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The GH-Method

Viscoelastic and Viscoplastic Glucose Theory (VGT #114): A Study on the Inter-Relationships Between Risks of Cardiovascular Disease and Stroke versus Artery Rupture and Artery Blockage While Applying Time-Domain Energy, Space-Domain VGT Energy, and Frequency-Domain Energy and Using a Patient's 11 Annual Data from 1/1/2012 to 7/19/2022 Based on GH-Method: Math-Physical Medicine (No. 704)

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Keywords: Viscoelastic; Viscoplastic; Cardiovascular disease; Glucose; Blood pressure; Blood lipids; Postprandial plasma glucose; Fasting plasma glucose; Type 2 diabetes

Abbreviations: CVD: cardiovascular disease; T2D: type 2 diabetes; PPG: postprandial plasma glucose; FPG: fasting plasma glucose; SD: space domain; TD: time domain; FD: frequency domain; MPM: math-physical medicine

1. INTRODUCTION

Persistent high glucose situations (hyperglycemia) create damage to the structural integrity of arteries in both the heart and brain. After that, high blood pressures (hypertension) contribute to the rupture possibility of the weakening arteries, while high blood lipids (hyperlipidemia) build up plaques inside of the artery walls and then increase the blood flow blockage possibility of arteries. According to statistical findings from many published medical papers, the CVD/Stroke occurrence rate from artery rupture is around 20%-25%, and the CVD/Stroke occurrence rate from artery blockage is around 75%-80%.

The author has collected 3+ million personal health data over the past 13 years. In 2014, he further developed a Metabolism index (MI) model with 10 categories (mi, i=1,10). Within this MI model, it contains 3 specific biomarker categories for medical conditions: glucose (m2), blood pressure (m3), and blood lipids (m4). Based on this Metabolism Index model, he has extended it into a risk estimation model for several medical complications, including cancers, chronic kidney diseases (CKD), cardiovascular diseases (CVD), or strokes. This particular study investigates the close relationship of one specific output symptom of risk percentages of having CVD/Stroke complication with two primary input causes, artery rupture and artery blockage. In this study, the artery rupture is simulated with a simple formula of "glucose (m2) * 40% + blood pressure (m3) * 60%), while the artery blockage is simulated with another simple formula of "glucose (m2) * 40% + blood lipids (m4) * 60%). Although both artery rupture and blockage are complex biomedical scenarios, these two simplified mathematical formulas can shed some light on the 2 medical conditions with CVD/Stroke risk estimations. Viewing a combined picture, Diabetes contributes ~40%, Hypertension contributes ~30%, and Hyperlipidemia contributes ~30%, respectively, to the risk of developing CVD/Stroke complications.

The space-domain (SD) strain-stress hysteresis loop area's associated energy

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analysis method is chosen as the primary research tool which will be described briefly in the Methods section. (To limit the number of words, the author decides to omit the more detailed explanation of his research method in this article.) For an energy comparison study, the author has further included 3 results from time-domain (TD) squared amplitude analysis, SD-VGT hysteresis loops, and frequency-domain (FD) curve areas.

The three selected mi (input causes), m2, m3, and m4, have already gone through a "normalization process" by dividing each medical condition with its corresponding dividing line of healthy vs. unhealthy. Here are the values: 120 mg/dL for m2 (glucose), 120/80/60 for m3 (BP: SBP/DBP/HR), and 150/40/130/200 for m4 (blood lipids: TG/HDL/LDL/Total Cholesterol). Using this "normalization process", it can then remove the dependency of the individual unit or certain unique biophysical characteristics associated with each influential cause, i.e. m2, m3, and m4.

