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Research Article

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Impact on Daily Glucose Levels from Measured Versus Predicted Body Weight, FPG, PPG over 8.5 years: Analysis using GH-Method's Math-Physical Medicine Model (No. 999, VMT #397, 12/16-17/2023)

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Abstract

After 18 years of studying at seven universities and pursuing various careers in professional engineering, founding seven start-ups, and managing high-tech businesses, the 63-year-old author faced severe, lifethreatening health issues in 2010. This experience prompted him to undertake a self-study of internal medicine and food nutrition in order to save his own life.

Individuals with chronic diseases often face challenges in managing their body weight and glucose levels, which fluctuate constantly and over extended periods. Drawing on his 30 years of industrial experience in engineering design and the electronics semiconductor business, the author recognized the significance of "prediction" in averting failures in machines, structures, and business operations. He applied predictive analysis techniques from engineering and enterprise systems to enhance damage prevention and reduce the likelihood of breakdowns or failures. The author initially directed his medical research towards developing predictive equations for three key biomarkers: body weight, fasting morning glucose, and post-meal glucose. His prediction formulas for these three biomarkers demonstrated exceptionally high accuracy and very high waveform similarities, both exceeding 99%, In this study, the space-domain viscoplastic medicine energy theory (SD-VMT) was utilized to analyze the dynamic relationships between daily average glucose (eAG or M2) and three key biomarkers: body weight (BW), fasting plasma glucose (FPG), and postprandial plasma glucose (PPG).

In summary, *the findings from the author's last 8.5 years data analyses show the following SD-VMT energy ratios, expressed as "measured vs. predicted":*

- ***BW: 32% vs. 32% (R = 95% vs. 96%)***
- ***FPG: 38% vs. 38% (R = 94% vs. 92%)***
- ***PPG: 30% vs. 30% (R = 99% vs. 91%)***
- ***Total SD-VMT energy = 237 from measured vs. 237 from predicted.***

These identical energy ratios and total energies suggest that both measured and predicted biomarkers have the same effect on the formation of daily averaged glucose (a basis for evaluating HbA1C). ***FPG (an indicator of pancreatic beta cells' health state in terms of insulin quality and quantity) offers the largest influence or "energy influx" of 38%.*** *However, the slightly different correlation (R) indicates small variations among waveforms (i.e., curve shapes) of annual curves. Additionally, daily predictions of PPG exhibit slightly lower correlation (99.9%) and accuracy (99.7%) due to* ***the consideration of only three major influential factors from the 22 identified influential factors in his PPG prediction equation.***

