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The GH-Method

Viscoelastic and Viscoplastic Glucose Theory (VGT #129): The Third Sensitivity Study of Normalization Factors Using Three Different Energy Methods, Time Domain, Space Domain, and Frequency Domain, to Calculate Energies or Degrees of Influence on the Total Fasting Plasma Glucose (FPG) in the Early Morning versus Pre-COVID FPG and Post-COVID FPG Over 4+ Years from 5/8/2018 to 8/14/2022 Based on Math-Physical Medicine Method (No. 720)

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Keywords: Viscoelastic; Viscoplastic; Postprandial plasma glucose; Fasting plasma glucose; Type 2 diabetes; Fast Fourier transform

Abbreviations: FFT: fast Fourier transform; T2D: type 2 diabetes; PPG: postprandial plasma glucose; FPG: fasting plasma glucose; FD: frequency domain; SD: space domain; TD: time domain; MPM: math-physical medicine

1. INTRODUCTION

The author has conducted medical research work using viscoelastic or viscoplastic glucose theory (VGT) starting on 1/8/2022 with Paper No. 578. During the 7-month research period, he has written 123 medical papers and 5 economics papers where he learned in depth the subtlety and things to watch out for by applying this specific research tool.

In the beginning, he selected multiple input viscosities without using any normalization factors (NF); therefore, he obtained some enlarged or dwindled stress components due to differences in their originally inherited measurement units. Afterward, he has learned that some meaningful NF values should be used before calculating the hysteresis loop areas of the stress-strain diagram, i.e. input causes versus output symptoms diagram for the biomedical studies. At times, NF is used in reverse, such as using 120 mg/dL divided by glucose values or utilizing 4,000 steps divided by the post-meal walking steps. This is due to the glucose level following the pattern of "lower the better" whereas exercise amount is "more the better."

In this article, the mathematical ratio of day number count for pre-Covid period versus post-Covid period is "40% versus 60%". He then studies the contribution of energy (or degree of influence) of the total fasting plasma glucose (FPG) of 1,560 days versus 621 pre-COVID days (40% of total days) from 5/8/2018 to 1/18/2020 and 930 post-COVID days (60% of total days) from 1/19/2020 to 8/13/2022. The major contrast revealed in his FPG levels is resulted from the two vastly different lifestyles. The pre-Covid period had heavy international traveling which disturbed his diet, exercise, and sleep, while the post-Covid period is a quarantined lifestyle without any traveling and outside dining. Other than diet and exercise, sleep and stress are the secondary factors of FPG formation. During the pre-Covid period, the sleep disturbance and stress associated with traveling caused his FPG to increase. In contrast, during the post-Covid period, he

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mostly stayed at home; therefore, his sleep disturbance and stress from traveling were avoided and the stress from the possibility of catching the viral infection was also greatly minimized.

At first, he thought about using the 120 mg/dL level. This 120 mg/dL is a generalized break-even line of daily diabetes. Although he could use 100 mg/dL or lower for the break-even line of pre-diabetic FPG, this change of normalization factor does not make any significant difference in his results. This "divided by 120" NF would provide the energy contribution results from each group of meals, such as "pre-Covid energy of 53% to 57% > post-Covid energy of 43% to 47%". The calculated energy ratios have revealed the FPG's biophysical characteristics resulting from the "FPG level in each period". The average pre-Covid FPG level is higher than the average post-Covid FPG level by 16 mg/dL.

However, these types of calculated energy contributions, i.e. divided by 120, are missing the "overall impact on the total FPG from each period by including influences from the day number count %". As a result, by utilizing this second approach, he inserted another set of energy calculations using a modified NF value of "NF = (input/120) * (day number %)" to conduct the same energy analyses via both SD-VGT and FD-FFT. Under this additional "influence of day number count %", the newly calculated energy contribution results are: "post-Covid energy of 53% to 63% > pre-Covid energy of 37% to 47%". This set of calculated energies uncovered the specific influences from the "day number counts in each time period".

