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The GH-Method

Viscoelastic and Viscoplastic Glucose Theory (VGT #139): Using Energy Ratios of 3 Input Causes (Different PPG Ranges) from Space-Domain VGT Analysis Results to Estimate the Predicted Value and Behavior of a Symptom Output (Total PPG) Over a Period of 7+ Years from 5/1/2015 to 8/24/2022 Based on Math-Physical Medicine Method (No. 730)

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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, who does not often rely on statistical resources, usually applies his developed math-physical medicine (MPM) methodology and tools to conduct his biomedical research work. If using statistics, we can easily "tweak and extract the results that we want" to a certain degree; however, we cannot change the output results that are derived or proved by the basic laws of physics. In fact, most observed and known phenomena under the sun indeed follow the basic laws of physics. We can only try to understand the event phenomenon and/or interpret the observed results using physics principles. Furthermore, his biomedical research work does not utilize any health institutions' surveyed or collected data or other patients' collected data. Instead, he mostly uses the collected and processed 3+ million data from his own health conditions and lifestyle details for his medical research work during the past 13 years.

He has conducted various biomedical research work using engineering viscoelastic or viscoplastic glucose theory (VGT) since 1/8/2022 with his Paper No. 578 upon the advice of his academic advisor, Professor Norman Jones, at MIT given him in December of 2021. During this past 8-month period, he has written 137 papers using this approach where he has learned in depth the subtlety and things to watch out for by applying this specific VGT research tool in his biomedical research work. To date, he further realized that the SD-VGT energy ratio for each input cause can also be served as a "weighting factor" of inputs for his predicted symptom's output value and its behavior. Not only was he analyzing the associated energy of causes, but he is now able to connect those multiple medical input causes with the predicted symptom of specific medical output.

The symptom used in this study is the total postprandial plasma glucose (PPG) over a long period of 7+ years from 5/1/2015 to 8/24/2022. There are 3 input causes of low PPG (0-105 mg/dL), medium PPG (106-120 mg/dL), and high PPG (121-400 mg/dL). All of these PPG values are represented via 4 different waveforms at 15-minute intervals. The data processing work of this paper is conducted using both his developed Chronic

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software and the VGT software module on his iPhone device.

In the following methods section, he provides a brief description of this SD-VGT tool using English words instead of physics or engineering theories with complex mathematical equations.

Furthermore, he has developed an equation for his predicted PPG as listed below:

Predicted total PPG
= ((Summation of SD energy from 3 causes)
= (Low PPG component value* SD Low PPG energy ratio of 30% + Medium PPG component value* SD Medium PPG energy ratio of 33%+ High PPG component value* SD High PPG energy ratio of 37%)

Finally, he calculates the prediction accuracy and correlation between measured PPG versus predicted PPG.

Prediction Accuracy
= (predicted PPG - measured PPG) / measured PPG

2. METHODS

2.1 The author's case of diabetes and complications

The author has been a severe T2D patient since 1996. He weighed 220 lb. (100 kg, BMI 32.5) at that time with a one-time glucose reading of 380 mg/dL. By 2010, he still weighed 198 lb. (BMI 29.2) with average daily glucose of 250 mg/dL (HbA1C of 10%). During that year, his triglycerides reached 1161b (hyperlipidemia) and albumin-creatinine ratio (ACR) at 116 (kidney issues). He also suffered from five cardiac episodes within a decade from 1993 through 2003 caused by work stress and diabetes. In 2010, three independent physicians warned him about his urgent need for kidney dialysis treatment and the risk of his life-threatening health situation such as dying from his severe diabetic complications. Other than the cerebrovascular disease (stroke), he has suffered most of the known diabetic complications, including both macro-vascular & micro-vascular complications, nerve damage as in retinopathy and foot ulcer, as well as a hormonal disturbance, e.g. hypothyroidism.

In 2010, he decided to launch his self-study on endocrinology, diabetes, and food nutrition to save his own life. After developing the metabolism model in 2024, during 2015 and 2016, he developed four prediction models related to diabetes conditions: weight, PPG, fasting plasma glucose (FPG), and A1C. As a result, from using his developed mathematical metabolism index (MI) model in 2014 and those 4 prediction tools, by end of 2016, his weight was reduced from 220 lbs. (100 kg, BMI 32.5) to 176 lbs. (89 kg, BMI 26.0), waistline from 44 inches (112 cm) to 33 inches (84 cm), average finger glucose reading from 250 mg/dL to 120 mg/dL, and lab-tested A1C from 10% to ~6.5%. One of his major accomplishments is that he no longer takes any diabetes medications as of 12/8/2015.

