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The GH-Method

Viscoelastic Medicine Theory (VMT #346): FPG in Early Morning versus Body Weight, Body Temperature, and Sleep Score and Applying the Viscoplastic Energy Model of GH-Method: Math-Physical Medicine (No. 947)

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Abstract

The author employs statistical methods to calculate correlation coefficients (R) between his fasting plasma glucose (FPG) in the early morning and three key biomarkers: body weight (BW), body temperature (BT), and sleep score (SS). The author's time-domain (TD) analysis reveals the following three findings: - The correlation (R) between FPG and BW is 84% over the period from 1/1/13 to 10/27/23; - FPG and BT exhibit a 75% correlation over the period from 1/1/21 to 10/27/23; - FPG and SS are correlated at 76% over the period from 1/1/15 to 10/27/23. All of these three correlations exceed 75%, indicating significant shape similarities existed between FPG curve and these three influential waveforms. It's worth noting that these correlations are based on different data collection periods with different starting dates and the same ending date. Consequently, these three influential factors are chosen as input stresses, while FPG is considered as the output strain, for the analysis of a space-domain viscoplastic medicine theory (SD-VMT). In this SD-VMT analysis, he constructs a stress-strain (input-output) diagram and quantifies the enclosed area within the stress-strain curve as the corresponding energy value. The resulting SD-VMT energy ratios are as follows: - FPG vs. BW = 40%; - FPG vs. BT = 39%; - FPG vs. SS = 21%. Interestingly, when using the VMT prediction method, the predicted FPG versus the measured FPG demonstrates an impressive 99.8% prediction accuracy and a 69% correlation. In summary, these findings suggest that both body weight and body temperature exhibit stronger associations with FPG compared to the sleep score. However, even the sleep score maintains a noticeable and reasonably strong relationship with FPG.

Keywords: Viscoelastic; Viscoplastic; Diabetes; Exercise; Body weight; Body temperature; Sleep score

Abbreviations: MI: metabolism index; BW: body weight; BT: body temperature; SS: sleep score 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

The author employs statistical methods to calculate correlation coefficients (R) between his fasting plasma glucose (FPG) in the early morning and three key biomarkers: body weight (BW), body temperature (BT), and sleep score (SS). The author's time-domain (TD) analysis reveals the following three findings:

-The correlation (R) between FPG and BW is 84% over the period from 1/1/13 to 10/27/23.

-FPG and BT exhibit a 75% correlation over the period from 1/1/21 to 10/27/23.

-FPG and SS are correlated at 76% over the period from 1/1/15 to 10/27/23.

Consequently, these three influential factors are chosen as input stresses, while FPG is considered as the output strain, for the analysis of a space-domain viscoplastic medicine theory (SD-VMT). In this SD-VMT analysis, he constructs a stress-strain (input-output) diagram and quantifies the enclosed area within the stress-strain curve as the corresponding energy value.

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.

Pathophysiological explanations and statistical data regarding relationship between FPG and body weight:

There is a strong correlation between fasting plasma glucose (FPG) levels and body weight (BW). Pathophysiologically, excess body weight, particularly in the form of body fat, is closely associated with insulin resistance. Insulin resistance refers to a diminished response of cells to the hormone insulin, leading to elevated blood glucose levels.

Excessive body weight, especially abdominal obesity, promotes the release of pro-inflammatory molecules called adipokines and cytokines. These molecules contribute to a chronic state of low-grade inflammation, which further impairs insulin signaling and glucose uptake by cells.

Additionally, adipose tissue, particularly visceral fat, secretes increased amounts of free fatty acids, which can interfere with insulin action in peripheral tissues such as muscles and liver. As a result, cells become less responsive to insulin, leading to elevated FPG levels.

Statistical data consistently demonstrates the close relationship between FPG and body weight. Numerous studies have shown that overweight and obese individuals are at a higher risk of developing impaired fasting glucose (IFG) and ultimately, type 2 diabetes.

One large-scale study, the National Health and Nutrition Examination Survey (NHANES), observed a positive gradient between higher body mass index (BMI) categories and the prevalence of IFG or diabetes. The data revealed that as BMI increased, the likelihood of having elevated FPG levels significantly rose.

Furthermore, interventions aimed at reducing body weight, such as lifestyle modifications involving dietary changes and increased physical activity, have been proven effective in improving FPG levels. Weight loss interventions have shown to enhance insulin sensitivity and lower FPG levels, leading to better glycemic control.

In conclusion, the pathophysiological explanations supporting the relationship between FPG and body weight are well-established, and statistical data consistently demonstrates the correlation between these two variables. Managing and maintaining a healthy body weight is vital for preventing and managing elevated FPG levels and reducing the risk of developing type 2 diabetes.

Pathophysiological explanations and statistical data regarding relationship between FPG and body temperature:

Currently, there is limited research available regarding the direct relationship between fasting plasma glucose (FPG) levels and body temperature. However, there are some pathophysiological explanations and statistical data that can be discussed.