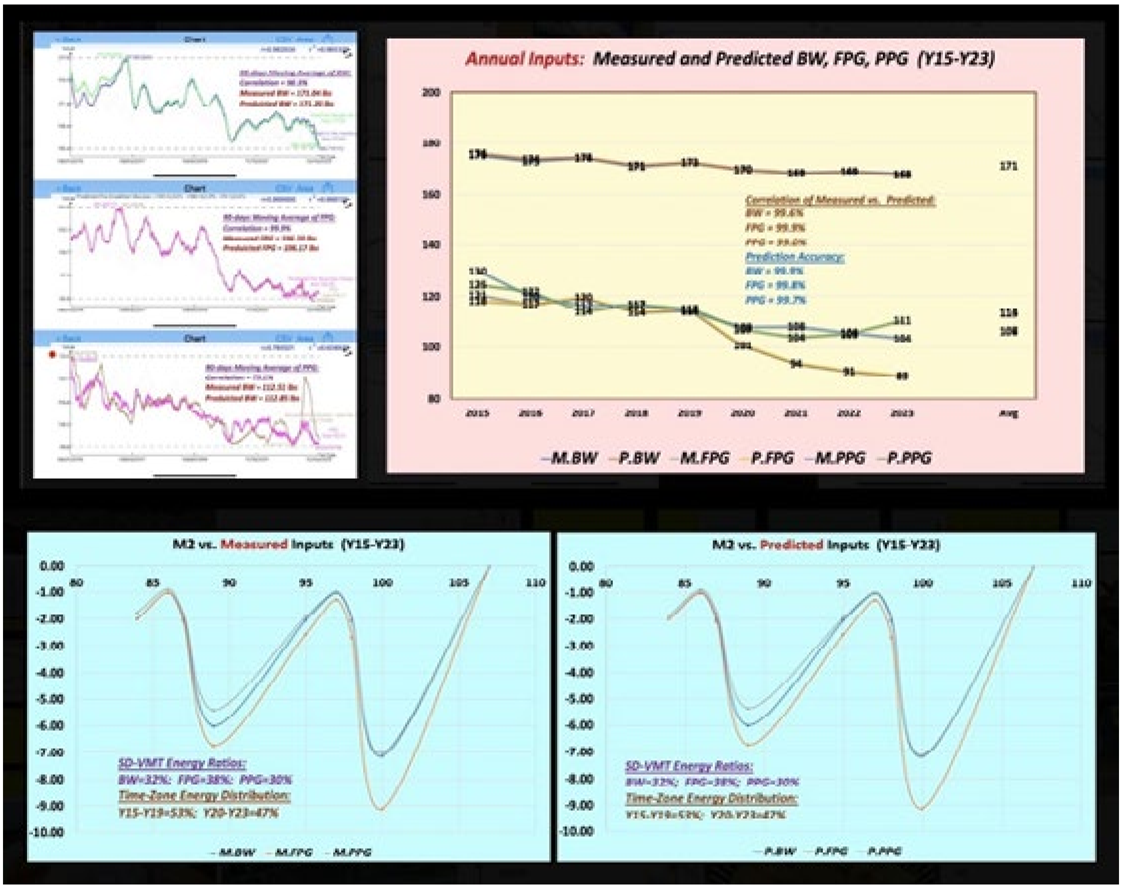
The time-zone energy distributions were found to have identical ratios between measured and predicted:

- ***2013-2018: 53% vs. 53%***
- ***2019-2023: 47% vs. 47%***

Key Message

Both measured and predicted biomarkers have an identical influential effect on daily average glucose (or HbA1c values).

Improved predictions can indeed lead to better health outcomes and accurate prediction of biomarkers can offer early warnings to patients before health damage occurs, epitomizing the essential spirit of "preventive medicine."



1. Introduction

After 18 years of studying at seven universities and pursuing various careers in professional engineering, founding seven start-ups, and managing high-tech businesses, the 63-year-old author faced severe, lifethreatening health issues in 2010. This experience prompted him to undertake a self-study of internal medicine and food nutrition in order to save his own life.

Individuals with chronic diseases often face challenges in managing their body weight and glucose levels, which fluctuate constantly and over extended periods. Drawing on his 30 years of industrial experience in engineering design and the electronics semiconductor business, the author recognized the significance of "prediction" in averting failures in machines, structures, and business operations. He applied predictive analysis techniques from engineering and enterprise systems to enhance damage prevention and reduce the likelihood of breakdowns or failures.

The author initially directed his medical research towards developing predictive equations for three key biomarkers: body weight, fasting morning glucose, and post-meal glucose. His prediction formulas for these three biomarkers demonstrated exceptionally high accuracy and very high waveform similarities, both exceeding 99%, In this study, the space-domain viscoplastic medicine energy theory (SD-VMT) was utilized to analyze the dynamic relationships between daily average glucose (eAG or M2) and three key biomarkers: body weight (BW), fasting plasma glucose (FPG), and postprandial plasma glucose (PPG).

2. Biomedical Information

The following sections contain excerpts and concise information drawn from multiple medical articles, which have been meticulously reviewed by the author of this paper. The author has adopted this approach as an alternative to including a conventional reference list at the end of this document, with the intention of optimizing his valuable research time. It is essential to clarify that these sections do not constitute part of the author's original contribution but have been included to aid the author in his future reviews and offer valuable insights to other readers with an interest in these subjects.

