The GH-Method

Viscoelastic and Viscoplastic Glucose Theory (VGT #138): Another Longevity Study of Health Age Estimation (Health Age 2 Model) Using SD-VGT Energy Analysis Results of Health Age 1 versus Three Different Energy Contributions from Cardiovascular Diseases, Chronic Kidney Disease, and Various Cancers Over 10+ Years from 1/1/2012 to 8/19/2022 Based on Math-Physical Medicine Method (No. 729)

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Note: This article is the extension of Paper No. 725.

Keywords: Viscoelastic; Viscoplastic; Cardiovascular disease; Chronic kidney disease; Cancer; 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 recently read two reports regarding gerontology and geriatrics titled, "Biological age, not birthdate may reveal healthy longevity" written by the University of California - San Diego, and "Reversing Your Epigenetic Age, Is That Possible?" written by Lewis Chang, Ph.D., a Scientific Editorial Manager of R&D at Metagenics. The findings in these 2 reports have matched many of his published research papers on the subject of longevity. As a future reference, he has kept these 2 short excerpts in Papers No. 723 and No. 724, separately.

The author does not often rely on statistics tools, health institutions surveyed data, or other patients collected data in his research work. Instead, he uses collected data from his own health conditions and lifestyle details during the past 13 years while utilizing his developed math-physical medicine (MPM) methodology and research tools.

In 2014, he applied a mathematical topology concept, nonlinear algebra, and geometric algebra operations along with engineering finite-element technique, to develop a comprehensive mathematical algorithm for measuring human metabolism status, the metabolism index (MI) model.

This MI model contains ten specific categories, including four output categories of medical conditions (m1=body weight, m2=glucose, m3=blood pressure, and m4=lipids), and six input categories of lifestyle details (physical exercise=m5, drinking water=m6, sleep=m7, stress=m8, food quantity and quality=m9, and daily life routines=m10). These 10 categories are comprised of approximately 500 detailed elements which include 4 basic chronic disease categories and 6 basic lifestyle categories. He also defined two new resulting parameters: the metabolism index or MI, as the combined and normalized score of the above 10 metabolism categories and 500 elements using his developed algorithm, along with the general health status unit

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(GHSU), as the 90-day moving average value of MI.

A physical analogy of this mathematical metabolism model is similar to a model of "using multiple nails that are encircled by many rubber bands". For example, first, we hammer 10 nails into a piece of flat wood with an initial shape of a circle, then take 3,628,800 (=10!) rubber bands to encircle these 10 nails. The ~3.6 million rubber bands, indicating the big number of nails' inter-relationships, show the possible relationships existing among the 10 nails (10 original metabolism data). Some rubber bands encircle 2 or 3 nails and so on until the last rubber band encircles all of the 10 nails together (no rubber band to encircle a single nail is allowed since it does not create tension). Now, if we move any one of the nails outward (i.e., moving away from the center of the nail circle), then this moving action would create some internal tension inside the encircled rubber band. Moving one nail "outward" means one of the ten metabolism categories is becoming "unhealthy" which would cause some stress to our body. Of course, we can also move some or all of the 10 nails outward at the same time, but with different moving distances. If we can measure the summation of the internal tension created in the affected rubber bands, then this summarized tension force is equivalent to the total metabolism value or the overall health conditions. The higher tension means a higher metabolism value which develops into an unhealthy situation. The author uses the above-described scenario of moving nails and their encircled rubber bands to explain his developed mathematical metabolism index model of human health.

From 1/1/2012 to 8/24/2022, he has collected more than 3 million pieces of data on his biomedical conditions and personal lifestyle details.

Regarding his medical research tools, the author has conducted medical research work using viscoelastic or viscoplastic glucose theory (VGT) starting on 1/8/2022 with Paper No. 578. During this past 8-month research period, he has written 136 papers 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.

In summary, recently, he has applied the following three energy analysis approaches to his various biomedical research work. First, the time-domain (TD) energy is defined as the squared amplitude of average food or average exercise (from a rudimentary physics definition). Second, the space-domain (SD) energy is defined as the areas of the hysteresis loop or stress-strain curve (from engineering viscoelasticity or viscoplasticity time-dependency definition). Third, the frequency-domain (FD) energy is defined as the enclosed area of the frequency curve in FD after going through a fast Fourier transform (FFT) operation from a TD variable of strain multiplied with stress (from a physics wave theory definition).

