

The GH-Method

Viscoelastic Medicine theory (VMT #424): Study of annual lab-tested HbA1C versus 5 glucose components of k-line glucose diagram using Viscoplastic Energy Model of GH-Method: Math-Physical Medicine (No. 1026)

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Abstract

Hemoglobin A1C (HbA1C) indicates average blood glucose levels over roughly 3 months, reflecting glucose attachment to hemoglobin in red blood cells. Hyperglycemia, defined as blood sugar levels consistently above 180 mg/dL, increases HbA1C due to more glucose binding to hemoglobin. This heightened glycation, glucose's attachment process to hemoglobin, stems from elevated glucose. Prolonged hyperglycemia can harm internal organs, potentially leading to life-threatening diseases. On the flip side, hypoglycemia (blood sugar levels below 70 mg/dL) results in lower HbA1C levels due to reduced glycation. Severe hypoglycemia can trigger insulin shock, which might be fatal.

Daily averaged postprandial plasma glucose (PPG) levels indicating the blood sugar concentration after meals, also affect HbA1C. Consistently high daily PPG levels raise HbA1C over time.

Therefore, HbA1C gives an overview of long-term blood glucose levels, influenced by both hypoglycemia and hyperglycemia as well.

In 2019, the author adapted the K-line concept from stock market analysis to create a continuous glucose diagram featuring five key data points: opening glucose (at 0-minute), closing glucose (at 180 minutes), minimum and maximum glucose levels (usually around 45-75 minutes), and averaged glucose. The Introduction section of this article provides a brief description of a K-line chart, also known as a candlestick chart.

The glucose study involved two HbA1c sets: one from finger-prick tests (F.A1C, four daily readings) and another from continuous glucose monitoring (CGM) sensors (S.A1C, 96 daily

readings). Additionally, the author compared these with his quarterly laboratory-tested A1C data (L.A1C).

Using data collected between 5/5/2018 and 1/27/2024, the author's annual lab-tested A1C data served as the output strain in viscoplastic energy analysis, with the 5 K-line-based glucose as inputs.

In summary, the space-domain viscoplastic medicine theory (SD-VMT) offers the following ranked energy percentages, from high to low: - Hyperglycemia (Maximum) at 23%; - Hyperglycemia (Minimum) at 21%; - Daily average glucose at 19%; - Closed glucose (at 180-minute) at 19%; - Open glucose (at 0-minute) at 18%.

Additionally, the period of Y18-Y21 contributes to 50% of the total energy, whereas the period of Y22-Y24 contributes 50% also.

Special Observation:

A weak correlation is observed between the laboratory A1C data and the two glucose-based A1C data (14%-18%). The correlations between F.A1C and five inputs are high (87% to 95%), while the correlations between L.A1C and five inputs are low (21% to 45%). The stress-strain curve patterns between lab and finger A1C are dramatically different.

Key message:

T2D patients should prioritize attention to the hypoglycemia situation, followed by the hyperglycemia.

In both the time-domain and space-domain, the lab-A1C shows a noticeable difference from the two measures A1C (both finger and sensor).

Keywords: Viscoelastic; Viscoplastic; Diabetes; Glucose; Insulin; Hyperglycemia; Hemoglobin

Abbreviations: CGM: continuous glucose monitoring; T2D: type 2 diabetes; PPG: postprandial plasma glucose; FPG: fasting plasma glucose; SD: space-domain; VMT: viscoelastic medicine theory; FFT: Fast Fourier Transform

1. INTRODUCTION

Hemoglobin A1C (HbA1C) indicates average blood glucose levels over roughly 3 months, reflecting glucose attachment to hemoglobin in red blood cells. Hyperglycemia, defined as blood sugar levels consistently above 180 mg/dL, increases HbA1C due to more glucose binding to hemoglobin. This heightened glycation, glucose's attachment process to hemoglobin, stems from elevated glucose. Prolonged hyperglycemia can harm internal organs, potentially leading to life-threatening diseases. On the flip side, hypoglycemia (blood sugar levels below 70 mg/dL) results in lower HbA1C levels due to reduced glycation. Severe hypoglycemia can trigger insulin shock, which might be fatal.

