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Viscoelastic and Viscoplastic Glucose Theory (VGT #141): Using Time-Domain, Space-Domain, and Frequency-Domain Energy Analysis Methods to Investigate the Energy Ratios of Contribution or Degree of Influence on Laboratory-Tested A1C Resulting from Finger-Pierced A1C and Sensor-Measured A1C over a Period from 5/8/2018 to 9/1/2022 Based on Math-Physical Medicine Method (No. 733)

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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. When statistics is used, 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 proven through the basic laws of physics (engineering is an extension of physics or an applied physics). In fact, many observed and known phenomena of objects under the sun, including the biomedical field, indeed follow the basic laws of physics. We can only try to understand the phenomena and/or interpret the results using physics principles or engineering techniques, but we cannot tweak or twist them.

His biomedical research work does not utilize surveyed or collected data from any health institution or collected data from other patients. Instead, he mostly uses the 3+ million collected and processed data from his own health conditions and lifestyle details during the past 13 years for his medical research work.

He has conducted various biomedical research work using engineering viscoelastic or viscoplastic glucose theory (VGT) since 1/8/2022 beginning with Paper No. 578 upon the advice of his MIT advisor, Professor Norman Jones, in December 2021. During this past 8-month period, he has written 140 papers using this time-dependency approach where he has learned in depth the subtlety and things to watch out for by applying this specific VGT research tool in various biomedical research work. Not only has he been analyzing the associated energy of causes, but he is now able to connect the multiple medical input cause energies with the symptom of certain specific medical output or biomarker.

The symptom used in this study is the laboratory-tested HbA1C values (Lab A1C). There are two independent input variables of HbA1C based on his finger-pierced glucoses (Finger A1C of F. A1C) and HbA1C based on a sensor continuously monitored glucoses (Sensor A1C or S. A1C). *There is no normalization process for these 2 viscosities, F.A1C and S.A1C, needed since all of the A1C values, including Lab A1C, are represented according to international standards.*

The author started to collect his finger-pierced glucose 4 times a day on 1/1/2012 and started to measure his daily glucoses 96 times a day with 15-minute time intervals using the same brand of continuous glucose monitoring device since 5/8/2018. However, he has to do his blood work at a certified medical laboratory to obtain his lab A1C results. Due to the COVID pandemic, his lab work schedules have been disturbed. Nevertheless, over 1,577 days from 5/8/2018 to 9/1/2022, he has conducted a total of 17 lab tests. Therefore, ***the average number of days per test is 93 days*** *which matches well with the average life span of red blood cells.* Both his finger A1C and sensor A1C have been calculated daily. In this study, he selects these two A1C values from his database with the same dates as the lab tests.

In the following Methods section, he provides a brief description of the TD, SD-VGT, and FD tools using English words instead of theories of physics and engineering with complex mathematical equations.

Methods

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.

Brief Introduction of Math-Physical Medicine (MPM) Research

The author has collected 3+ million pieces of 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 CVD, CHD, stroke, CKD, 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.

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 FFT analysis method with a comparison against the traditional TD 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 time periods.

For the frequency domain, the eighth step is to define a "hybrid input variable" by using ***"strain*stress"*** which yields another accurate estimation of energy ratio similar to the SD-VGT energy ratio associated with the hysteresis loop. The ninth step is to present these hybrid models' results of (strain*stress) in TD and then perform the FFT operation to convert them into 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.

Results

Figure 1 depicts analysis results using TD, SD, and FD of the LAB A1C versus both finger A1C and Sensor A1C.