Pathophysiologically, glucose metabolism and body temperature regulation are both influenced by complex physiological processes. Insulin, a key hormone involved in glucose regulation, plays a crucial role in modulating body temperature. It affects thermogenesis, the process of heat production in the body, and can influence peripheral blood flow and heat dissipation.

Moreover, glucose metabolism is intricately linked with energy homeostasis. The body's metabolic rate and thermogenic processes can be affected by variations in glucose levels. Dysregulation of glucose metabolism, such as insulin resistance or diabetes, can disrupt these processes and potentially impact body temperature regulation.

While direct statistical data specifically addressing the relationship between FPG and body temperature is limited, certain studies have indirectly explored the association between glucose metabolism and body temperature changes.

For example, some studies have indicated that individuals with poorly controlled diabetes may experience alterations in body temperature regulation. Chronic hyperglycemia or hypoglycemia can potentially affect the hypothalamic thermoregulatory centers, leading to disturbances in body temperature control.

Additionally, research has shown that certain medications used to manage diabetes, such as insulin or hypoglycemic agents, may influence body temperature. These medications can impact glucose metabolism, potentially affecting thermogenic processes and thus body temperature regulation.

However, it is important to note that the relationship between FPG and body temperature is still not well-established, and further research is warranted to better understand their interplay.

In summary, while there are some pathophysiological explanations related to glucose metabolism and body temperature regulation, and indirect observations of possible associations between FPG control and body temperature changes, direct statistical data specifically elucidating their relationship is still limited. Further studies are needed to establish a more comprehensive understanding of the connection between FPG levels and body temperature.

Pathophysiological explanations and statistical data regarding relationship between FPG and quality of sleep:

There is growing evidence suggesting a relationship between fasting plasma glucose (FPG) levels and the quality of sleep. Pathophysiologically, disruptions in glucose metabolism, such as insulin resistance or impaired insulin secretion, can influence sleep patterns and vice versa.

Insulin resistance, a key feature of type 2 diabetes, has been associated with sleep disturbances. Insulin resistance can affect the central nervous system and alter neurotransmitter activity, potentially leading to difficulties falling asleep, maintaining sleep, or experiencing restorative sleep. In turn, poor sleep quality and sleep deprivation have been shown to negatively impact glucose metabolism, leading to higher FPG levels.

Furthermore, there is evidence linking changes in the circadian rhythm, the body's internal clock regulating sleep-wake cycles, with disturbances in glucose metabolism. Disruptions in the circadian rhythm, such as shift work or irregular sleep schedules, have been associated with increased risk of insulin resistance and impaired glucose tolerance. These disruptions can lead to alterations in hormone secretion, including melatonin and cortisol, which can have profound effects on both sleep quality and glucose regulation.

Statistical data supports the association between FPG and the quality of sleep. Several studies have demonstrated that individuals with poor sleep quality, shorter sleep duration, or sleep disorders such as

obstructive sleep apnea (OSA) are more likely to have higher FPG levels and an increased risk of developing type 2 diabetes.

The landmark Sleep Heart Health Study showed that individuals with OSA, a condition characterized by repeated episodes of interrupted breathing during sleep, have a higher prevalence of insulin resistance and impaired glucose metabolism compared to those without OSA. This suggests that OSA-related sleep disturbances contribute to dysregulation of glucose metabolism and elevated FPG levels.

Other studies have shown that sleep deprivation, either acute or chronic, can lead to insulin resistance and impaired glucose tolerance. One well-known study restricted healthy individuals to just four hours of sleep per night for six nights. At the end of the study, participants' glucose tolerance tests indicated impaired glucose metabolism, with increased FPG levels and reduced insulin sensitivity.

Overall, these findings imply a bidirectional relationship between FPG levels and the quality of sleep. Elevated FPG levels can contribute to sleep disturbances, while poor sleep quality or duration can lead to dysregulation of glucose metabolism and higher FPG levels. Improving sleep quality and addressing sleep disorders may play a role in managing FPG levels and reducing the risk of developing type 2 diabetes.

In conclusion, the pathophysiological explanations and statistical data suggest a significant association between FPG levels and the quality of sleep. Understanding and addressing these relationships are crucial for optimal management of glucose metabolism and overall health.

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 output and data tables.

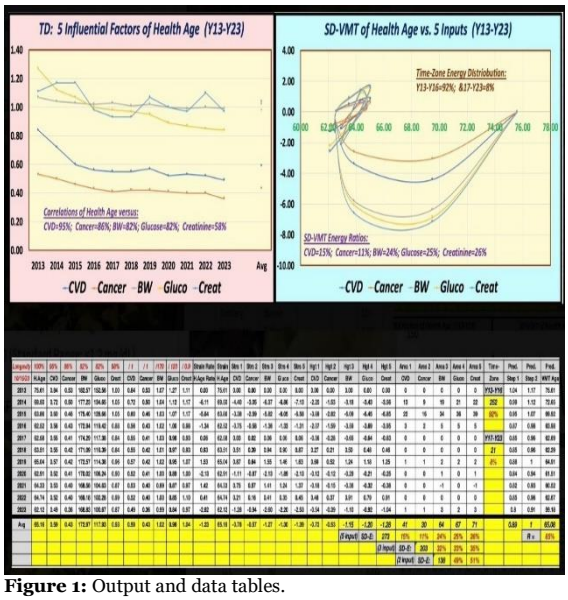

Figure 1: Output and data tables.