2. METHODS

2.1 Brief introduction of math-physical medicine (MPM) research

The author has collected 3+ million data regarding his health condition and lifestyle details over the past 13 years. He spent the entire year of 2014 developing a metabolism index (MI) model using a topology concept, nonlinear algebra, algebraic geometry, and finite element method. This MI model contains various measured biomarkers and recorded lifestyle details along with their induced new biomedical variables for an additional ~1.5 million data. Detailed data of his body weight, glucose, blood pressure, heart rate, blood lipids, body temperature, and blood oxygen level, along with important lifestyle details, including diet, exercise, sleep, stress, water intake, and daily life routines are included in the MI database. In addition, these lifestyle details also include some lifetime bad habits and certain environmental exposures. Fortunately, the author has none of these lifetime bad habits and an extremely low degree of exposure to environmental factors. The developed MI model has a total of 10 categories covering approximately 500 detailed elements that constitute his defined "metabolism index model" which are the building blocks or root causes for diabetes and other chronic disease-induced complications, including but not limited to cardiovascular disease (CVD), chronic heart disease (CHD), stroke, chronic kidney disease (CKD), diabetic retinopathy (DR), neuropathy, foot ulcer, hypothyroidism, dementia, and various cancers. The end result of the MI development work is a combined MI value within any selected period with 73.5% as its dividing line between a healthy and unhealthy state. The MI serves as the foundation for many of his follow-up medical research work.

During the period from 2015 to 2017, he focused his research on type 2 diabetes (T2D), especially glucose, including fasting plasma glucose (FPG), PPG, estimated average glucose (eAG), and hemoglobin A1C (HbA1C). During the following period from 2018 to 2022, he concentrated on researching medical complications resulting from diabetes, chronic diseases, and metabolic disorders which include heart problems, stroke, kidney problems, retinopathy, neuropathy, foot ulcer, diabetic skin fungal infection, hypothyroidism, diabetic constipation, dementia, and various cancers. He also developed a few mathematical risk models to calculate the probability percentages of developing various diabetic complications based on this MI model. From his previous medical research work with 700+ published papers, he has identified and learned that the associated energy of hyperglycemic conditions is the primary source of causing many diabetic complications which lead to death. Therefore, a thorough knowledge of these energies is vital for achieving a better understanding of the dangerous complications.

2.2 TD, SD, and FD analysis tools

This section has brief descriptions of TD correlation analysis with other observational results, SD VGT analysis with hysteresis loop area's energy results, and FD analysis with frequency curve area's energy results.

First of all, by using a TD analysis tool, we can examine the curves' moving trend and pattern visually along with their correlation numerically. We can also study the extremely high or low data values in the dataset. The visual observation or calculation-derived interpretations are a part of statistical analysis results which can indeed provide some useful hints or even derive some accurate conclusions. However, we must be aware of the limitations of the selected data size and time window and also be cautious of the appropriate statistics tool we choose.

The author would like to describe the essence of his developed "hybrid model" that combines both the SD viscoelastic/plastic VGT analysis method and FD fast Fourier transform (FFT) analysis method together with a comparison against the traditional time-domain statistical correlation analysis.

It is described in 10 steps in the English language instead of using mathematical equations to explain it. In this article, he has applied both the SD-VGT operations (steps 1-7) and the FD-FFT operations (steps 8-10). As a result, it is aimed at readers who do not have an extensive background in those academic subjects of engineering, physics & mathematics.

The first step is to collect the output data or symptom (strain or ε) on a time scale. The second step is to calculate the output change rate with time (dε/dt), i.e. the change rate of strain or symptom over each period. The third step is to gather the input data or cause (viscosity or η) on a time scale. The fourth step is to calculate the time-dependent input or cause (time-dependent stress or σ) by multiplying dε/dt and η together. The "time-dependent input or cause equation" of "stress σ = strain change rate of dε/dt * viscosity η" is the essential part of this "time dependency". The fifth step is to plot the input-output (i.e. stress-strain or cause-symptom) curve in a two-dimensional space-domain or SD (x-axis versus y-axis) with strain (output or symptom) on the x-axis and stresses (time-dependent inputs, causes, or stresses) on the y-axis.