In the field of medical research, hidden biophysical behaviors and complex inter-relationships exist among lifestyle details, medical conditions, chronic diseases, and certain medical complications, such as heart attacks, stroke, kidney failure, cancers, dementia, and even longevity concerns. He has noticed that most medical subjects with their associated data, both medical output symptoms, and influential input causes, are "time-dependent" which means that all biomedical variables change from time to time because body living cells are organic and dynamically changing. This is what Professor Norman Jones, the author's adviser at MIT, suggested to him in December of 2021 and why he utilizes the VGT from physics and engineering as one of his main tools to conduct his medical research work since then. Of course, one of the major challenges of VGT analysis is always related to data mining, data selection, and data preparation.

The organization of this article has three parts:

The first part is focusing on the observation and investigation of the annual risk of CVD/Stroke output symptom with its two primary input causes, artery rupture and artery blockage in TD. The TD energy is the square of averaged rupture and blockage variables.

The second part is conducting an SD-VGT study of CVD/Stroke versus two biomedical conditions, artery rupture, and artery blockage. The analysis results can provide some explanations regarding the differences of contribution between rupture and blockage, as well as this deadly disease risk distribution among 3 separate periods which can indicate the progression of CVD/Stroke risks over 3 time periods.

The third part is conducting an FD-FFT study of CVD/Stroke versus two biomedical conditions, artery rupture and artery blockage using the fast Fourier transformation technique. This FD energy contribution ratio between rupture versus blockage can then be used to compare against those two similar energy results using the TD tool and SD tool, respectively.

1.1 Specific medical information

The author's history of diabetes, chronic diseases & CVD

The author has been a severe T2D patient since 1996. He weighed 220 lb. (100 kg, BMI 32.5) at that time. 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 1161, and his albumin-creatinine (ACR) ratio at 116. He also suffered from five cardiac episodes within a decade. In 2010, three independent physicians warned him about his need for kidney dialysis treatment and his future risk of 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 as well as nerve damage.

In 2010, he decided to launch his self-study on endocrinology, diabetes, and food nutrition to save his own life. 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 the four 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.

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 early 2020, living in a COVID-19 quarantined lifestyle, not only has he written snd 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. These good results are due to his non-traveling, low-stress, and regular daily life routines. Of course, his knowledge of chronic diseases, practical lifestyle management experiences, and development of various high-tech tools contribute 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 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 111 biomedical research cases and 5 economics research cases.

Again, to date, he has spent around 40,000 hours self-studying and researching medicine and he has read around 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 700+ medical research notes and published 650+ papers in 100+ various medical and engineering journals. Moreover, he has also given ~120 presentations at ~65 international medical conferences. He has continuously dedicated his time (11-12 hours per day and work each day of a year, without rest) and efforts to his medical research work and shared his findings and learnings with other patients worldwide.

2. RESEARCH METHODS

Here is a brief explanation of 3 distinctive energy analysis tools used in his recent medical research work. This description is aimed at readers who do not have an extensive background in the academic fields of engineering, physics & mathematics.

The first approach is to estimate the TD energy associated with different waveforms of influential causes and output symptom. The TD energy is calculated with the squared amplitudes of the average inputs (causes) or output (symptoms). Basic physics course has taught us that "the energy carried by a wave is directly proportional to the square of this wave's amplitude".

The second approach is to apply the viscoelastic or viscoplastic glucose theory (VGT) from engineering and physics to construct a set of SD diagrams with stress-strain curves and then by calculating the enclosed area of the SD strain-stress curve or "hysteresis loop" to obtain the associated SD-VGT energy or degree of influence. The SD-VGT method is useful for investigating the "time-dependent" biomarker behaviors which can be applied to the majority of subjects in the fields of medicine, engineering, economics, psychology, social science, and others. The created, stored, or dissipated energy during the process of uploading and downloading is estimated using the calculated hysteresis loop area size.

The author will describe in plain English words the 6 steps of the VGT method, instead of using mathematical equations and numbers to explain the same concept.