Pathophysiological explanations of Relationship Between Daily Averaged Glucose and Body weight, Fasting Morning Glucose, and Post-Meal Glucose

The relationship between daily averaged glucose and body weight, fasting morning glucose, and postmeal glucose can be explained through various pathophysiological mechanisms.

- **Body Weight:** Increased body weight can lead to insulin resistance, which in turn can cause higher blood glucose levels. Adipose tissue produces hormones and inflammatory substances that can impair insulin sensitivity and lead to elevated blood glucose levels.
- **Fasting Morning Glucose:** In the early morning, the body's hormonal balance and the effect of the dawn phenomenon can cause an increase in fasting morning glucose. This may be influenced by the release of counter-regulatory hormones such

as cortisol and growth hormone, leading to higher blood glucose levels.

• **Post-Meal Glucose:** After consuming a meal, blood glucose levels rise as the body metabolizes carbohydrates and sugar. In individuals with impaired glucose tolerance, post-meal glucose levels can remain elevated for longer periods due to delayed insulin response or insulin resistance.

These pathophysiological explanations illustrate how factors such as body weight, hormonal fluctuations, and insulin sensitivity can impact daily averaged glucose levels. Understanding these relationships can be valuable in managing and predicting glucose levels in individuals with diabetes or other metabolic conditions.

4. MPM Background

To learn more about his developed GH-Method: math-physical medicine (MPM) methodology, readers can read the following three papers selected from his published 760+ papers. The first paper, No. 386 (Reference 1) describes his MPM methodology in a general conceptual format. The second paper, No. 387 (Reference 2) outlines the history of his personalized diabetes research, various application tools, and the differences between biochemical medicine (BCM) approach versus the MPM approach. The third paper, No. 397 (Reference 3) depicts a general flow diagram containing ~10 key MPM research methods and different tools.

5. The Author's Diabetes History

The author was a severe T2D patient since 1995. He weighed 220 lb. (100 kg) at that time. By 2010, he still weighed 198 lb. with an average daily glucose of 250 mg/dL (HbA1C at 10%). During that year, his triglycerides reached 1161 (high risk for CVD and stroke) and his albumin-creatinine ratio (ACR) at 116 (high risk for chronic kidney disease). He also suffered from five cardiac episodes within a decade. In 2010, three independent physicians warned him regarding the need for kidney dialysis treatment and the future high risk of dying from his severe diabetic complications.

In 2010, he decided to self-study endocrinology with an emphasis on diabetes and food nutrition. He spent the entire year of 2014 to develop a metabolism index (MI) mathematical model. During 2015 and 2016, he developed four mathematical prediction models related to diabetes conditions: weight, PPG, fasting plasma glucose (FPG), and HbA1C (A1C). Through using his developed mathematical metabolism index (MI) model and the other four glucose prediction tools, by the end of 2016, his weight was reduced from 220 lbs. (100 kg) to 176 lbs. (89 kg), waistline from 44 inches (112 cm) to 33 inches (84 cm), average fingerpiercing glucose from 250 mg/dL to 120 mg/dL, and A1C from 10% to ~6.5%. One of his major accomplishments is that he no longer takes any diabetes-related medications since 12/8/2015.

In 2017, he achieved excellent results on all fronts, especially his glucose control. However, during the preCOVID period, including both 2018 and 2019, he traveled to ~50 international cities to attend 65+ medical conferences and made ~120 oral presentations. This hectic schedule inflicted damage to his diabetes control caused by stress, dining out frequently, post-meal exercise disruption, and jet lag, along with the overall negative metabolic impact from the irregular life patterns; therefore, his glucose control was somewhat affected during the two-year traveling period of 2018-2019.