The sixth step is to calculate the total enclosed area within these stress-strain curves or input-output curves (i.e. the hysteresis loops), which is also an indicator of associated energies (either created energy or dissipated energy) of this input and output dataset. These energy values can also be considered as the degrees of influence on output by inputs. The seventh step is assembling the area values of the selected periods to compare the "historical progression and contribution of medical condition" over certain time periods. For the frequency domain, the eighth step is to define a "hybrid input variable" by using "strain*stress" which yields another accurate estimation of energy ratio similar to the SD-VGT energy ratio associated with the hysteresis loop. The ninth step is to present these hybrid models' results of (strain*stress) in a time domain and then perform the fast Fourier transformation (FFT) operation to convert them into a frequency domain. The enclosed area of the frequency curve (where the x-axis is the frequency and the y-axis is the amplitude of energy) can be used to estimate the total FD-FFT energy. The tenth step is to compare these FD energy results against the SD-VGT energy results, or even TD energy results.

After providing the above 10-step description, the author would still like to use the following set of VGT stress-strain mathematical equations in a two-dimensional SD to address the selected medical variables:

Strain
= ε (time-dependency characteristics of individual strain value at the present time duration)

Stress
= σ (based on the change rate of strain multiplying with a chosen viscosity factor η)
= η * (dε/dt)
= η * (d-strain/d-time)
= (viscosity factor η using individual viscosity factor at present time duration) * (strain at present quarter - strain at previous time duration)

Some of these inputs (causes or viscosity factors) are further normalized by dividing them or being divided by a normalization factor using certain established health standards or medical pieces of knowledge. Some examples of normalization factors are 6.0 for HbA1C, 120 mg/dL for glucose, 25 for body mass index (BMI), 4,000 steps after each meal, 10,000 or 12,000 steps for daily walking exercise depending on time-period selection, 13 grams to 20 grams of carbs/sugar intake amount per meal depends on time-period selection. If using the originally collected data, i.e. the non-normalized data, it would distort the numerical comparison of the hysteresis loop areas. Using this "normalization process", we can remove the dependency of the individual unit or certain unique characteristics associated with each viscosity factor. This process allows us to convert the originally collected variables into a set of "dimensionless variables" for easier numerical comparison and result interpretation.

In this particular study, he has used two sets of "normalization factors": (1) 120 mg/dL; (2) 120n* (specific day number / total day number).

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 his 2 data tables.

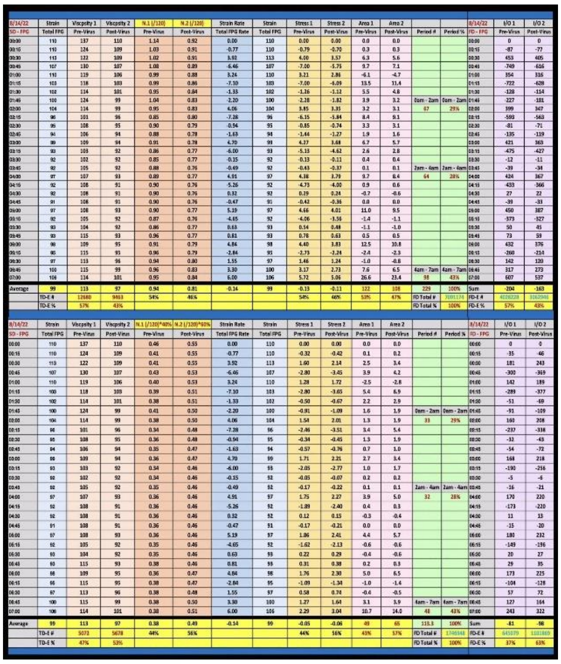

Figure 1: Data table.

Figure 2 displays the TD analysis results.

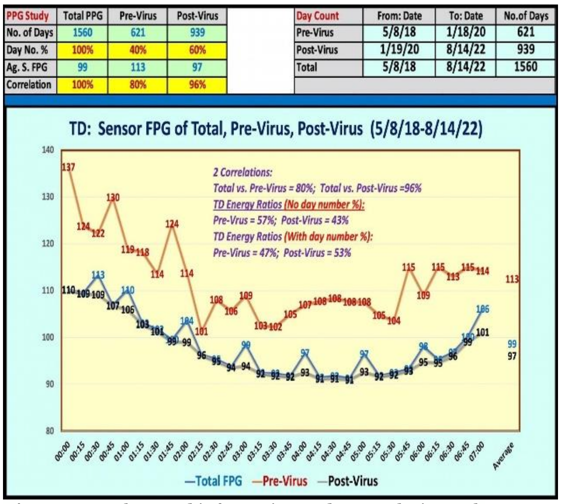

Figure 2: Background information and TD analysis results.