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" is expressed by "stress σ = strain change rate of dε/dt * viscosity η" which is the essential part of "time-dependency". The fifth step is to plot the input-output (stress-strain or cause-symptom) curve in a 2-dimensional 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 the stress-strain curves or input-output curves (the hysteresis loops) using the trapezoid formula, which is also an indicator of associated energies or degrees of influence of input on output (either created energy or dissipated energy through this process of inputting and outputting.

After providing the above 6-step English description, the author also briefly provides the following VGT stress-strain mathematical equations in SD to address the unique "time-dependent characteristics" of selected medical variables (both biomedical symptoms and influential causes). Here, he wants to use the strain rate multiplied with the viscosity (input) as the stress component:

Strain
= ε
= 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 by certain established health standards or "break-even" line values, such as 120 mg/dL for glucose, and 25.0 for body mass index (BMI), etc. In this study, the chosen normalization factor for his diet is 1.0 since the normalization process is already included in the original data of m2, m3, and m4.

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", it can remove the dependency of the individual unit or certain unique characteristics associated with each variable. This process allows us to convert the originally collected variables into a set of "dimensionless variables" for easier numerical comparison and result interpretation.

The third approach is to develop a newly-defined variable of (strain * stress) from SD as the new wave's amplitude in a TD and then apply the wave theory to go through a fast Fourier transform (FTT) operation to calculate the enclosed area of this new variable created frequency curve in FD. The FD-FFT energy is the enclosed area of this frequency curve.

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 displays the TD-correlation analysis results, the SD-VGT analysis results, and the FD-FFT analysis results.

Figure 2 depicts the input and processed data table and the results comparison using these three tools.

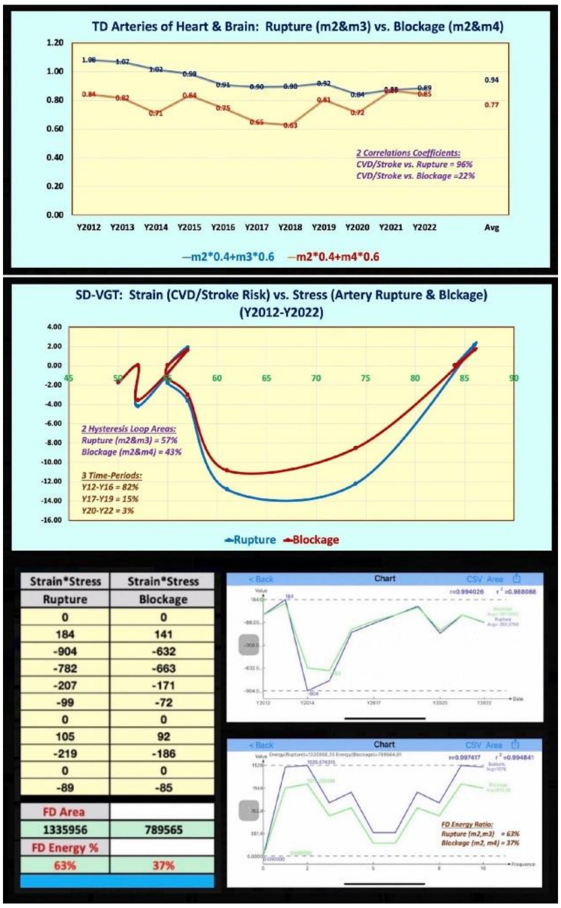
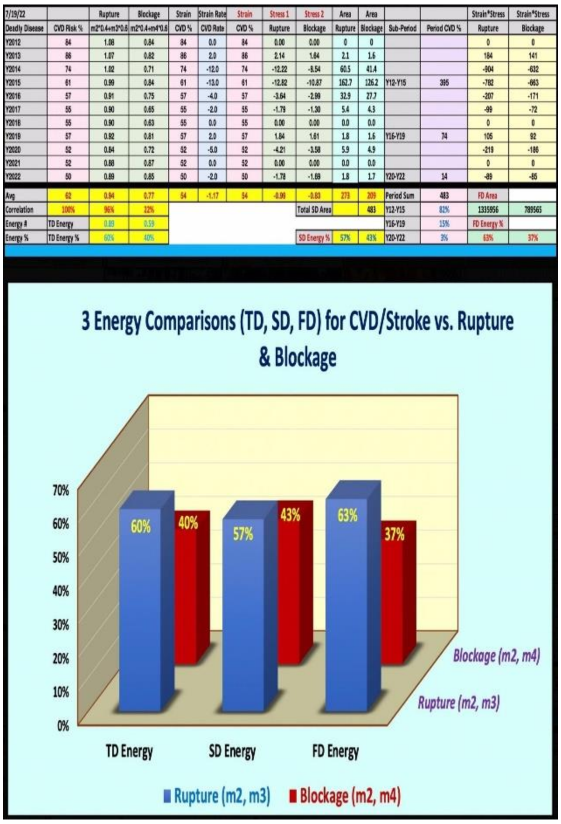