4. CONCLUSION

All of these three correlations between FPG versus body weight, body temperature, and sleep score, respectively exceed 75%, indicating significant shape similarities existed between FPG curve and these three influential waveforms. It's worth noting that these correlations are based on different data collection periods with different starting dates and the same ending date.

Consequently, these three influential factors are chosen as input stresses, while FPG is considered as the output strain, for the analysis of a space-domain viscoplastic medicine theory (SD-VMT). In this SD-VMT analysis, he constructs a stress-strain (input-output) diagram and quantifies the enclosed area within the stress-strain curve as the corresponding energy value.

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Interestingly, when using the VMT prediction method, the predicted FPG versus the measured FPG demonstrates an impressive 99.8% prediction accuracy and a 69% correlation.

In summary, these findings suggest that both body weight and body temperature exhibit stronger associations with FPG compared to the sleep score. However, even the sleep score maintains a noticeable and reasonably strong relationship with FPG.

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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Viscoelastic and Viscoplastic Glucose Theory Application in Medicine

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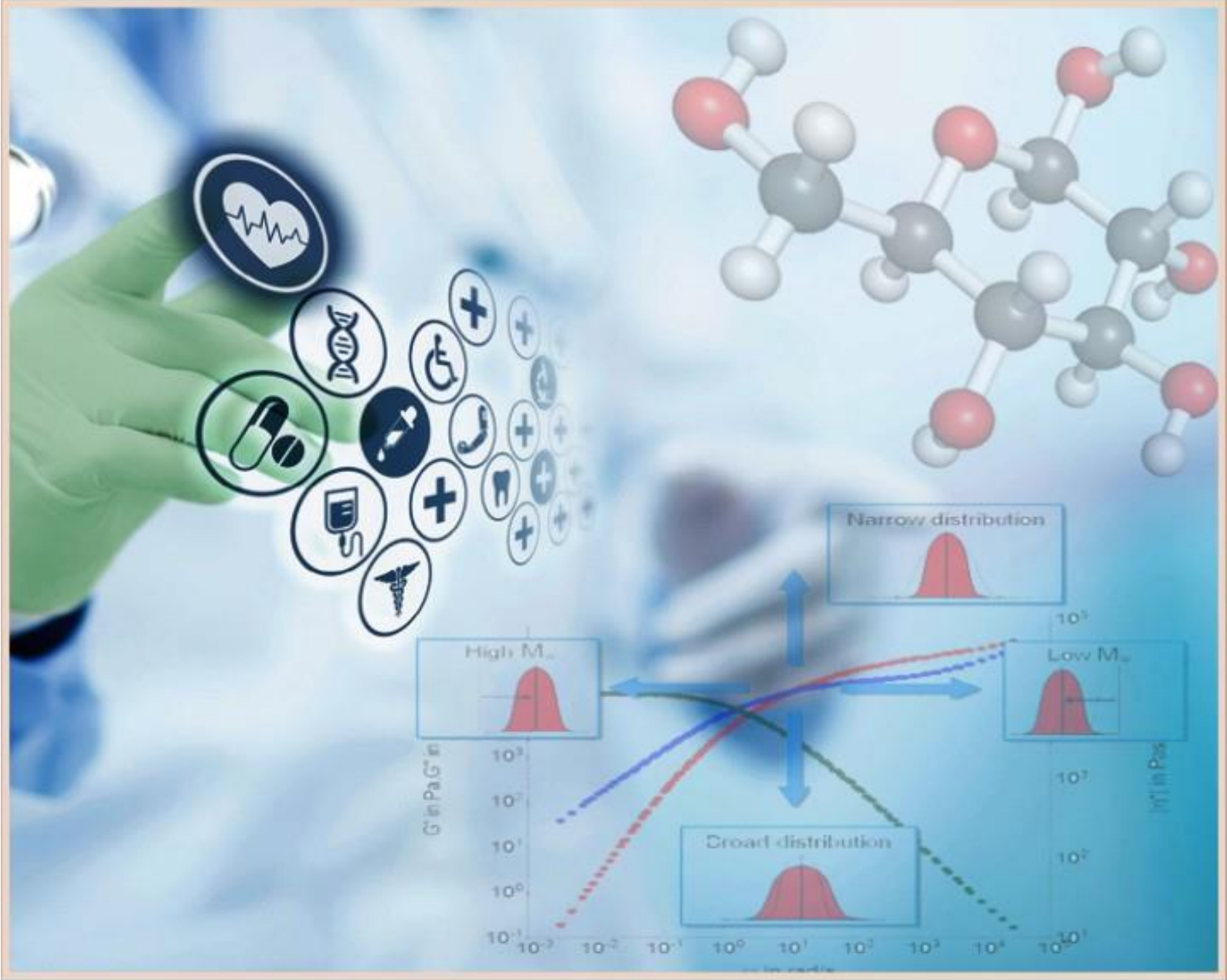

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