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The GH-Method

Viscoelastic or Viscoplastic Glucose Theory (VGT #113): A Study on the Influences of Body Weight, Glucose, Blood Pressure, and Blood Lipids for 3 Deadly Diseases and Longevity Concerns Applying Time-Domain Observations and Space-Domain VGT Stress-Strain Curves Behavior Studies from a Patient's Data Collected Over 10.5 Years from 1/1/2012 to 7/17/2022 Based on GH-Method: Math-Physical Medicine (No. 703)

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Keywords: Viscoelastic; Viscoplastic; Body weight; Glucose; Blood pressure; Blood lipids; Carbohydrates; Sugar; Postprandial plasma glucose; Fasting plasma glucose; Type 2 diabetes

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

1. INTRODUCTION

The author utilizes 3+ million personal health data collected over 13 years along with his developed Metabolism index (MI) model with 10 categories (mi, i=1,10) in 2014 and 3 risk prediction models for cardiovascular disease (CVD), chronic kidney disease (CKD), and variety of cancers. This particular study investigates the close relationship of 4 outputs, CVD, CKD, Cancers, and Longevity versus 4 common inputs of m1 (body weight), me2 (glucose), m3 (blood pressure), and m4 (blood lipids). The data covers 10.5 years from 1/1/2012 to 7/17/2022. His MI score includes 4 chronic medical conditions, obesity, diabetes, hypertension, hyperlipidemia, and 6 lifestyle details, diet and food, water intake, exercise, sleep, stress, and daily life routines.

The mathematical model of calculating various deadly disease risk probability % (mortality rate) of developing CVD, CKD, or a variety of cancers or Cancers is mainly based on the MI model with differently assigned weighting factors related to certain biomarkers, such as blood pressure and glucose on macro-vessel's rupture; lipids and glucose on macro-vessel's blockage; albumin to creatinine ratio (ACR) and glucose on micro-vessels damage in the kidney; obesity, hyperglycemia, and environmental factors on certain cancers, such as adiposity-related (PDAR) cancers.

The SD strain-stress curve's energy analysis method is chosen as the primary research tool which will be described briefly in the Methods section. To save this article's number of words, he decides to omit the more detailed explanation of his research method in this article.

These four selected inputs or causes, m1, m2, m3, and m4, have already gone through a "normalization process" by dividing each medical condition with its corresponding dividing line's value of healthy vs. unhealthy, e.g. 170 lbs. (corresponding with BMI 25.0) for m1 (body weight), 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). By using this normalization process, it can then remove the dependency of the individual unit or certain unique

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biophysical characteristics associated with each influential cause, i.e. m1, m2, m3, 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 the observation and investigation of 3 deadly disease risk behaviors of 3 symptoms, i.e. CVD, CKD, and Cancers as well as the 4 causes, m1, m2, m3, and m4 in a time domain (TD).

The second part is conducting three separate SD-VGT studies of CVD, CKD, and Cancers versus the same 4 metabolism index inputs, m1, m2, m3, and m4. This analysis explains the differences in the degree of influence from m1 through m4 on these deadly diseases. Furthermore, it also investigates the deadly disease risks within different periods which shows the progression and status of the 3 diseases over 3 periods.

The third part is the comparison between the case of longevity versus the same 4 metabolism index element and the case of longevity versus 3 deadly diseases, CVD, CKD, and Cancers. Longevity is defined as the age difference between the effective health age (MI-based formula) and the biological real age. A negative age difference means better longevity.

1.1 The author's medical history

The author's case of diabetes, obesity, and other complications

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 ratio (ACR) at 116. He also suffered from five cardiac episodes within a decade. In 2010, three independent physicians warned him regarding his need for kidney dialysis treatment and his future high risk of dying from his severe diabetic complications. Besides the cerebrovascular disease (stroke), he has suffered most of the known diabetic complications, including macro-vascular and micro-vascular complications.

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 heavier traveling period.