Figure 1: Energy analysis results using TD, SD-VGT, and FD-FFT.



7/19/22		Rupture	Blockage	Strain	Strain Rate	Strain	Stress 1	Stress 2	Area	Area			Strain*Stress	Strain*Stress
Deadly Disease	CVD Risk %	m2*0.4+m3*0.6	m2*0.4+m4*0.6	CVD %	CVD Rate	CVD %	Rupture	Blockage	Rupture	Blockage	Sub-Period	Period CVD %	Rupture	Blockage
Y2012	84	1.08	0.84	84	0.0	84	0.00	0.00	0	0			0	0
Y2013	86	1.07	0.82	86	2.0	86	2.14	1.84	2.1	1.6			184	141
Y2014	74	1.02	0.71	74	-12.0	74	-12.22	-8.54	60.5	41.4			-904	-632
Y2015	61	0.99	0.84	61	-13.0	61	-12.82	-10.87	162.7	126.2	Y12-Y15	395	-782	-663
Y2016	57	0.91	0.75	57	-4.0	57	-3.64	-2.99	32.9	27.7			-207	-171
Y2017	55	0.90	0.65	55	-2.0	55	-1.79	-1.30	5.4	4.3			-99	-72
Y2018	55	0.90	0.63	55	0.0	55	0.00	0.00	0.0	0.0			0	0
Y2019	57	0.92	0.81	57	2.0	57	1.84	1.61	1.8	1.6	Y16-Y19	74	105	92
Y2020	52	0.84	0.72	52	-5.0	52	-4.21	-3.58	5.9	4.9			-219	-186
Y2021	52	0.88	0.87	52	0.0	52	0.00	0.00	0.0	0.0			0	0
Y2022	50	0.89	0.85	50	-2.0	50	-1.78	-1.69	1.8	1.7	Y20-Y22	14	-89	-85
Avg	62	0.94	0.77	54	-1.17	54	-0.99	-0.83	273	209	Period Sum	483	FD Area	
Correlation	100%	96%	22%					Total SD Area		483	Y12-Y15	82%	1335956	789565
Energy #	TD Energy	0.89	0.59								Y16-Y19	15%	FD Energy %	
Energy %	TD Energy %	60%	40%					SD Energy %	57%	43%	Y20-Y22	3%	63%	37%

Figure 2: Data table and bar chart comparisons of 3 sets of energies.

4. CONCLUSION

In summary, there are 4 conclusions from the TD correlations and curve observations, SD-VGT hysteresis loop area analysis results, and FD-FFT frequency curve analysis results, from the energy contribution study on CVD/Stroke risk versus artery rupture and artery blockage.