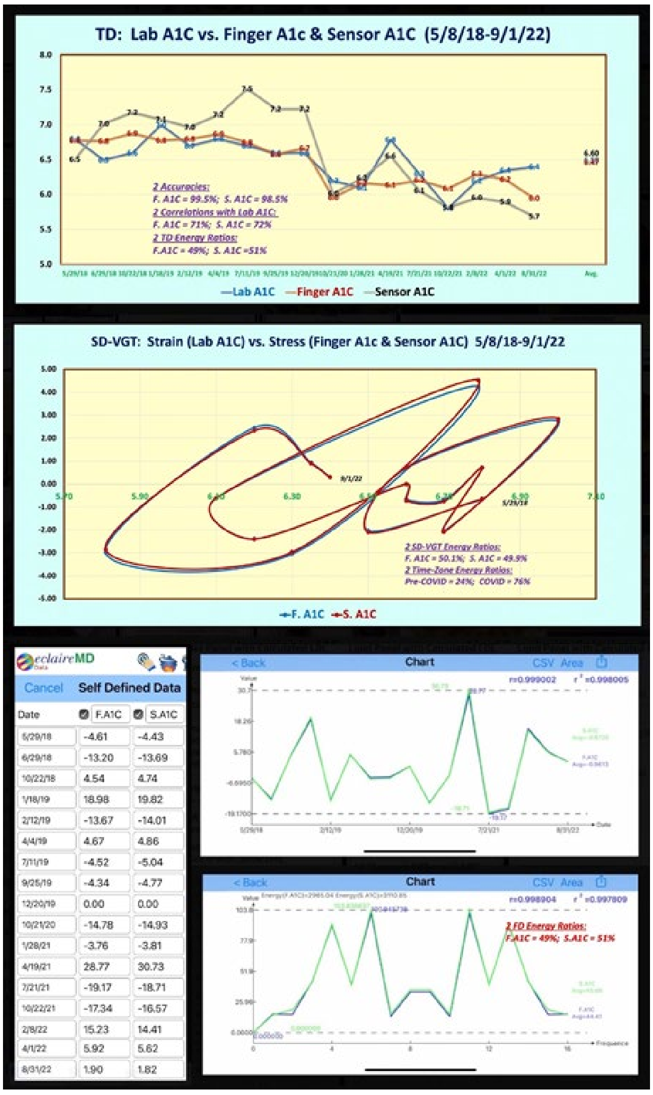
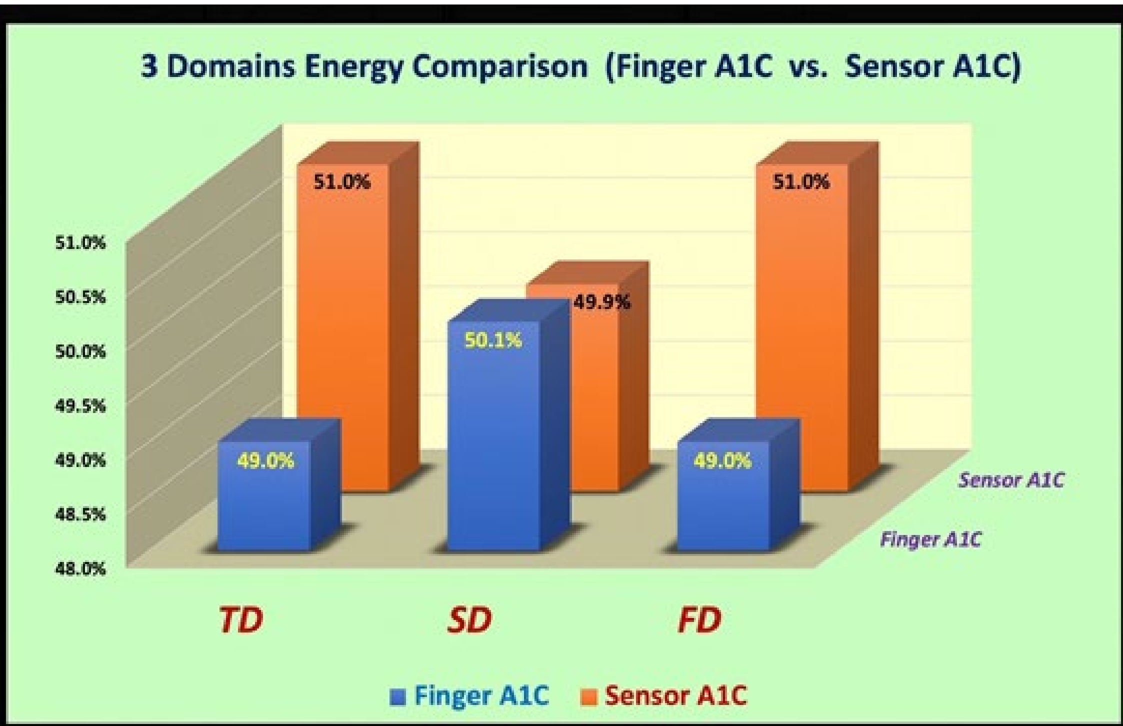