Figure 3 depicts 2 SD-VGT analysis results.

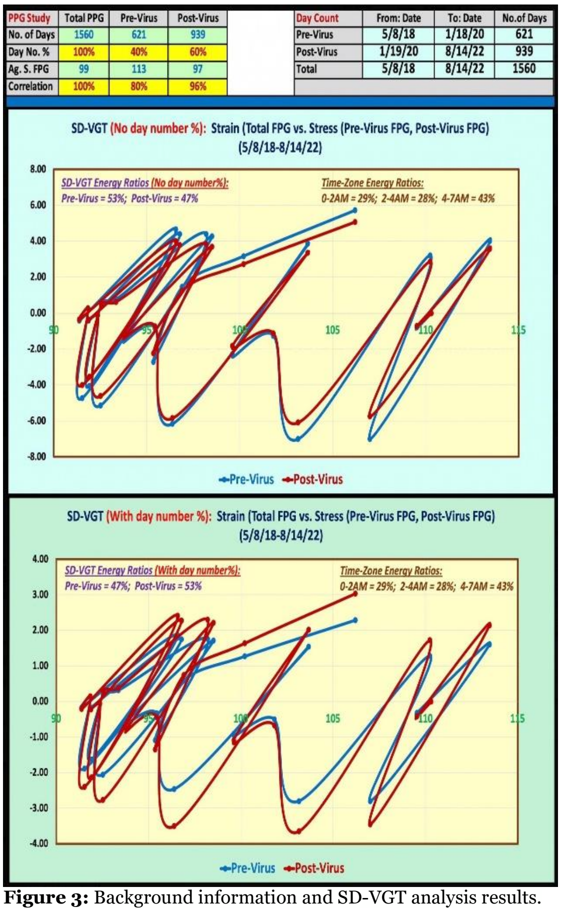

Figure 3: Background information and SD-VGT analysis results.

Figure 4 reflects 2 FD-FFT analysis results.

Figure 5 illustrates the energy comparison of using 3 research tools with both "no day numbers" and "with day numbers" for both the pre-virus and post-virus periods.

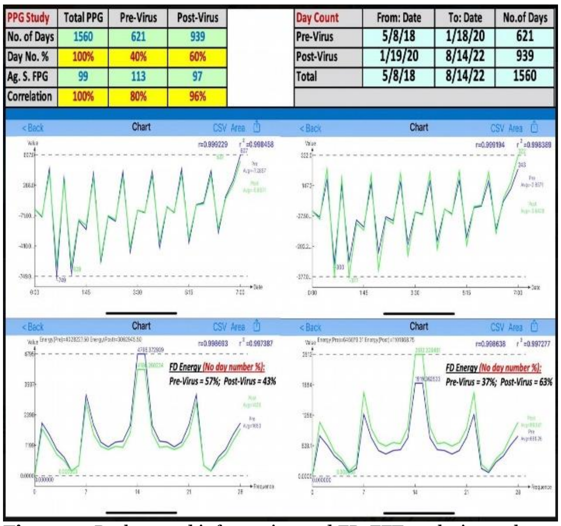

Figure 4: Background information and FD-FFT analysis results.

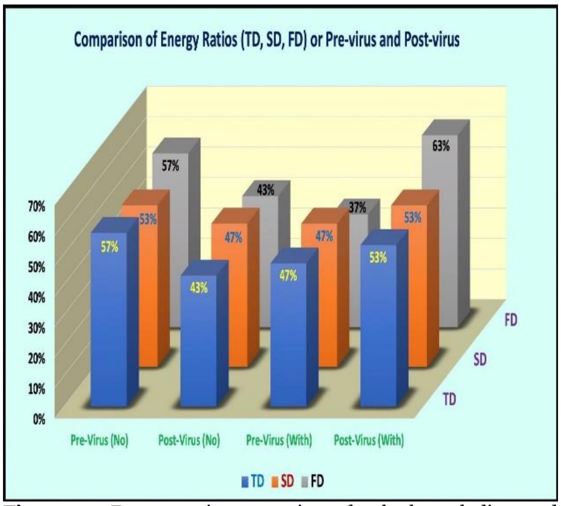

Figure 5: Energy ratio comparison for both excluding and including meal numbers into normalization factors.