Around that time (2014-2017), he started to focus on preventive medicine instead of blindly trusting and depending on medical treatments only. He also gambled on his belief that most human organs have the inherent ability to self-repair themselves through lifestyle improvements by taking good care of them - even though it can only accomplish a certain degree of repairing or healing dependent on different organ cells and their status of damage.

In 2017, he has achieved excellent results on all fronts, especially glucose control. However, during the pre-COVID period of 2018 and 2019, he traveled to approximately 50+ international cities to attend 65+ medical conferences and made ~120 oral presentations. This hectic schedule inflicted damage to his diabetes control, through dining out frequently, post-meal exercise disruption, jet lag, and along with the overall metabolic impact due to his irregular life patterns through a busy travel schedule; therefore, his glucose control and overall metabolism state were somewhat affected during this two-year heavy traveling period.

Since 1/19/2020, living in a COVID-19 quarantined lifestyle, not only has he written and published ~500 medical papers in 100+ journals, but he has also reached his best health conditions in the past 26 years. By the beginning of 2022, his weight was further reduced to 168 lbs. (BMI 24.8) along with a 5.8% A1C value (beginning level of pre-diabetes), without having any medication interventions or insulin injections. During the period from 1/1/2022 to 8/20/2022, his average FPG is 93 mg/dL, PPG is 113 mg/dL, and daily glucose is 106 mg/dL. These good results are due to his non-traveling, low-stress, and regular daily life routines. Of course, the accumulated knowledge of chronic diseases, various complications, practical lifestyle management experiences, and development of many high-tech tools along with his medical research academic findings have contributed to his excellent health status since 1/19/2020, the beginning date of his self-quarantined life.

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. He has maintained the same measurement pattern to the present day. In his research work, he uses his CGM sensor glucose at a time interval of 15 minutes (96 data per day). Incidentally, the average sensor glucoses between 5-minute intervals and 15-minute intervals has only a 0.6% difference (average glucose of 111.86 mg/dL for 5 minutes and average glucose of 111.18 mg/dL for 15 minutes with a correlation of 94% between these two sensor glucose curves) during the period from 2/19/20 to 7/22/22.

Therefore, over the past 13 years, he could study and analyze his collected 3+ million data regarding his health status, medical conditions, and lifestyle details. He applies his knowledge, models, and tools from mathematics, physics, engineering, and computer science to conduct his medical research work. His research work has a goal of achieving both "high precision" and "quantitative proof" in the medical findings for the ultimate objectives of "preventive medicine".

The following timetable provides a rough sketch of the emphasis in his medical research during each stage:

2000-2013: Self-study diabetes and food nutrition, developing a data collection and analysis software.

2014: Develop a mathematical model of metabolism, using engineering modeling and advanced mathematics.

2015: Weight & FPG prediction models, using neuroscience.

2016: PPG & HbA1C prediction models, using optical physics, artificial intelligence (AI), and neuroscience.

2017: Complications due to macro-vascular research, such as cardiovascular disease (CVD), coronary heart diseases (CHD), and stroke, using pattern analysis and segmentation analysis.

2018: Complications due to micro-vascular research such as kidney (CKD), bladder, foot, and eye issues (DR).

2019: CGM big data analysis, using wave theory, energy theory, frequency domain analysis, quantum mechanics, and AI.

2020: Cancer, dementia, longevity, geriatrics, DR, hypothyroidism, diabetic foot, diabetic fungal infection, and linkage between metabolism and immunity, learning about certain infectious diseases, such as COVID-19.

2021: Applications of linear elastic glucose theory (LEGT) and perturbation theory from quantum mechanics on medical research subjects, such as chronic diseases and their complications, cancer, and dementia.

2022: Applications of viscoelastic/viscoplastic glucose theory (LEGT) on 128 biomedical research cases and 5 economics research cases.

Again, to date, he has spent ~40,000 hours self-studying and researching medicine and he has read 3,000+ published medical papers online. He has collected and calculated more than three million pieces of data regarding his own medical conditions and lifestyle details. In addition, he has written and published 700+ medical research papers in 100+ various medicine, physics, mathematics, and engineering journals. Moreover, he has also given 120+ presentations at 70+ international medical conferences. He has continuously dedicated his time (11-12 hours per day and work each day of a year, without rest during the past 13 years) and efforts to his medical research work and shared his findings and learnings with other patients worldwide. In addition, he has also spent the past 12 years developing and maintaining a medicine and health software APP on his iPhone which functions as his private numerical laboratory to process the various experimental datasets of his medical conditions and lifestyle details.

2.2 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 important for achieving a better understanding of the dangerous complications.