Since 2020, living in a COVID-19 quarantined lifestyle, not only has he published 400+ 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 the 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 difference in average sensor glucoses between 5-minute intervals and 15-minute intervals is only 0.7% (average glucose of 112.15 mg/dL for 5 minutes and average glucose of 111.33 mg/dL for 15 minutes with a correlation of 96% between these two sensor glucose curves) during the period from 2/19/20- to 5/9/22.

Therefore, over the past 13 years, he could study and analyze the 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 is based on the aims of achieving both "high precision" with "quantitative proof" in the medical findings 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 CVD, coronary heart diseases (CHD), and stroke, using pattern analysis and segmentation analysis.

2018: Complications due to micro-vascular research such as 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 108 biomedical research cases and 4 economics research cases.

Again, to date, he has spent around 40,000 hours self-studying and researching medicine, including reading 3000+ published medical papers. He has collected and calculated more than three million pieces of data regarding his 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 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 space-domain (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 (i.e. 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 these stress-strain curves or input-output curves (i.e. 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 6-step description, the author 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 m1 through m4.

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" 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 a frequency-domain (FD). The FD-FFT energy is the enclosed area of this frequency curve. This frequency energy analysis is not included in this article.

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.

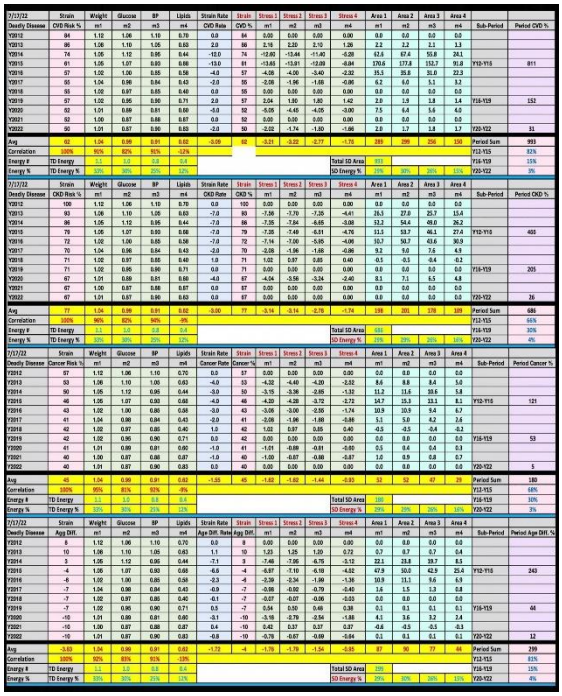

Figure 1: 4 data tables.

Figure 2 displays the TD-correlation analysis results.

Figure 3 reflects three SD-VGT analysis results of CVD, CKD, and Cancers versus the same causes of m1, m2, m3, and m4.

Figure 4 depicts the SD-VGT analysis results of Longevity versus the same causes of m1, m2, m3, m4, and Longevity versus 3 deadly diseases, CVD, CKD, and Cancers.

Figure 5 illustrates 2 bar charts of energy's numerical comparison.

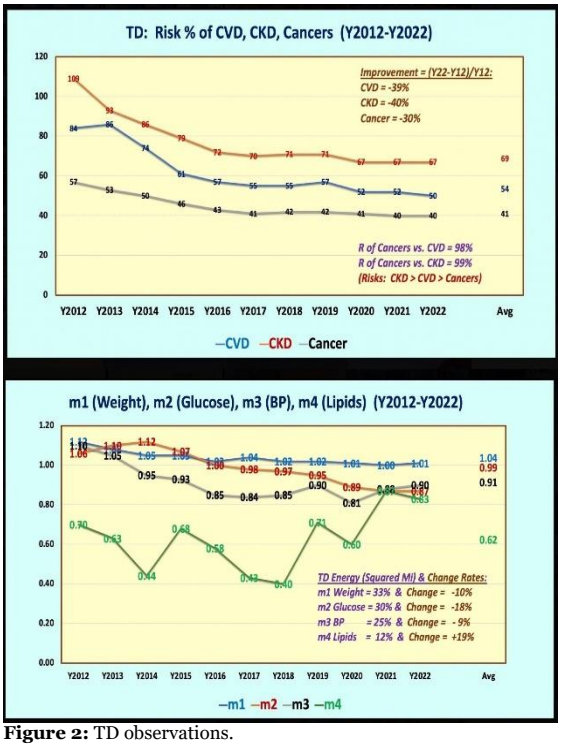

Figure 2: TD observations.