4. CONCLUSION

In summary, there are 6 key findings from this third special sensitivity study of normalization factors in biomedical energy analysis:

(1) From the TD diagram, the average FPG values are 99 mg/dL for total, 113 mg/dL for pre-Covid meals, 97 mg/dL for post-Covid meals. The Covid-induced quarantined lifestyle has reduced his average FPG by 16 mg/dL.

(2) From the TD diagram, the two correlation coefficients are: Total FPG vs. Pre-Covid FPG = 80%; Total FPG vs. Post-Covid FPG = 96%. The post-Covid FPG waveform is a smoother curve, while the total FPG and pre-Covid FPG waveforms have many zig-zags as in wave fluctuations within a short time duration.

(3) TD squared-amplitude energy analysis results of "no day numbers" and "with day numbers" are: For the "no day number count % in normalization factors" case: The TD squared amplitude energy ratios are: Pre-Covid = 57%; Post-Covid = 43%. The higher average FPG value of the pre-virus period has a stronger influence on the total FPG. However, for the "with meal number count % in normalization factors" case: The TD squared amplitude energy ratios are: Pre-virus = 47%; Post-virus = 53%. The post-Covid FPG has more impact on the total FPG due to its higher day number count of 60% of total days.

(4) From the SD-VGT analysis results, there are two energy ratios from "no day number count" and "with day number count" which are: For the "no day number count % in normalization factors" case: The SD-VGT energy ratios are: Pre-Covid = 53%; Post-Covid= 47%. The higher average FPG value of the pre-covid period has a stronger influence on the total FPG. However, for the "with day number count % in normalization factors" case: The SD-VGT energy ratios are: Pre-Covid = 47%; Post-Covid = 53%. The post-virus FPG has more impact on the total FPG due to its higher day number count of 60% of total days.

(5) From the SD-VGT analysis results, the author has also analyzed the 3 different time-zone's energy distributions. Again, there are two energy ratios from "no day number count" and "with day number count" which are: For the "no day number count % in normalization factors" case: The SD-VGT energy ratios are: 0-2 hours = 29%; 2-4 hours = 28%; and 4-7 hours = 43%. For the "with day number count % in NF" case: The SD-VGT energy ratios are the same as "no day number count in NF": 0-2 hours = 29%; 2-4 hours = 28%; and 4-7 hours = 43%. It is interesting to observe that, regardless of the inclusion or exclusion of day numbers inside the normalization factors, the two time-zone energy ratios are identical to each other. In addition, the average energy per hour is ~14% for these 7 sleeping hours.

(6) From the FD-FFT analysis results, there are two energy ratios from "no day number count" and "with day number count" which are: For the "no day number count % in NF" case: The FD-FFT energy ratios are: Pre-Covid = 57%; Post-virus = 43%. However, for

"with day number count in NF" case: The FD-FFT energy ratios are: Pre-Covid = 37%; Post-virus = 63%.

In summary, excluding the day numbers into the normalization factors, the time period's biophysical characteristics of higher average FPG value (pre-Covid period) would contribute more energy to the total FPG. However, once including the day numbers into the normalization factors, the FPG of the period associated with the higher day number count (post-Covid period) would contribute more energy to the total FPG. This third NF sensitivity study has derived similar conclusions as his two previous Papers, No.718 (total PPG versus home-cook, cafe, airline) and No.719 (total PPG versus pre-Covid and post-Covid). This research method has the ability to discover a deeper understanding of certain biophysical behaviors of various biomedical variables, i.e. biomarkers. This article has also proven the usefulness of the author's developed math-physical medicine (MPM) research methodology in biomedical research.