(1) Viewing the two TD curves of rupture (0.4*m2+0.6*m3) and blockage (0.4*m2+0.6*m4), the “rupture curve” has been reduced by 11% from 1.00 in 2012 to 0.89 in 2022. But, the “blockage curve” has been bouncing between a range of 0.63 to 0.87, and from 0.84 in 2012 to 0.85 in 2022. His m4 values (blood lipids) have always been less than 1.0 (means healthy), despite its noticeable fluctuations within the past 10.5 years period. His averaged rupture (from BP) value is 0.94 which is higher than the averaged blockage (lipids) value of 0.77. This means that his blood lipids are under better control than his blood pressure. Using the TD statistical method, the correlation is 99% between CVD vs. rupture (BP) and 22% between CVD vs. blockage (lipids). Using the TD squared amplitude energy method, the ratio of rupture (BP) vs. blockage (lipids) is 60% vs. 40%. If purely based on these results from the statistical correlation and the TD squared amplitude, it seems that his CVD risk would be more possible in the ruptured case than in the blockage case. But, these findings resulted from the author’s personal data which has a higher average blood pressure (rupture) of 0.94 than average lipid (blockage) of 0.77. Based on other statistical results from many patients, the CVD or Stroke occurrences are 75% to 80% from the blockage case which is 3 to 4 times more often than the ruptured case (~20% - 25%).

(2) In the SD VGT analyses comparing CVD vs. rupture and blockage, the ratio of CVD/Stroke risk contribution by rupture (BP) versus blockage (lipids) is 57% vs. 43%. Please remember that his TD energy ratio is 60% versus 40%. In the same set of SD-VGT curves, the CVD/Stroke risk distribution within 3 different periods are: the uncontrolled period of Y2012-Y2015 = 82%, the controlled period of Y2016-Y2019 = 15%, and the best controlled COVID-19 period of Y2020-Y2022 = 3%. This means that most of the damages were done during Y2012-Y2015.

(3) From the FD energy analysis, the ratio of CVD/Stroke risk contribution by rupture versus blockage is 63% versus 37% (the SD energy ratio is 57% vs. 43%, and the TD energy ratio is 60% versus 40%). The variable he used in the FD energy analysis is the (strain*stress) from SD.

(4) The bar chart diagram shows the comparison of 3 results from TD, SD, and FD. The 3 energy ratios of CVD/Stroke risk contribution by rupture versus blockage are as follows: TD has 60% : 40%; SD has 57% : 43%; FD has 63% : 37%.

It is a common knowledge that strong inputs from glucose, blood pressure, and blood lipids are influenced by many deadly diseases, such as CVD, or strokes. From this article, we can clearly see that the artery ruptures caused by diabetes and hypertension and artery blockage resulting from diabetes and hyperlipidemia do have significant contributions to CVD or Stroke. However, this type of math-physical medicine research tool can still offer a more quantified picture regarding certain important facts, for example, how the mortality rate changes within different periods.

The SD-VGT quantitative findings from this particular study have matched the public domain’s healthcare recommendations of “maintaining an ideal state of glucose, blood pressure, and lipids” to reduce the mortality rates from CVD or stroke. For the author’s case, he should pay more attention on his blood pressure since three conclusions from this study using his personal data are not completely matching with those statistical conclusions from many patients.

5. ACKNOWLEDGMENT

Without Professor Norman Jones at MIT as his academic advisor, the author would not be able to conduct this particular research work and published 700+ medical research papers. The author has never forgotten his advice to him that he should always focus on and enhance his basic strength in foundations, such as mathematics and physics, to make further improvements and advancements in science and engineering. More importantly, Professor Jones has also provided him with a personal example of doing outstanding teaching and research job with an excellent

work attitude, extreme focus, total dedication, and ultimate commitment to advancing both science and engineering.

6. 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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(1) Special Issue. The GH-Method. (https://www.theghmethod.com)

(2) Journal of Applied Material Science & Engineering Research (contact: Catherine)

(3) Advances in Bioengineering and Biomedical Science Research (contact: Sonny Hazi).