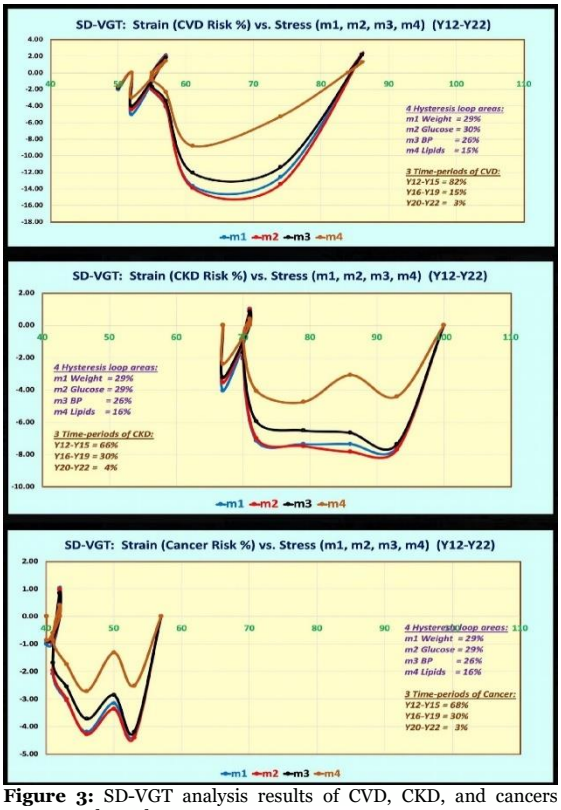

Figure 3: SD-VGT analysis results of CVD, CKD, and cancers versus m1 through m4.

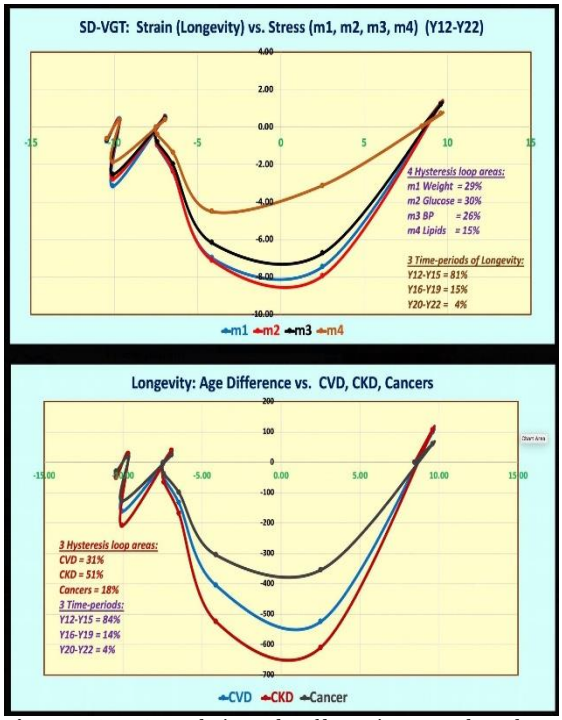

Figure 4: SD-VGT analysis results of longevity vs. m1 through m4 and longevity vs. CVD, CKD, cancers.