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Using data collected between 5/5/2018 and 1/27/2024, the author's annual lab-tested A1C data served as the output strain in viscoplastic energy analysis, with the 5 K-line-based glucose as inputs.

1.1 Biomedical and Engineering or Technical information:

The following sections contain excerpts and concise information 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.

What is the k-line representation of stock data analysis?

A K-line chart, also known as a candlestick chart, is commonly used to present stock data, particularly in financial analysis and trading. It provides a visual representation of the high, low, open, and close prices of a stock during a specific period. Each "candlestick" on the chart represents a period of time, such as a day, week, or month. Here is a brief explanation of the elements commonly found in a K-line chart:

- The body of the candle: The rectangular body represents the price range between the open and close prices of the stock during the selected time period. If the close price is higher than the open price, the body is typically filled or colored (often green or white) to indicate a price increase, and if the close price is lower, the body is typically unfilled or colored differently (often red or black) to indicate a price decrease.

- The "wicks" or shadows: The lines extending from the top and bottom of the body of the candle represent the highest and lowest prices reached during the selected time period.

- The opening price: This is the price at which the stock began trading at the start of the time period represented by the candlestick.

- The closing price: This is the price at which the stock concluded trading at the end of the time period.

K-line charts are valuable for identifying patterns and trends in stock prices and are widely used in technical analysis to make informed decisions about buying, selling, or holding stocks.

Why a1C values derived from both finger-pierced glucose and CGM sensor glucose are different from lab-tested a1C values?

The discrepancy between A1C values derived from finger-pierced glucose and CGM sensor glucose compared to lab-tested A1C values can be attributed to several factors.

Firstly, finger-pierced glucose and CGM sensor glucose provide real-time measurements of blood glucose levels, which can fluctuate throughout the day based on various factors such as diet, exercise, and stress. As a result, the A1C values calculated from these measurements may reflect short-term variations in blood glucose levels and may not accurately represent the average blood glucose levels over a longer period. (The author's note: This statement seems false which does not make mathematical sense. An averaged value represents the "averaged number" regardless the time period is longer or shorter).

On the other hand, lab-tested A1C values are obtained through standardized laboratory tests that measure the average blood glucose levels over the past two to three months. These values provide a more comprehensive and stable assessment of overall blood glucose control. (The author's note: Lab-tested A1C values are subject to many influential factors as well).

Furthermore, discrepancies between A1C values derived from different measurement methods can also be influenced by the calibration and accuracy of the devices used. Finger-pierced glucose meters and CGM sensors may have inherent limitations and variability in their measurements, leading to differences in A1C values compared to lab-tested results.

It is important to consider these factors when interpreting A1C values from different sources and to consult with healthcare specialists for a comprehensive assessment of blood glucose control.

How is it possible to obtain three different A1C values, such as 6.5%, 6.8%, and 7.1%,

from A1C measurements at three different labs within the same day?

There are several reasons why having A1C measurements at three different labs within the same day can result in slightly different values, such as 6.5%, 6.8%, and 7.1%: (The author's note: 0.6% difference over 6.5% is 9% error and over 7.1% is 8.5% error. A near 10% of error should not be considered as "slight difference".)

Laboratory Methods and Equipment:
Different laboratories may use varying methods and technologies to analyze A1C levels. This can lead to minor discrepancies in results due to differences in assay methods, equipment calibration, and measurement precision.

Standardization and Quality Control:
Laboratories may have different quality control measures, calibration standards, and testing protocols. Variations in adherence to standardized procedures can result in differences in A1C values.

Precision and Accuracy:
While A1C tests are generally highly accurate, there can still be slight variability in the precision of measurements between different labs. This can lead to small differences in the reported A1C values.

Sample Handling and Processing:
Differences in sample handling, storage, and processing protocols between labs can impact the integrity and accuracy of A1C measurements. Variations in sample processing can lead to discrepancies in results.