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Viscoelastic and Viscoplastic Glucose Theory Application in Medicine

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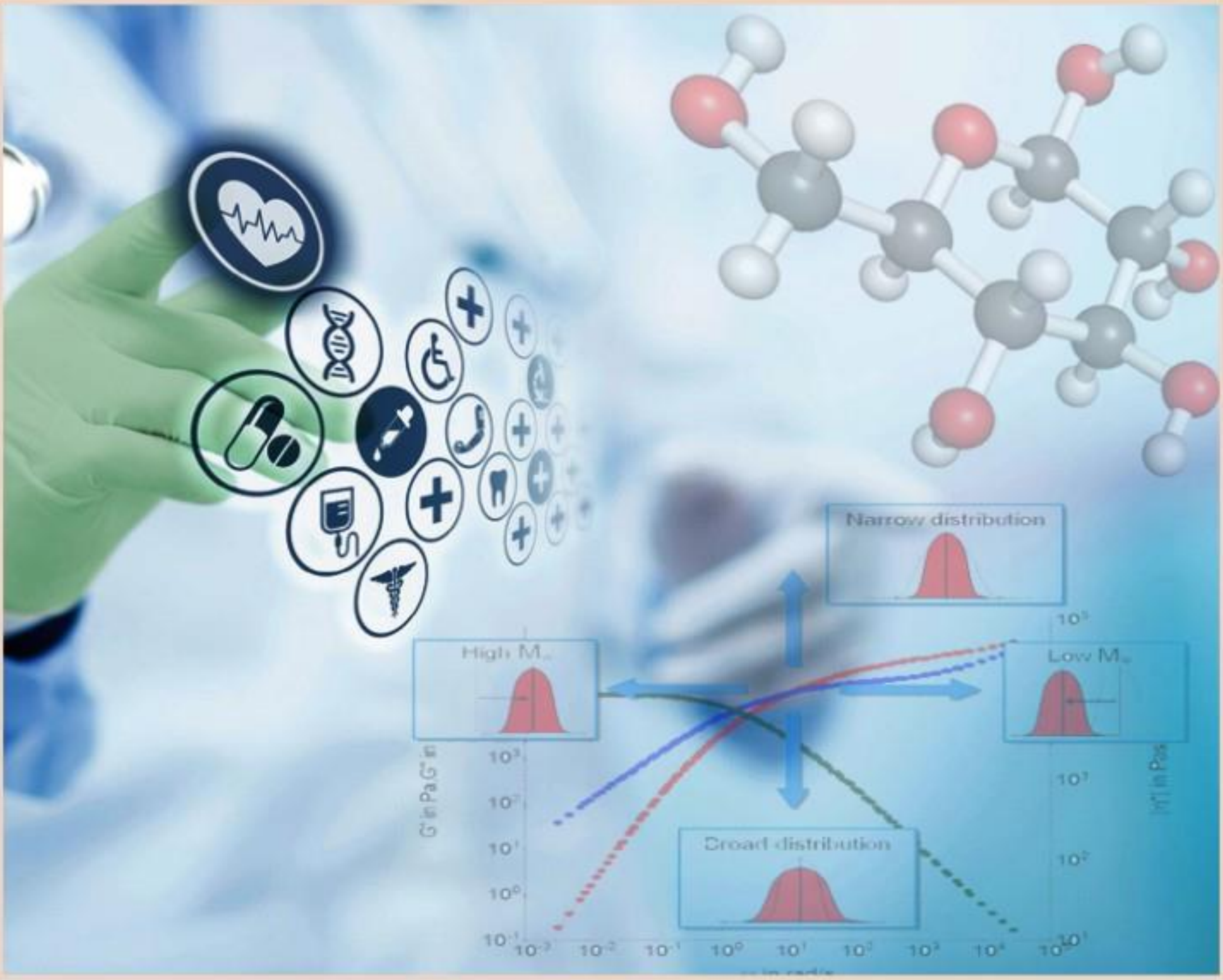

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