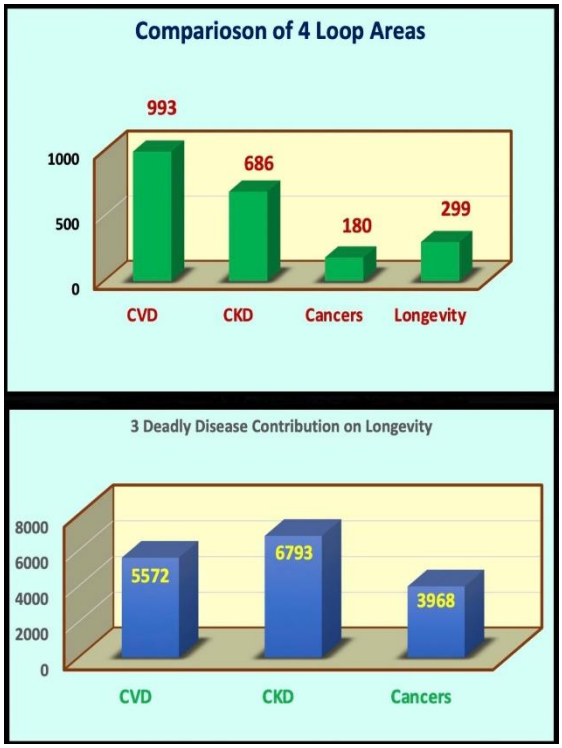

Figure 5: 2 bar chart comparisons of hysteresis loop areas.

4. CONCLUSION

In summary, there are 9 observations from the TD curve observations and 5 separate SD-VGT analysis results to study different relationships between Longevity, CVD, CKD, and Cancers versus m1, m2, m3, m4, or Longevity versus CVD, CKD, and Cancers.

(1) From 3 TD curves of CVD, CKD, and Cancers, the average risk levels over 10.5 years are 69% for CKD (highest), 54% for CVD (middle), and 41% for cancers (lowest). As mentioned in the section of the author's medical history, he suffered 5 cardiac episodes from 1993 to 2005. He also faced kidney trouble and needed dialysis treatment in 2010. Thus far, he has not discovered any threat of cancer. This study's chosen period only covers 10.5 years from 2012 to 2022. Therefore, the realities in his past medical history have also been quantitatively re-confirmed by the TD average risk ranking of "CKD > CVD > Cancers". Furthermore, the combination of reducing 10% of m1 (weight), 18% of m2 (glucose), and 9% of m3 (blood pressure) has resulted in the observed reductions in risks of having 3 individual deadly diseases: 39% for CVD, 40% for CKD, and 30% for cancers. It should be pointed out that m4 (blood lipids) has always been less than 1.0 (healthy) despite its noticeable fluctuations within this period of 10.5 years.

(2) He faced a death threat in 2010, therefore, he has changed his lifestyle since 2010 and also stopped taking all of his medications on 12/8/2015. The collected biomarkers have demonstrated his body's natural reaction to existing medical conditions, including obesity, diabetes, hypertension hyperlipidemia, CVD, CKD, and other complications under the strong influence of his lifestyle modifications. These lifestyle management actions have resulted in remarkable improvements in his conditions of obesity, T2D, and hypertension (he had hyperlipidemia in 2010 with a triglyceride level of 1161). Therefore, the results in the study have shown the direct linkage between his chosen 3 medical complications (CVD, CKD, and Cancers) and 4 chronic disease biomarkers, i.e. m1, m2, m3, and m4, without any medication intervention.

(3) In the 3 SD VGT analyses of comparing CVD, CKD, Cancers vs. the same m1 through m4, the ratio of disease contribution % by 4 mi elements are: 29% : 30% : 26% : 15% for m1; 29% : 29% : 26% : 16% for m2; 29% : 29% : 26% : 16% for m3; 29% : 30% : 26% : 15% for m4. An interesting pattern is observed - m1 and m4 have an identical energy distribution pattern while m2 and m3 have another identical energy distribution pattern although all of them are extremely close to each other.

(4) The author has purposely placed the 3 disease risk curves on the same x-axis scales, i.e. between 40% to 110% risk levels. As we can see, the CVD curve covers the range of 50% to 84%; the CKD curve covers the range of 67% to 100%; the Cancer curve covers the range of 40% to 57%. Therefore, the strain-stress curves are located according to the order of CKD > CVD > Cancer (from higher% right to lower% left) which is the same as the TD's observed ranking of average disease risk percentages.