This article is a continuation of his previous Paper No. 725 regarding his health age versus 3 deadly disease risks, cardiovascular disease (CVD), chronic kidney disease (CKD), and Cancers. The data processing work of this paper is conducted using both his developed Chronic software and the VGT software module on the 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 two mathematical equations for estimated health ages as listed below:

Health Age 1
= Chronological real Age * (1+((MI-0.735)/0.735)/2)

Age difference
= estimated health age 1 - chronological real age

Where MI is a daily "metabolism index" value which is a combined score of 4 biomarkers of weight, glucose, blood pressure, and blood lipids along with 6 lifestyle details of food, water intake, exercise, sleep, stress, and daily life routines.

Health Age 2
= ((Summation of SD energy from 3 deadly diseases) * (Age difference)) + (chronological real age)

Where:

Summation of SD energy from 3 deadly diseases
= (annual CVD risk % * SD CVD energy ratio of 34% + annual CKD risk % * SD CKD energy ratio of 42%+ annual Cancer risk % * SD Cancer energy ratio of 24%)

Furthermore, a positive number of age difference means a shorter expected lifespan and a negative number of age difference indicates a longer expected lifespan.

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 inputvariable" 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 * ($d\varepsilon/dt$)
= 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, 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 SD-VGT analysis results with data table from Paper No. 725.

Figure 2 depicts the health age 2 data table and comparison TD diagram of 3 curves, i.e. chronological real age, health age 1, and health age 2.

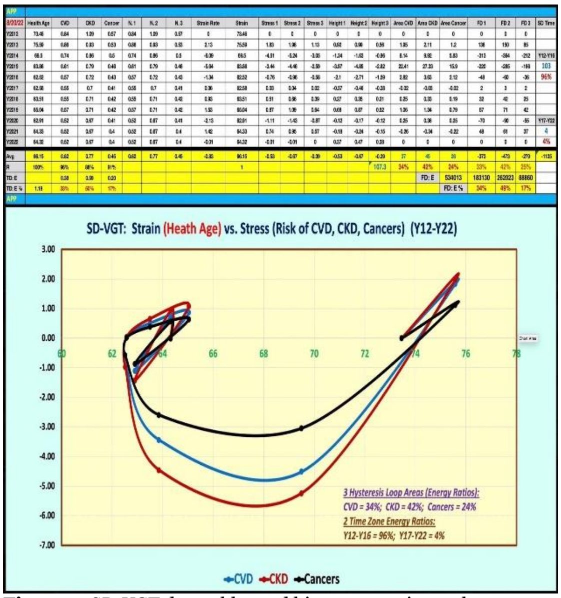
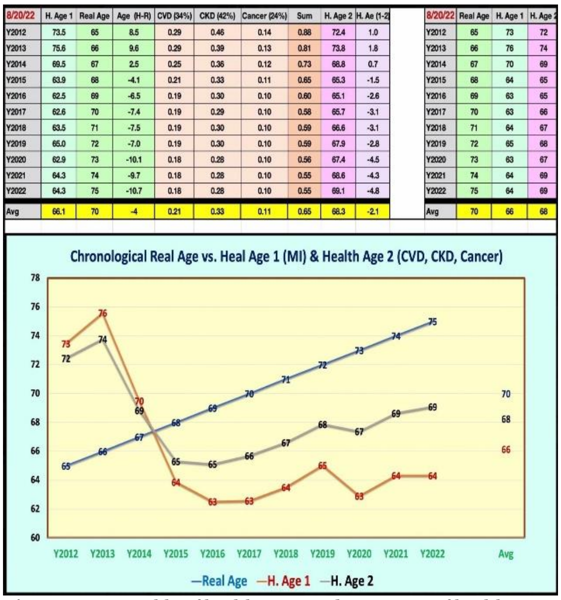


Figure 1: SD-VGT data tables and his energy ratio results.