He started his COVID-19 selfquarantined life on 1/19/2020. By 10/16/2022, his weight was further reduced to ~164 lbs. (BMI 24.22) and his A1C was at 6.0% without any medication intervention or insulin injection. In fact, with the special COVID-19 quarantine lifestyle since early 2020, not only has he written and published ~500 new research articles in various medical and engineering journals, but he has also achieved his best health conditions for the past 27 years. These achievements have resulted from his non-traveling, low-stress, and regular daily life routines. Of course, his indepth knowledge of chronic diseases, sufficient practical lifestyle management experiences, and his own developed high-tech tools have also contributed to his excellent health improvements.

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. Furthermore, he extracted the 5minute intervals from every 15minute interval for a total of 96 glucose data each day stored in his computer software.

Through the author's medical research work over 40,000 hours and read over 4,000 published medical papers online in the past 13 years, he discovered and became convinced that good life habits of not smoking, moderate or no alcohol intake, avoiding illicit drugs; along with eating the right food with wellbalanced nutrition, persistent exercise, having a sufficient and good quality of sleep, reducing all kinds of unnecessary stress, maintaining a regular daily life routine contribute to the risk reduction of having many diseases, including CVD, stroke, kidney problems, micro blood vessels issues, peripheral nervous system problems, and even cancers and dementia. In addition, a long-term healthy lifestyle can even "repair" some damaged internal organs, with different required time-length depending on the particular organ's cell lifespan. For example, he has "self-repaired" about 35% of his damaged pancreatic beta cells during the past 10 years.

6. Energy Theory

The human body and organs have around 37 trillion live cells which are composed of different organic cells that require energy infusion from glucose carried by red blood cells; and energy consumption from laborwork or exercise. When the residual energy (resulting from the plastic glucose scenario) is stored inside our bodies, it will cause different degrees of damage or influence to many of our internal organs.

According to physics, energies associated with the glucose waves are proportional to the square of the glucose amplitude. The residual energies from elevated glucoses are circulating inside the body via blood vessels which then impact all of the internal organs to cause different degrees of damage or influence, e.g. diabetic complications. Elevated glucose

(hyperglycemia) causes damage to the structural integrity of blood vessels. When it combines with both hypertension (rupture of arteries) and hyperlipidemia (blockage of arteries), CVD or Stroke happens. Similarly, many other deadly diseases could result from these excessive energies which would finally shorten our lifespan. For an example, the combination of hyperglycemia and hypertension would cause micro-blood vessel's leakage in kidney systems which is one of the major cause of CKD.

The author then applied Fast Fourier Transform (FFT) operations to convert the input wave from a time domain into a frequency domain. The y-axis amplitude values in the frequency domain indicate the proportional energy levels associated with each different frequency component of input occurrence. ***Both output symptom value (i.e.strain amplitude in the time domain) and output symptom fluctuation rate (i.e. the strain rate and strain frequency) are influencing the energy level (i.e. the Y-amplitude in the frequency domain).***

Currently, many people live a sedentary lifestyle and lack sufficient exercise to burn off the energy influx which causes them to become overweight or obese. Being overweight and having obesity leads to a variety of chronic diseases, particularly diabetes. In addition, many types of processed food add unnecessary ingredients and harmful chemicals that are toxic to the bodies, which lead to the development of many other deadly diseases, such as cancers. For example, ~85% of worldwide diabetes patients are overweight, and ~75% of patients with cardiac illnesses or surgeries have diabetes conditions.

In engineering analysis, when the load is applied to the structure, it bends or twists, i.e. deform; however, when the load is removed, it will either be restored to its original shape (i.e, elastic case) or remain in a deformed shape (i.e. plastic case). In a biomedical system, the glucose level will increase after eating carbohydrates or sugar from food; therefore, the carbohydrates and sugar function as the energy supply.