2.3 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 the assembly of the area values of the selected periods to compare the "historical progression and contribution of medical condition" over certain 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 TD and then perform the fast Fourier transformation (FFT) operation to convert them into an FD. 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 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, his selected normalization factors for CVD risk, CKD risk, and Cancer risk are 1. These 3 diseases' risk probability % are developed based on his developed metabolism index (MI) model which is normalized on the same scales already.

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 the data table of the SD-VGT analysis results and predicted PPG results.

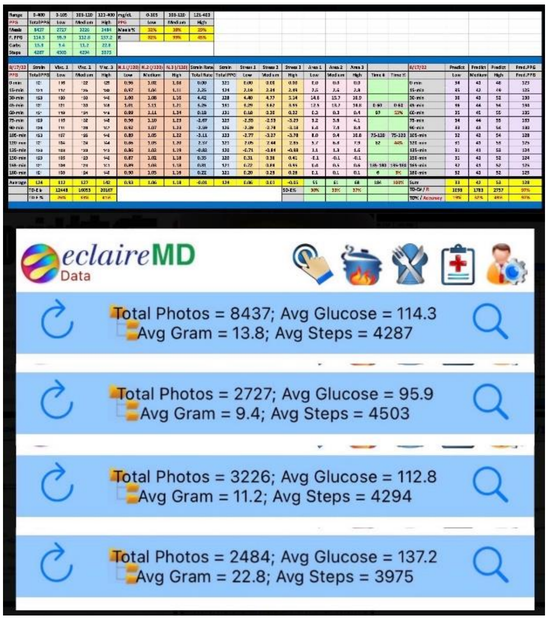

Figure 1: SD-VGT data tables and predicted PPG results.

Figure 2 depicts the total PPG analyses in both TD and SD with the comparison between measured PPG versus predicted PPG.

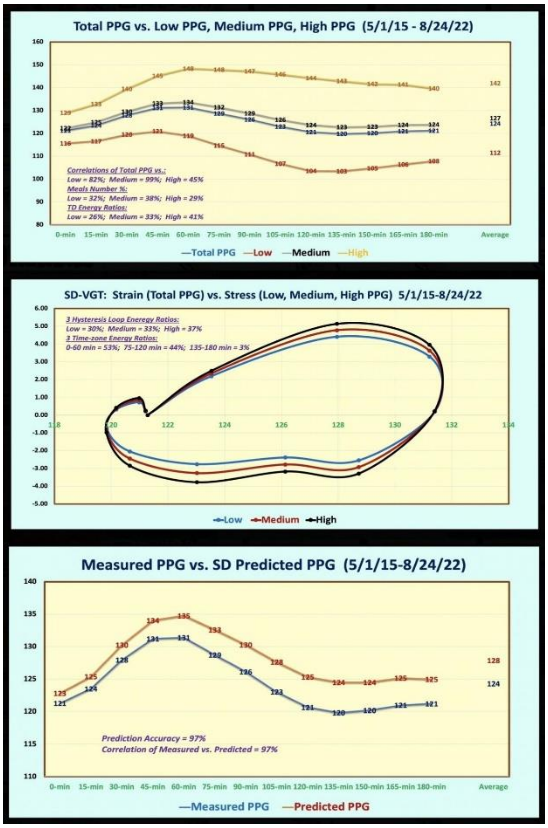

Figure 2: TD, SD analysis results with a comparison of measured PPG vs. predicted PPG.

4. CONCLUSION

In summary, there are 4 key findings from this study on the output symptom of total PPG versus 3 input causes of low PPG, medium PPG, high PPG and his predicted PPG versus his measured PPG.

(1) From the TD diagram, the average PPG values are: Total PPG = 124 mg/dL, Low PPG = 112 mg/dL, Medium PPG = 127 mg/dL, Low PPG = 142 mg/dL. The correlations between the total PPG versus: low PPG = 82%, medium PPG = 99%, and high PPG = 45%.

(2) From the SD-VGT analysis results, the SD energy ratios for "total PPG" are: Low PPG = 30%; Medium PPG = 33%; and High PPG = 37%. The three different energy ratios have been used in the calculation of his predicted PPG as "weighting factors": "Predicted total PPG= (Summation of SD energy from 3 causes) = (Low PPG component value* SD Low PPG energy ratio of 30% + Medium PPG component value* SD Medium PPG energy ratio of 33%+ High PPG component value* SD High PPG energy ratio of 37%)". The high PPG energy is greater than the medium PPG energy which is further greater than the low PPG energy.

(3) The SD-VGT time-zone energy analysis results are: 0-60 minutes = 53%, 75-120 minutes = 44%, and 135-180 minutes = 3%. It is evident that the PPG energy generated via food during the first hour is 53%, the PPG energy dissipated via exercise during the second hour is 44%, and the left-over energy during the third hour is 3%.