8/20/22	H. Age 1	Real Age	Age (H-R)	CVD (34%)	CKD (42%)	Cancer (24%)	Sum	H. Age 2	H. Ae (1-2)
Y2012	73.5	65	8.5	0.29	0.46	0.14	0.88	72.4	1.0
Y2013	75.6	66	9.6	0.29	0.39	0.13	0.81	73.8	1.8
Y2014	69.5	67	2.5	0.25	0.36	0.12	0.73	68.8	0.7
Y2015	63.9	68	-4.1	0.21	0.33	0.11	0.65	65.3	-1.5
Y2016	62.5	69	-6.5	0.19	0.30	0.10	0.60	65.1	-2.6
Y2017	62.6	70	-7.4	0.19	0.29	0.10	0.58	65.7	-3.1
Y2018	63.5	71	-7.5	0.19	0.30	0.10	0.59	66.6	-3.1
Y2019	65.0	72	-7.0	0.19	0.30	0.10	0.59	67.9	-2.8
Y2020	62.9	73	-10.1	0.18	0.28	0.10	0.56	67.4	-4.5
Y2021	64.3	74	-9.7	0.18	0.28	0.10	0.55	68.6	-4.3
Y2022	64.3	75	-10.7	0.18	0.28	0.10	0.55	69.1	-4.8
Avg	66.1	70	-4	0.21	0.33	0.11	0.65	68.3	-2.1

8/20/22	Real Age	H. Age 1	H. Age 2
Y2012	65	73	72
Y2013	66	76	74
Y2014	67	70	69
Y2015	68	64	65
Y2016	69	63	65
Y2017	70	63	66
Y2018	71	64	67
Y2019	72	65	68
Y2020	73	63	67
Y2021	74	64	69
Y2022	75	64	69
Avg	70	66	68

Figure 2: Data table of health age 2 and TD curves of health age 1, health age 2, and real age.

4. CONCLUSION

In summary, there are 3 key findings from this study on his health age 1 based on the metabolism index (MI) model and his health age 2 based on 3 risks and energies of CVD, CKD, and Cancers.

(1) From the TD diagram, his health age 1 was 73 at the beginning of 2012, when his real age was 65, and 76 when his real age was 66 in 2013. At the turn-around year of 2015, his health age was 64, when his real age was 68, and finally in 2022, with the health age of 64 when his real age is 75. His average health age 1 is 66 and his average real age is 70.

(2) From the same TD diagram, his health age 2 was 72 in the beginning of 2012, when his real age was 65, to 74 in the following year of 2013, when his real age was 66. At the turn-around year of 2015, his health age was 65, when his real age was 68, and finally in 2022, with the health age of 69 when his real age is 75. His average health age 2 is 68 and his average real age is 70. It is noticed that health ages 2 are higher than health ages 1.

(3) From the SD-VGT analysis results in Paper No. 725, the SD energy ratios for "health age" are: CVD = 34%; CKD = 42%; and Cancer = 24%. These 3 different energy ratios have been used in the calculation of his health age 2 as follows: Health Age 2 = ((Summation of SD energy from 3 deadly diseases) * (Age difference)) + (real age). Where: "Summation of SD energy from 3 deadly diseases = (annual CVD risk % * SD CVD energy ratio of 34% + annual CKD risk % * SD CKD energy ratio of 42%+ annual Cancer risk % * SD Cancer energy ratio of 24%)"

In summary, from the results of the SD-VGT analysis, it is clear that the CKD risk contributes the most to his health (42%), the CVD risk is the next disease (34%), while his Cancer risk contributes the least (24%) to his health age. The "contribution" word here can be interpreted as the "risk on longevity".

His health age 1 model is developed using the metabolism index (MI) model which covers a collection of many diseases resulting in his lifespan reduction. However, the health age 2 model is developed using the SD-VGT energy from 3 deadly diseases only, CVD, CKD, and Cancers (about 50% of the total death cases in the US). Generally speaking, an improvement to overall metabolism would offer more benefits to his health conditions and disease prevention than 3 selected diseases only. That is why his health ages 2 is higher than his health ages 1.