After having labor work or exercise, the glucose level will decrease. As a result, the exercise burns off the energy, which is similar to load removal in the engineering case. In the biomedical case, both processes of energy influx and energy dissipation take some time which is not as simple and quick as the structural load removal in the engineering case. Therefore, the age difference and 3 input behaviors are "dynamic" in nature, i.e. timedependent. This time-dependent nature leads to a "viscoelastic or viscoplastic" situation. ***For the author's case, it is "viscoplastic" since most of his biomarkers are continuously improved during the past 13-year time window.***

Time-Dependent Output Strain and Stress of (Viscous Input*Output Rate):

Hooke's law of linear elasticity is expressed as:
Strain (ε:epsilon)= Stress (σ: sigma) / Young's modulus (E)

For biomedical glucose application, his developed linear elastic glucose theory (LEGT) is expressed as:
PPG (strain) = carbs/sugar (stress) * GH.p-Modulus (a positive number) + post-meal walking ksteps * GH.w-Modulus (a negative number)
Where GH.p-Modulus is reciprocal of Young's modulus E.

However, in viscoelasticity or viscoplasticity theory, the stress is expressed as:
Stress = viscosity factor (η: eta) * strain rate (dε/dt)
Where strain is expressed as Greek epsilon or ε.

In this article, in order to construct an "ellipse-like" diagram in a stressstrain space domain (e.g. "hysteresis loop") covering both the positive side and negative side of space, he has modified the definition of strain as follows:

Strain= (body weight at certain specific time instant)

He also calculates his strain rate using the following formula:
Strain rate = (body weight at next time instant) - (body weight at present time instant)

The risk probability % of developing into CVD, CKD, Cancer is calculated based on his developed metabolism index model (MI) in 2014. His MI value is calculated using inputs of 4 chronic conditions, i.e. weight, glucose, blood pressure, and lipids; and 6 lifestyle details, i.e. diet, drinking water, exercise, sleep, stress, and daily routines. These 10 metabolism categories further contain ~500 elements with millions of input data collected and processed since 2010. For individual deadly disease risk probability %, his mathematical model contains certain specific weighting factors for simulating certain risk percentages associated with different deadly diseases, such as metabolic disorderinduced CVD, stroke, kidney failure, cancers, dementia; artery damage in heart and brain, micro-vessel damage in kidney, and immunity-related infectious diseases, such as COVID death.

Some of explored deadly diseases and longevity characteristics using the ***viscoplastic medicine theory (VMT)*** include stress relaxation, creep, hysteresis loop, and material stiffness, damping effect ***based on time-dependent stress and strain*** which are different from his previous research findings using ***linear elastic glucose theory (LEGT)*** and ***nonlinear plastic glucose theory (NPGT).***

7. Results

No.999																			
Measured					/ 170	/ 90	/ 120	S. Rate	Strain	Strs 1	Strs 2	Strs 3	Hgt 1	Hgt 2	Hgt 3	Area 1	Area 2	Area 3	Time
12/16/23	M2%	M.BW	M.FPG	M.PPG	M.BW	M.FPG	M.PPG	M2%	M2%	M.BW	M.FPG	M.PPG	M.BW	M.FPG	M.PPG	M.BW	M.FPG	M.PPG	Zone
2015	107	175	121	130	1.03	1.34	1.08	0.00	107	0.00	0.00	0.00	0.00	0.00	0.00	0	0	0	Y15-Y19
2016	100	173	117	120	1.02	1.30	1.00	-7.00	100	-7.12	-9.10	-7.01	-3.56	-4.55	-3.51	25	32	25	126
2017	98	174	120	117	1.03	1.33	0.97	-2.00	98	-2.05	-2.66	-1.94	-4.59	-5.88	-4.48	9	12	9	53%
2018	97	171	114	117	1.01	1.26	0.97	-1.00	97	-1.01	-1.26	-0.97	-1.53	-1.96	-1.46	2	2	1	
2019	95	173	115	114	1.02	1.27	0.95	-2.00	95	-2.03	-2.55	-1.90	-1.52	-1.90	-1.44	3	4	3	
2020	89	170	101	108	1.00	1.12	0.90	-6.00	89	-6.00	-6.73	-5.40	-4.02	-4.64	-3.65	24	28	22	Y20-Y23
2021	87	169	94	108	0.99	1.04	0.90	-2.00	87	-1.98	-2.08	-1.80	-3.99	-4.41	-3.60	8	9	7	111
2022	86	169	91	106	1.00	1.01	0.88	-1.00	86	-1.00	-1.01	-0.88	-1.49	-1.55	-1.34	1	2	1	47%
2023	84	168	89	104	0.99	0.99	0.86	-2.00	84	-1.98	-1.97	-1.73	-1.48	-1.48	-1.31	3	3	3	
Avg	94	171.4	106.7	113.7	1.01	1.19	0.95	-2.56	94	-2.57	-3.04	-2.40	-2.46	-2.93	-2.31	75.2	90.6	70.9	
Correl.	100%	95%	94%	99%										SD-E:	236.7	32%	38%	30%	