Figure 1: TD, SD, and FD analysis results

Figure 2 shows the comparison of his energy ratios of finger A1C versus sensor A1C in 3 domains, and the supporting data table.



9/1/22 HbA1C	Strain Lab A1C	Viscosity 1 Finger A1C	Viscosity 2 Sensor A1C	9/1/22 HbA1C	/ 1 Norm 1	/ 1 Norm 2	Strain Rate Lab A1C Rate	Strain Lab A1C	Stress 1 F. A1C	Stress 2 S. A1C	Area F.A1C	Area S.A1C	Time Zone	9/1/22 HbA1C	FD: F.A1C	FD: S.A1C
5/29/18	6.6	6.8	6.5	5/29/18	6.78	6.51	-0.10	6.60	-0.68	-0.65	0.07	0.07		5/29/18	-4.61	-4.43
6/29/18	6.5	6.8	7.0	6/29/18	6.77	7.02	-0.30	6.50	-2.03	-2.11	0.41	0.41		6/29/18	-13.20	-13.69
10/22/18	6.6	6.9	7.2	10/22/18	6.88	7.18	0.10	6.60	0.69	0.72	-0.07	-0.07		10/22/18	4.54	4.74
1/18/19	7.0	6.8	7.1	1/18/19	6.78	7.08	0.40	7.00	2.71	2.83	0.68	0.71		1/18/19	18.98	19.82
2/12/19	6.7	6.8	7.0	2/12/19	6.80	6.97	-0.30	6.70	-2.04	-2.09	-0.10	-0.11		2/12/19	-13.67	-14.01
4/4/19	6.8	6.9	7.2	4/4/19	6.87	7.15	0.10	6.80	0.69	0.71	-0.07	-0.07		4/4/19	4.67	4.86
7/11/19	6.7	6.8	7.5	7/11/19	6.75	7.52	-0.10	6.70	-0.67	-0.75	0.00	0.00	Pre-COVID	7/11/19	-4.52	-5.04
9/25/19	6.6	6.6	7.2	9/25/19	6.58	7.23	-0.10	6.60	-0.66	-0.72	0.07	0.07	24%	9/25/19	-4.34	-4.77
12/20/19	6.6	6.7	7.2	12/20/19	6.67	7.23	0.00	6.60	0.00	0.00	0.00	0.00	2.00	12/20/19	0.00	0.00
10/21/20	6.2	6.0	6.0	10/21/20	5.96	6.02	-0.40	6.20	-2.38	-2.41	0.48	0.48		10/21/20	-14.78	-14.93
1/28/21	6.1	6.2	6.2	1/28/21	6.17	6.24	-0.10	6.10	-0.62	-0.62	0.15	0.15		1/28/21	-3.76	-3.81
4/19/21	6.8	6.1	6.6	4/19/21	6.14	6.56	0.69	6.79	4.24	4.53	1.25	1.35		4/19/21	28.77	30.73
7/21/21	6.3	6.2	6.1	7/21/21	6.21	6.06	-0.49	6.30	-3.04	-2.97	-0.29	-0.38		7/21/21	-19.17	-18.71
10/22/21	5.8	6.1	5.8	10/22/21	6.09	5.82	-0.49	5.81	-2.98	-2.85	1.48	1.43		10/22/21	-17.34	-16.57
2/8/22	6.2	6.3	6.0	2/8/22	6.30	5.96	0.39	6.20	2.46	2.32	-0.10	-0.10	COVID	2/8/22	15.23	14.41
4/1/22	6.4	6.2	5.9	4/1/22	6.22	5.90	0.15	6.35	0.93	0.88	0.25	0.24	76%	4/1/22	5.92	5.62
8/31/22	6.4	6.0	5.7	8/31/22	5.95	5.69	0.05	6.40	0.30	0.28	0.03	0.03	6.43	8/31/22	1.90	1.82
Avg.	6.50	6.47	6.60	Avg.	6.47	6.60	-0.03	6.50	-0.18	-0.17	4.23	4.21	8.43	FD Energy	2985	3111
Accuracy		99.5%	98.5%	Accuracy												
R	100%	71%	72%													
TD E: #	85.3	41.8	43.5	SD E: #					Total SD-E		F. A1C	S. A1C	Total FD-E	FD E: #	F. A1C	S. A1C
TD E: %		49.0%	51.0%	SD E: %					SD Area	8.43	50.1%	49.9%	FD-E %	FD E: %	49.0%	51.0%