Biological Variation:
The A1C test measures the average blood glucose levels over the past 2-3 months, and individual biological variability can influence the results. Factors such as diet, exercise, and medication can lead to slight variations in A1C levels.

It is important to note that differences of this magnitude, such as 0.3% to 0.6%, may not necessarily indicate a laboratory error. A1C tests have a certain margin of variability due to the factors mentioned above, and it is common for results to vary slightly between laboratories.

Having different A1C values from three different labs on the same day can be attributed to several factors:

Analytical Variation:

Each lab uses different equipment and methodologies, which can lead to variations in results. Even small differences in how the test is performed can affect the outcome.

Body Conditions:

The body's A1C levels can naturally fluctuate throughout the day due to physiological changes.

Sample Handling:

Differences in how blood samples are collected, stored, and processed can impact the results.

Calibration of Equipment:

If the machines are not calibrated similarly, this can lead to discrepancies.

Operator Error:

Human error in conducting the tests can also contribute to different results.

Lab Standards and Quality Control:

Different labs may adhere to different standards or have varying levels of quality control.

Environmental Factors:

Conditions like elevation, temperature and humidity in the lab can affect the results.

1.2 MPM Background:

To learn more about his developed GH-Method: math-physical medicine (MPM) methodology, readers can read the following three papers 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 the 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.

The author's diabetes history:

The author has had 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 developing 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 finger-piercing glucose from 250 mg/dL to 120 mg/dL, and A1C from 10% to ~6.5%. One of his major accomplishments is that he has no longer taken any diabetes-related medications since 12/8/2015.

In 2017, he achieved excellent results on all fronts, especially his glucose control. However, during the pre-COVID 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 self-quarantined 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 in-depth knowledge of chronic diseases, sufficient practical lifestyle management experiences, and his 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 checked his glucose measurements every 5 minutes for a total of 288 times each day. Furthermore, he extracted the 5-minute intervals from every 15-minute interval for 96 glucose data each day stored in his computer software.

Through the author's medical research work of over 40,000 hours and reading 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 well-balanced 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 lengths 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.

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 labor-work 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 glucose 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 example, the combination of hyperglycemia and hypertension would cause micro-blood vessel leakage in kidney systems which is one of the major causes 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) influence 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. deforms; 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, 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, 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. time-dependent. This time-dependent nature leads to a “viscoelastic or viscoplastic” situation. For the author’s case, it is “viscoplastic” since most of his biomarkers have 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:

$$\text{Strain } (\epsilon: \text{epsilon}) = \text{Stress } (\sigma: \text{sigma}) / \text{Young's modulus } (E)$$

For biomedical glucose application, his developed linear elastic glucose theory (LEGT) is expressed as:

$$\text{PPG (strain)} = \text{carbs/sugar (stress)} * \text{GH.p-Modulus (a positive number)} + \text{post-meal walking k-steps} * \text{GH.w-Modulus (a negative number)}$$

where GH.p-Modulus is the reciprocal of Young’s modulus E.

However, in viscoelasticity or viscoplasticity theory, the stress is expressed as:

$$\text{Stress} = \text{viscosity factor } (\eta: \text{eta}) * \text{strain rate } (d\epsilon/dt)$$

where strain is expressed as Greek epsilon or ϵ .

In this article, in order to construct an “ellipse-like” diagram in a stress-strain 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:

$$\text{Strain} = (\text{body weight at a certain specific time instant})$$

He also calculates his strain rate using the following formula:

$$\text{Strain rate} = (\text{body weight at next time instant}) - (\text{body weight at present time instant})$$

The risk probability % of developing into CVD, CKD, and 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 disorder-induced 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 the 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).

2. RESULTS

Figure 1 shows Input information.

Figure 2 shows both TD and SD results.

3. CONCLUSION

In summary, the space-domain viscoplastic medicine theory (SD-VMT) offers the following ranked energy percentages, from high to low:

- Hyperglycemia (Maximum) at 23%
- Hyperglycemia (Minimum) at 21%
- Daily average glucose at 19%
- Closed glucose (at 180-minute) at 19%
- Open glucose (at 0-minute) at 18%

Additionally, the period of Y18-Y21 contributes to 50% of the total energy, whereas the period of Y22-Y24 contributes 50% also.