(5) In the same set of 3 SD-VGT curves, the disease risk distribution of 3 time-periods: Y2012-Y2015 (Uncontrolled period), Y2016-Y2019 (controlled period), Y2020-Y2022 (the best controlled of COVID-19 period) are below: 82% : 15% : 3% for CVD; 66% : 30% : 4% for CKD; 68% : 30% : 3% for Cancer; 81% : 15% : 4% for Longevity. Again, the energy distribution patterns are similar between CVD and Longevity as well as CKD and Cancers. The 3 time-period risk contributions are extremely close to each other for these 3 diseases, i.e. 66-82% : 15-30% : 3-4%. The recent 2.5 years' COVID-19 period is best-controlled (3%-4%) which is better than the middle 4 years in the controlled period (15%-30%). The earlier 4-year period is the worst with the highest risks of having CVD, CKD, and Cancer 66%-82%).

(6) The author also wondered which scenario revealed more truthful and useful facts, whether "m1 through 4 influencing Longevity" and/or "CVD, CKD, Cancers influencing Longevity". Therefore, he has further conducted two separate but related SD-VGT studies. As he expected, all 7 curves looked similar with a "bowl shape". These 7 curve patterns (resulting from the strain change rate) look similar to each other because they use identical strain change rates, i.e. the identical Longevity (Age Difference) change rates. However, the hysteresis loop area sizes are varying from each other due to the different stress values, i.e. causes of m1 through m4, for each case. The ratio of Longevity contributions by m1, m2, m3, and m4 is 29% : 30% : 26% : 15% which is identical to the CVD case but still quite close to both CKD and Cancer cases. This finding proves that m1 through m4 are extremely important to longevity concerns. In other words, both weight and glucose have a higher degree of influence than blood pressure and blood lipids on 3 deadly diseases and longevity. Incidentally, longevity time-period distribution is 81% : 15% : 4% which is almost identical to CVD cases and also close to CKD and Cancer cases.

(7) The author tried another different SD-VGT analysis of Longevity versus CVD, CKD, and Cancers. The energy distributions are 31% from CVD; 51% from CKD; 18% from Cancers. This specific risk ranking order is similar to the findings of other TD and SD analysis results of CKD > CVD > Cancer. This set of contribution percentages also matches the findings from his medical history.

(8) The final 2 bar chart diagrams show the calculated hysteresis loop areas for 2 different cases. Although the absolute numbers do not have much meaning, their loop area size comparisons reveal one specific and significant viewpoint mathematically. In the upper diagram with loop areas from 4 cases, CVD, CKD, Cancers, and Longevity, their different bar heights (area sizes) are the results of different (square of disease risk change rate) with the same causes of m1 through m4. In the lower diagram with loop areas from 3 cases, CVD, CKD, and Cancers, their different bar heights (area sizes) are the results of different (individual disease risks as viscosities) with the same Longevity change rates. This explains the varying bar heights between CVD and CKD.

(9) People already know the strong influences of body weight, glucose, blood pressure, and blood lipids on deadly diseases, such as CVD, CKD, and Cancers. However, this kind of math-physical medicine research tool can offer a more quantified picture of how to utilize the control of m1, m2, m3, and m4 to reduce the mortality rates of the 3 deadly diseases. Incidentally, these deadly diseases occupied ~ 2/3 (66%) of recent US total death cases before the COVID pandemic.

The SD-VGT quantitative findings from this particular study have matched the public domain's healthcare recommendations of "maintaining an ideal state of body weight, glucose, blood pressure, and lipids" to reduce the mortality rates from CVD, CKD, and Cancers, and then achieve the ultimate goal of longevity.

This SD-VGT energy tool adopted from engineering and physics has further provided

some useful hints and realistic interpretations of complex biomedical results from CVD, CKD, Cancers, and longevity resulting from m1 through m4.

The math-physical medicine method indeed can reveal more subtle and deeper findings of biophysical phenomena. Some statistics tools deal only with the variable (symptom or cause) itself while the viscoelasticity or viscoplasticity method can focus on the squared symptom change rate multiplying with a cause, i.e. energy. The wave theory via Fourier transform also works with energy. The energy generated by the biomarker can provide a much wider view and deeper knowledge of the biomedical scenario than the biomarker itself.