Although this longevity study has used the author's own data, the concept behind is almost identical to the epigenetic age mentioned in other medical reports. He believes that his longevity studies can be served as a useful tool to prolong his lifespan in a healthy state. Other patients can also observe the findings from this article and follow his example to improve their prospects of longevity.

The research methodology behind this particular study has offered a subtle and deeper understanding of the complicated biophysical behaviors of longevity. 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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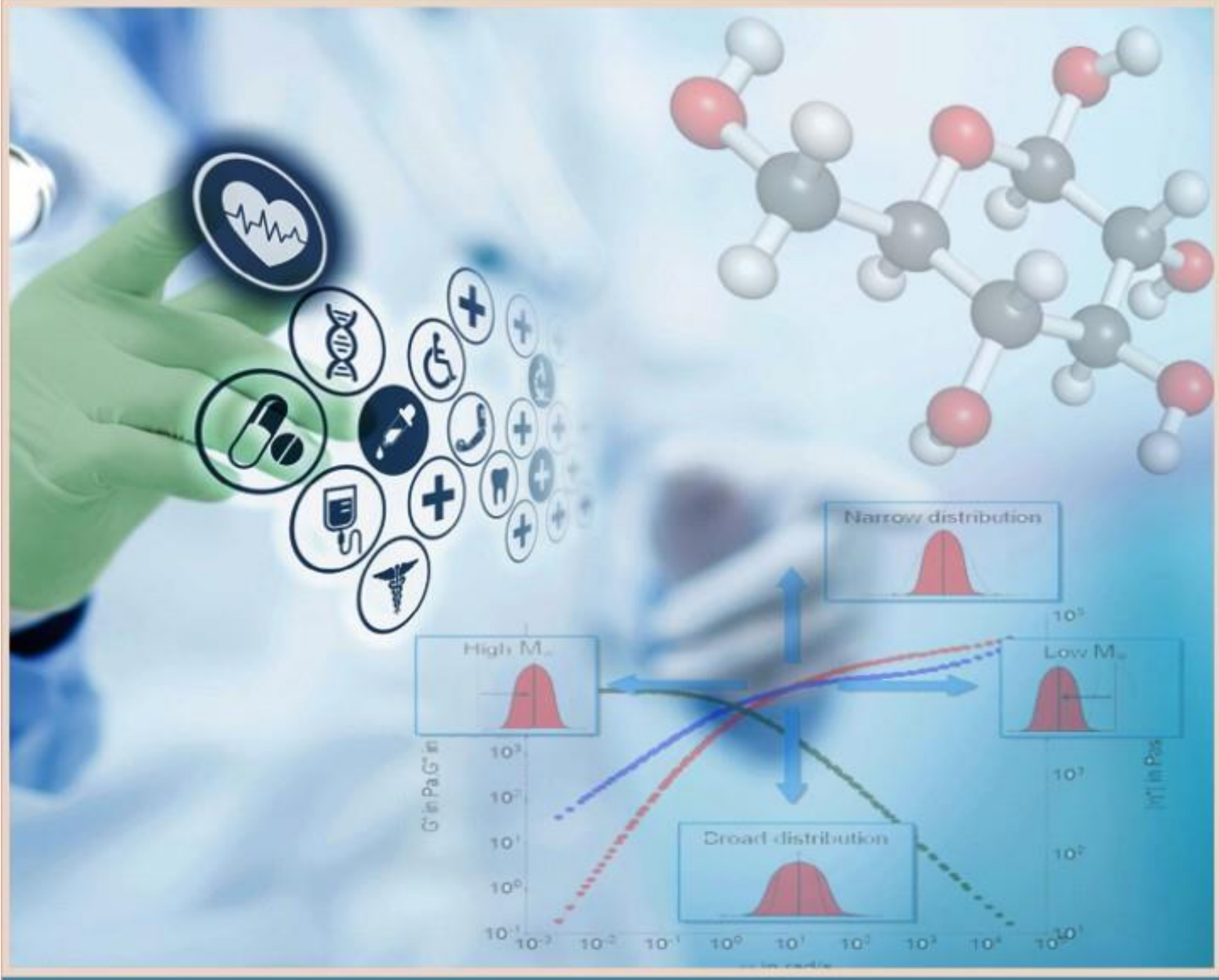

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