Figure 2: Comparison of energy ratios between Finger A1C versus Sensor A1C in 3 domains and the supporting data table

Conclusion

In summary, there are 5 findings from this study on ***the output symptom of the lab A1C versus 2 individual input data of finger A1C and sensor A1C.***

(1) From the TD diagram, ***the average A1C values are: Lab A1C = 6.50%, Finger A1C = 6.47%, Sensor A1C = 6.60%. The correlations between the Lab A1C versus: Finger A1C = 71%, Sensor A1C = 72%.*** *In conclusion, the accuracies of his 2 self-calculated A1C values are extremely high since they are very close to the average Lab A1C. Furthermore, the 71% and 72% of correlation coefficients indicated that these three A1C waveform shapes are quite similar to each other as well.*

(2) From the TD squared amplitude method, the energy ratios are: *Finger A1C = 49% versus Sensor A1C = 51%. These 2 self-calculated A1C values, i.e. Finger A1C and Sensor A1C, have an almost equal amount of influence on the Lab A1C. Or, we can say that* ***both Finger A1C and Sensor A1C are accurate enough for predicting the Lab A1C outcomes.***

(3) From the SD-VGT analysis results, the energy ratios are: ***Finger A1C = 50.1% versus Sensor A1C = 49.9%.*** *These two self-calculated A1C values, Finger A1C and Sensor A1C, have almost identical amounts of influence on the Lab A1C. These SD energy ratios are highly similar to the TD energy ratios.*

(4) The SD-VGT time-zone energy analysis results are: ***pre-COVID (Y18-Y19) = 24%, COVID (Y20-Y22) = 76%.*** *It is evident that the COVID pandemic period's energy is almost three times higher than the pre-COVID period's energy. Incidentally, the SD-VGT stress-strain diagrams of the 2 self-calculated A1C data, Finger A1C and Sensor A1C, have shown "****viscoplastic" behaviors.***

(5) From the FD-FFT analysis results, the energy ratios are: ***Finger A1C = 49% versus Sensor A1C = 51%****. These two self-calculated A1C values, Finger A1C and Sensor A1C, have an almost*

equal amount of influence on the Lab A1C. ***These FD energy ratios are identical with the TD energy ratios and very close to the SD energy ratios.***

The research methodology behind this particular study has offered a subtle and deeper understanding of the complicated biophysical behaviors of HbA1C. In addition, it has further proven the usefulness of math-physical medicine research methodology in biomedical research.

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.