No.999																			
Predicted					/ 170	/ 90	/ 120	S. Rate	Strain	Strs 1	Strs 2	Strs 3	Hgt 1	Hgt 2	Hgt 3	Area 1	Area 2	Area 3	Time
12/16/23	M2%	P.BW	P.FPG	P.PPG	P.BW	P.FPG	P.PPG	M2%	M2%	P.BW	P.FPG	P.PPG	P.BW	P.FPG	P.PPG	P.BW	P.FPG	P.PPG	Zone
2015	107	176	118	125	1.04	1.32	1.04	0.00	107	0.00	0.00	0.00	0.00	0.00	0.00	0	0	0	Y15-Y19
2016	100	174	117	122	1.02	1.30	1.02	-7.00	100	-7.16	-9.10	-7.11	-3.58	-4.55	-3.56	25	32	25	127
2017	98	175	120	114	1.03	1.33	0.95	-2.00	98	-2.05	-2.66	-1.90	-4.61	-5.88	-4.51	9	12	9	53%
2018	97	171	114	117	1.01	1.26	0.98	-1.00	97	-1.01	-1.26	-0.98	-1.53	-1.96	-1.44	2	2	1	
2019	95	173	115	115	1.02	1.27	0.96	-2.00	95	-2.03	-2.55	-1.93	-1.53	-1.91	-1.45	3	4	3	
2020	89	170	101	107	1.00	1.12	0.89	-6.00	89	-5.99	-6.72	-5.35	-4.01	-4.63	-3.64	24	28	22	Y20-Y23
2021	87	168	94	104	0.99	1.04	0.87	-2.00	87	-1.98	-2.08	-1.74	-3.99	-4.40	-3.55	8	9	7	111
2022	86	169	91	105	0.99	1.01	0.88	-1.00	86	-0.99	-1.01	-0.88	-1.49	-1.55	-1.31	1	2	1	47%
2023	84	168	89	111	0.99	0.99	0.92	-2.00	84	-1.97	-1.98	-1.84	-1.48	-1.49	-1.36	3	3	3	
Avg	94	171.5	106.5	113.3	1.01	1.18	0.94	-2.56	94	-2.58	-3.04	-2.41	-2.47	-2.93	-2.31	75.4	90.5	71.2	
Correl.	100%	96%	92%	91%										SD-E:	237	32%	38%	30%	
Correlation of M & P	99.6%	99.9%	90.0%																
Predict Accuracy	99.9%	99.8%	99.7%																