5. REFERENCES

For editing purposes, the majority of the references in this paper, which are self-references, have been removed. Only references from other authors' published sources remain. The bibliography of the author's original self-references can be viewed at www.eclairemd.com.

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Viscoelastic and Viscoplastic Glucose Theory Application in Medicine

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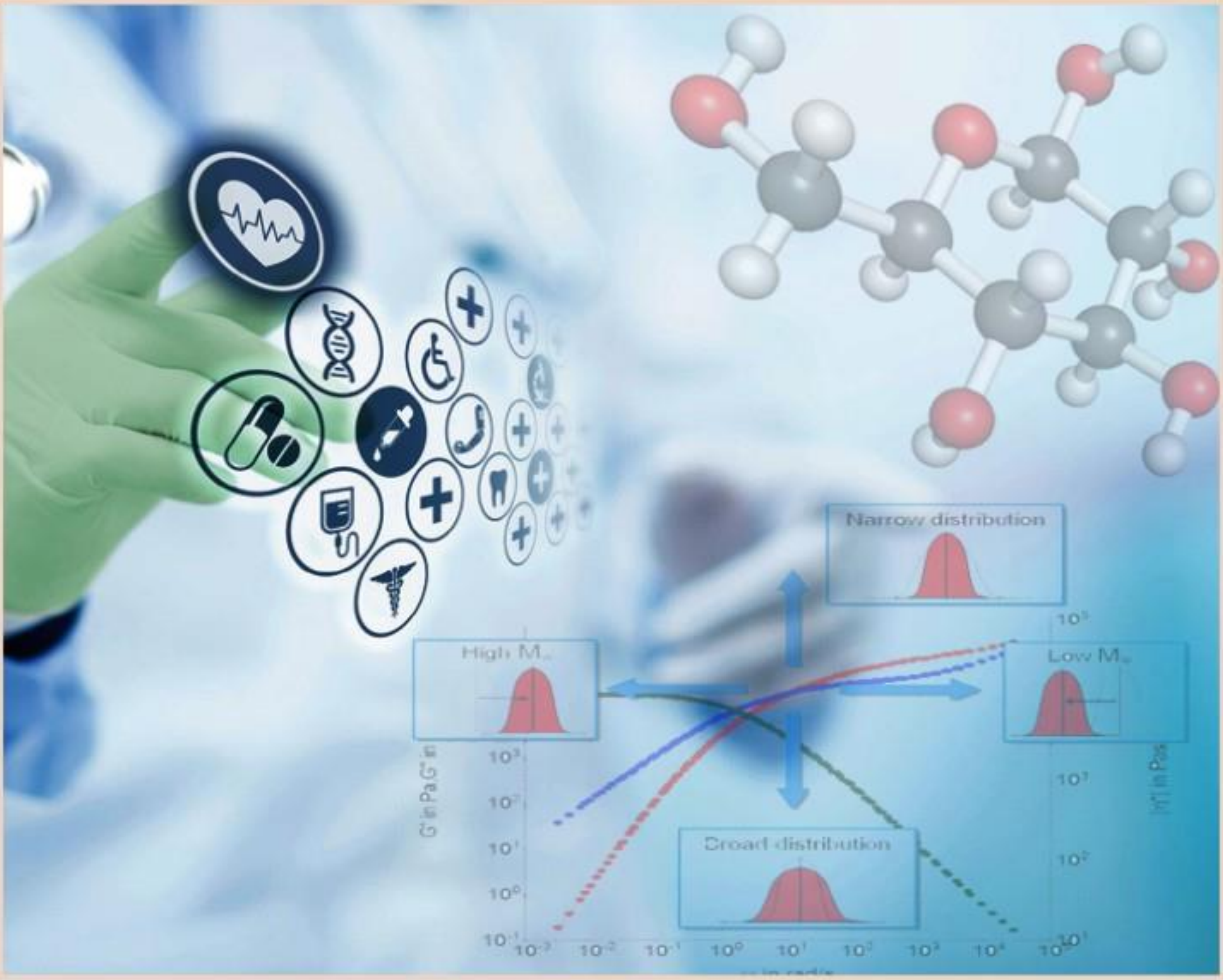

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