Special Observation:

A weak correlation is observed between the laboratory A1C data and the two glucose-based A1C data (14%-18%). The correlations

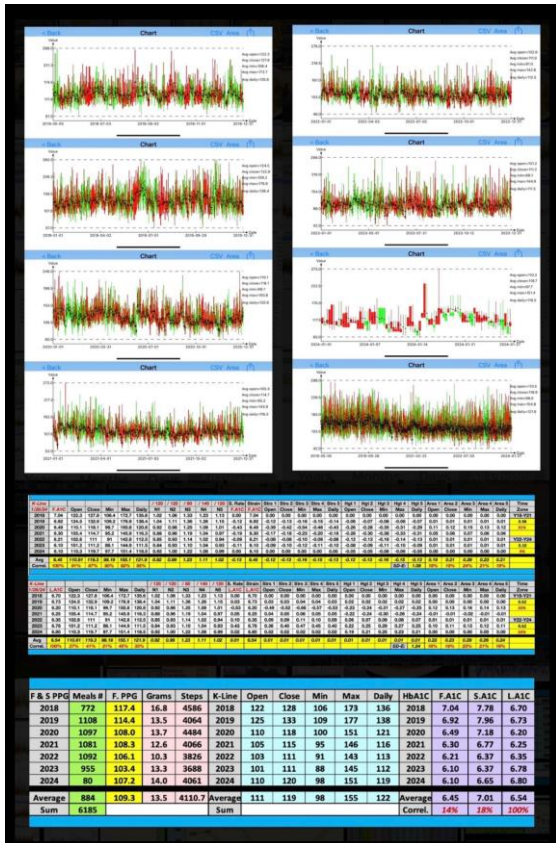


Figure 1: Input Information

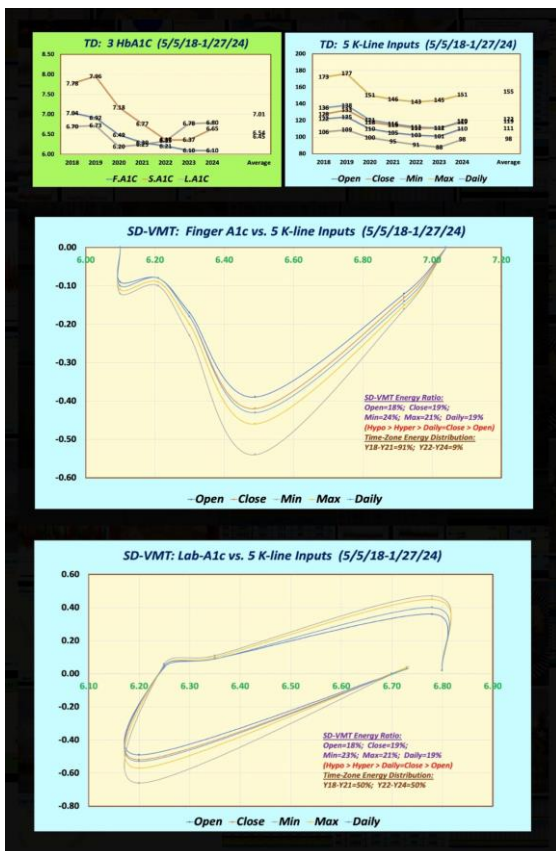


Figure 2: TD and SD results

between F.A1C and five inputs are high (87% to 95%), while the correlations between L.A1C and five inputs are low (21% to 45%). The stress-strain curve patterns between lab and finger A1C are dramatically different.

Key message:

T2D patients should prioritize attention to the hypoglycemia situation, followed by the hyperglycemia.

In both the time-domain and space-domain, the lab-A1C shows a noticeable difference from the two measures A1C (both finger and sensor).

4. 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.eclaircmd.com.

Readers may use this article as long as the work is properly cited, 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.

Viscoelastic and Viscoplastic Glucose Theory Application in Medicine

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