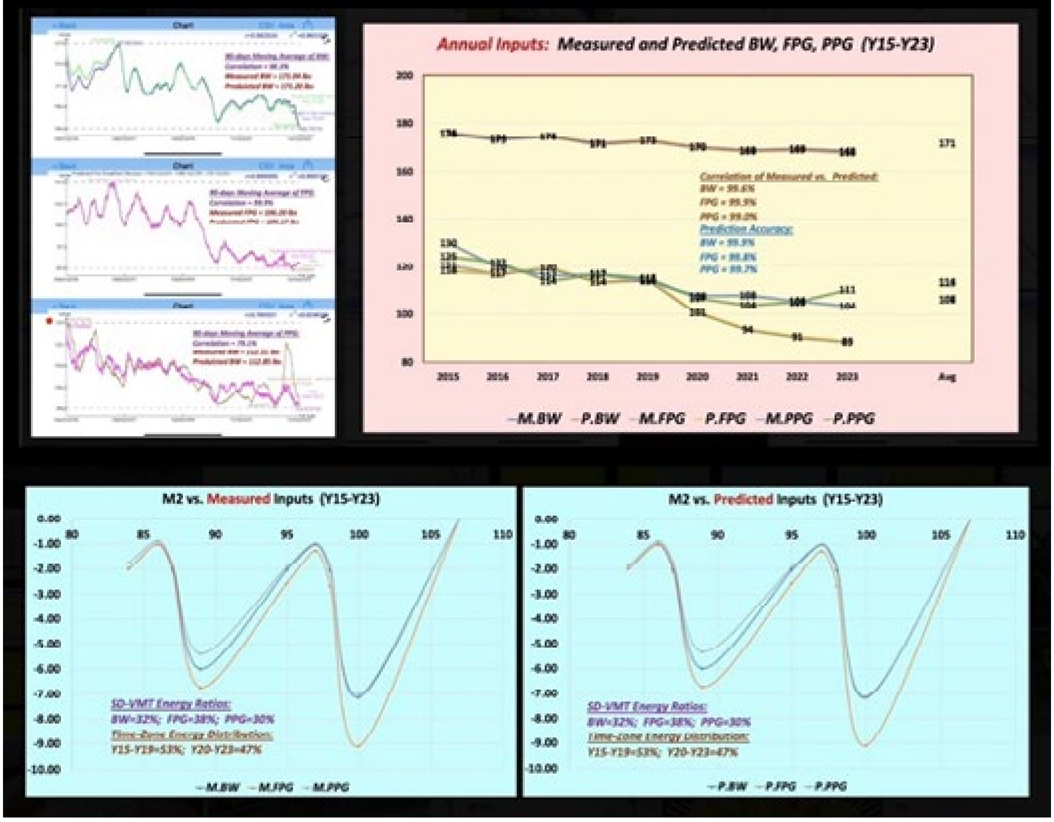


Figure 1: Data Tables, Inputs, and SD-VMT Energy Diagrams

8. Conclusions

In summary, the findings from the author's last 8.5 years data analyses show the following SD-VMT energy ratios, ***expressed as "measured vs. predicted":***

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- ***FPG: 38% vs. 38% (R = 94% vs. 92%)***
- ***PPG: 30% vs. 30% (R = 99% vs. 91%)***
- ***Total SD-VMT energy = 237 from measured vs. 237 from predicted.***

These identical energy ratios and total energies suggest that both measured and predicted biomarkers have the same effect on the formation of daily averaged glucose (a basis for evaluating HbA1C). ***FPG (an indicator of pancreatic beta cells' health state in terms of insulin quality and quantity) offers the largest influence or "energy influx" of 38%.*** However, the slightly different correlation (R) indicates small variations among waveforms (i.e., curveshapes) of annual curves. Additionally, daily predictions of PPG exhibit slightly lower correlation (99.9%) and accuracy (99.7%) due to ***the consideration of only three major influential factors from the 22 identified influential factors in his PPG prediction equation.***

The time-zone energy distributions were found to be identical between measured and predicted:

- ***2013-2018: 53%***
- ***2019-2023: 47%***

Key Message

From an energy perspective on the impact of body health, both measured and predicted biomarkers have the same influential effect. The energy shows the quantitative influences on the author's daily averaged glucoses (or HbA1c values) from these three biomarkers.

Improved predictions can indeed lead to better health outcomes, which epitomizes the essential spirit of "preventive medicine."

References:

For editing purposes, 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. Readers may use this article as long as the work is properly cited, and their use is educational and not for profit, and the author's original work is not altered. For reading more of the author's published VGT or FD analysis results on medical applications, please locate them through platforms for scientific research publications, such as ResearchGate, Google Scholar, etc.