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 and 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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For reading more of the author's published VGT analysis on medical research, please locate them through the following three specific journals:

(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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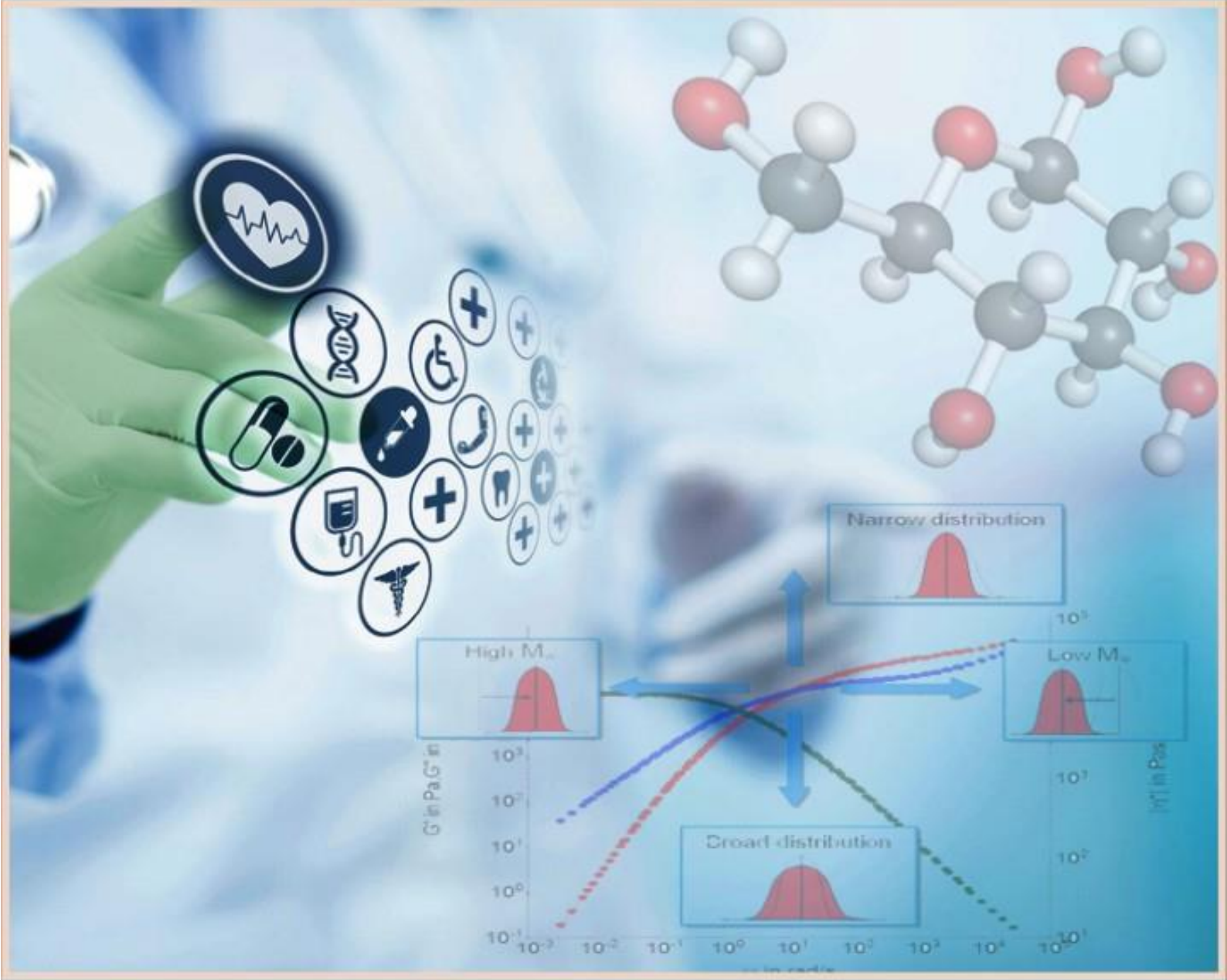

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