(4) His measured average PPG is 124 mg/dL and the predicted average PPG using the SD energy ratio weighting factor is 128 mg/dL. These two PPG waveforms have a correlation coefficient of 97% and also yielded a prediction accuracy of 97%.

In summary, his SD-predicted PPG has achieved an extremely high prediction accuracy of 97%. This has proven that using SD-VGT energy ratios as the weighting factors for each input cause is a reasonable way of calculating the predicted PPG.

The research methodology behind this particular study has offered a subtle and deeper understanding of the complicated biophysical behaviors of PPG. In addition, it has further proven the usefulness of math-physical medicine 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 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.

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Viscoelastic and Viscoplastic Glucose Theory Application in Medicine

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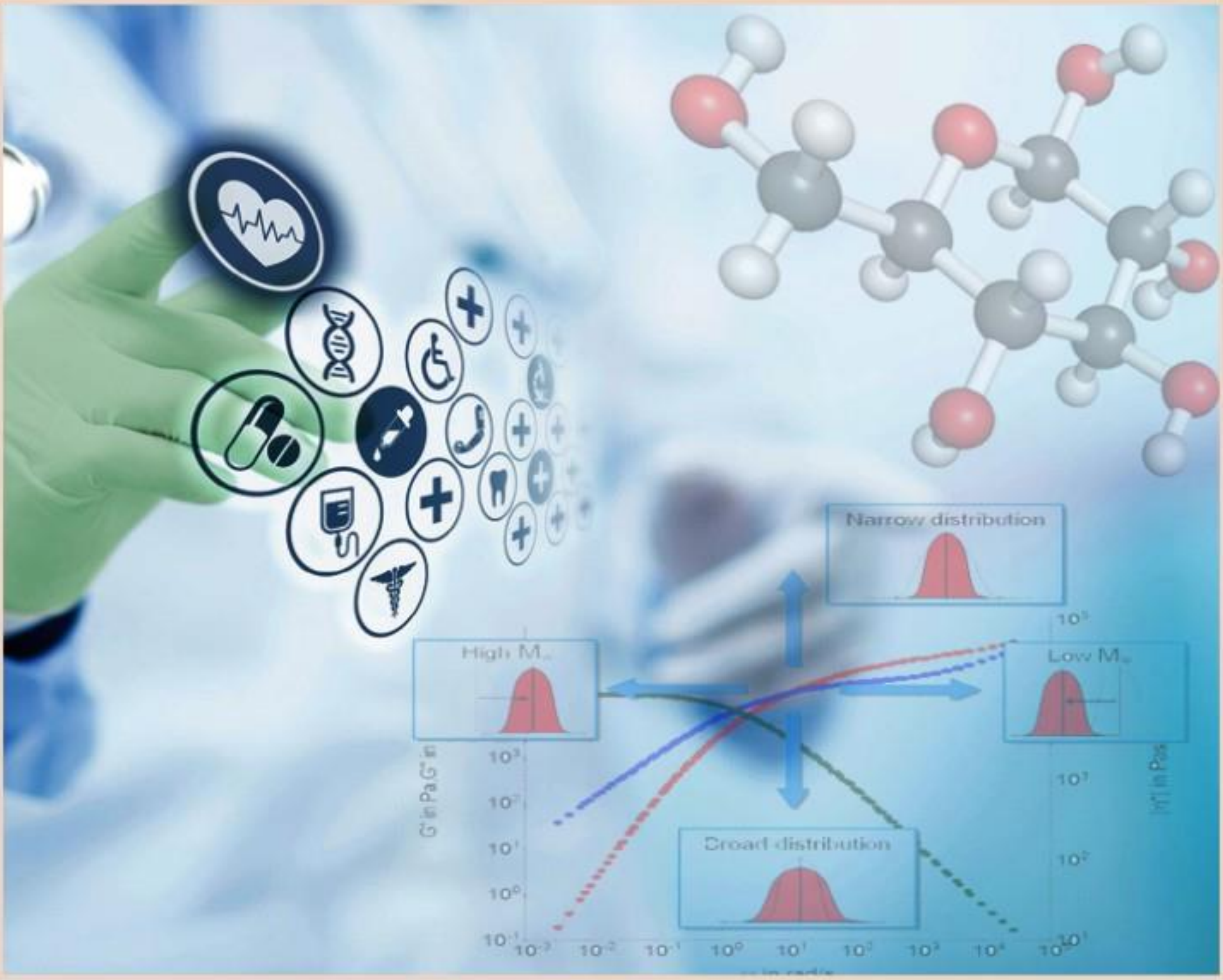

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