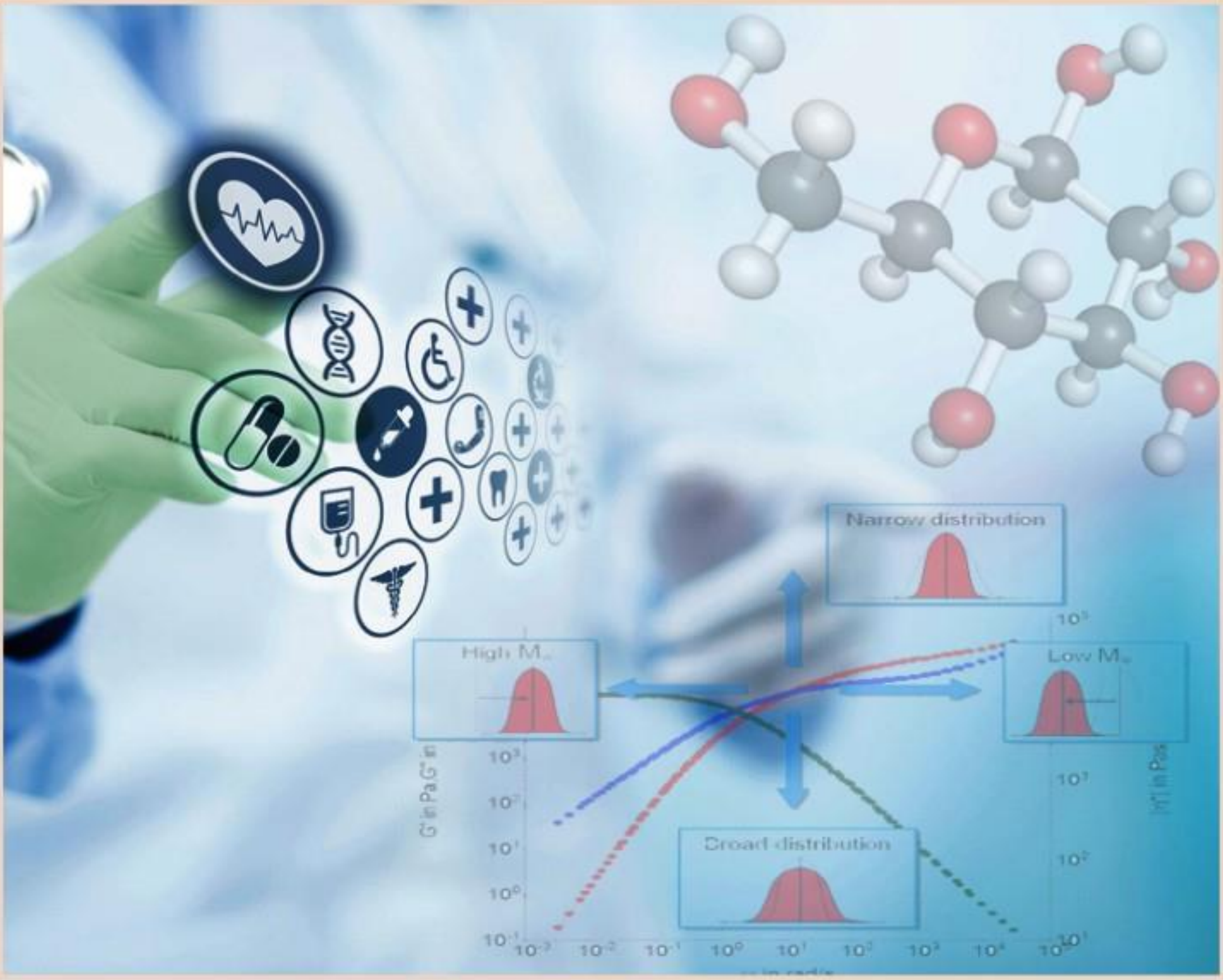

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