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A Simplified Diabetes Control Method by Applying Three GH-Moduli for Calculating Predicted Linear Postprandial Plasma Glucoses based on 12-year Lifestyle Data and Finger-Pierced Glucoses using GH-Method: Math-Physical Medicine, LEGT Part 28 (No. 417)

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Abstract

On 10/14/2020, the author wrote his first research note on his developed linear elastic glucose theory (LEGT). Over the past 5+ months, he has continuously conducted his research on this subject and completed a summary report, No. 415, LEGT Part 26 on 3/15/2021.

The majority of his research notes are based on sensor-collected data, from a self-monitoring of blood glucose (SMBG) device, synthesized the collected data into a PPG waveform with 180-minutes time span. On 3/22/2021, he started to examine the applicability of his LEGT on a nonlinear PPG wave in a time domain against his previously collected PPG data via the finger-piercing method over the past 12 years.

In summary, similar to the Young's modulus of engineering materials, the GH.p-Modulus for diet is the most important and complicated biomedical GH-modulus of those three defined GH-Moduli by the author. This GH.p is related to and also dependent on the patient's overall metabolic conditions, age, lifestyle, health, medical diseases, types of food, amount of carbs/sugar intake, and to some degree the chosen time-window for certain analyses. Nevertheless, its linear and elastic behaviors and general glucose characteristics are quite comparable to the Young's modulus of stress and strain in theory of elasticity of engineering. Thus far, all of the author's collected glucose data and behaviors appeared are very well within the defined "elastic" region. Therefore, his developed LEGT should be useful for other type 2 diabetes (T2D) patients to control their diabetes conditions.

Introduction

On 10/14/2020, the author wrote his first research note on his developed linear elastic glucose theory (LEGT). Over the past 5+ months, he has continuously conducted his research on this subject and completed a summary report, No. 415, LEGT Part 26 on 3/15/2021.

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Methods

MPM Background

To learn more about his developed GH-Method: math-physical medicine (MPM) methodology, readers can read the following three papers selected from the published 400+ medical 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.

The Author'S Case of Diabetes

The author was a severe type 2 diabetes patient since 1996. 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 of 10%). During that year, his triglycerides reached to 1161 (high risk for CVD and stroke) and 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 needs of kidney dialysis treatment and future high risk of dying from his severe diabetic complications.

In 2010, he decided to self-study endocrinology with emphasis on diabetes and food nutrition. During 2015 and 2016, he developed four mathematical prediction models related to diabetes conditions: weight, postprandial plasma glucose (PPG), fasting plasma glucose (FPG), and HbA1C (A1C). By applying his developed mathematical metabolism index (MI) model in 2014 and the four glucose prediction tools during 2015-2016, 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 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 medications starting from 12/8/2015.

In 2017, he had achieved excellent results on all fronts, especially his glucose control. However, during the pre-COVID period of 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, dinning out frequently, post-meal exercise disruption, jet lag, along with the overall negative metabolic impact from the irregular life patterns; therefore, his glucose control was affected during the two-year period of 2019-2020.

He started his self-quarantined life on 1/19/2020. By the end of 2020, his weight was further reduced to 165 lbs. (BMI 24.4) and his A1C was at 6.2% without any medications intervention or insulin injection. In fact, with the special COVID-19 quarantine lifestyle in 2020, not only has he published ~400 medical papers in various journals, but he has also achieved his best health conditions for the past 26 years. The good results are due to his non-traveling, low-stress, and regular daily life routines. Of course, his in-depth knowledge on chronic diseases, sufficient practical lifestyle management experiences, and his developed various high-tech tools contributed to his excellent health status since 1/19/2020.

On 5/5/2018, he applied a continuous glucose monitoring (CGM) sensor device on his upper arm and checks his glucose measurements every 15 minutes for a total of ~96 times each day. He has maintained the same measurement pattern to present day. Therefore, during the past 11 years, he could continuously investigate, study, and analyze his collected ~2 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 entire medical research work is based on the aims of achieving both "high precision" with "quantitative proof" in the medical findings, not just through linguistic expressions with qualitative words, vague statements, or complex medical terminologies.

Highlights of his Developed Linear Elastic Glucose Theory (LEGT)

The author self-studied internal medicine, including endocrinology and food nutrition over a 4-year period from 2010 to 2013. By the end of 2013, he has learned the primary connecting pathway moving from lifestyle to metabolism and immunity, which are two sides of the same coin, and then moving to both chronic diseases (caused by metabolic disorders) and infectious diseases (defended by our immune system), and finally to induce all kinds of diseases which lead to death.

Therefore, in 2014, he spent the entire year to develop a mathematical model of metabolism using topology concept of mathematics and finite element method of engineering which includes 10 categories and near 500 elements. All of its input data are more than 2 million thus far.

Due to the fact that PPG is the major factor of daily glucose composition and HbA1C measurement which affects diabetes conditions and its complications directly. Therefore, starting from 2015, he started to develop his prediction model for post-prandial plasma glucose (PPG). He has identified approximately 19 influential factors of PPG formation, where the health state of pancreatic beta cells insulin secretion (quantity) and insulin resistance (quality) are the most important and the fundamental factor. Since it occupies more than 2/3 of total influences on PPG, he chose it as the "baseline PPG". Once removing this biomedical factor of insulin (~50% to 80% or 67% of contribution), the other 18 remaining lifestyle details, ranging from ~20% to 50% or 33%, contribute to the final PPG formation. Taking a macro-view of PPG formation, the pancreatic beta cells accounts for ~50% to 67% and diet of lifestyle provides ~50%, while diet contributes ~33% and post-meal walking exercise contributes about -17% (negative correlation). Although the combined diet and exercise are about 1/3 of PPG, they are the only factors that diabetes patients can control. The current diabetes treatments by physicians to stabilize glucose levels are through medications and/or insulin injections. Unfortunately, this type of treatment attempts to alter the external symptom (i.e., output only) of the endocrinological diabetes disease but does not cure or even improve parts of the root cause. Only a long-term persistent effort of lifestyle management can truly "repair or improve" the damaged pancreatic beta cells.

Using various GH-Method: math-physical medicine tools on his collected big data, *he had an intuition that the existence for a linear relationship between his measure PPG and carbs/sugar intake amount with a multiplying coefficient around 1.0 to 3.0 for a longer time-window or 1.8 to 2.5 for a specific shorter time-window.*

In order to solve the puzzle of the predicted PPG, the first task is to identify an accurate but easy way to estimate carbs/sugar intake amount. Utilizing optical physics (relationship among visible food color, internal wavelength, molecular structure, and nutritional ingredients), big data analytics (~6 million collected food nutritional data and 160 million digits of meal photo), and AI (machine learning and self-correction), he developed a computer software program to predict the carbs/sugar amount in his food or meals via a picture with a prediction accuracy of >99% (for over 3,000 meals or food pictures). He then applied this GH.p-Modulus of linear coefficient at 1.8 to 2.5 to multiply his estimated carbs/sugar amount from the AI tool in order to obtain the incremental PPG from food. This observed linear coefficient of 1.8 to 2.5 was his first identified GH-modulus, the GH.p-Modulus.

Diet is the most complicated part of this puzzle. Actually, a predicted PPG wave is a dynamic physical phenomenon and a nonlinear mathematical problem. In order to simplify this difficult task at hand, he broke down this synthesized nonlinear system into 3 simpler linear systems or 3 straight-line segments, which are the pancreatic beta cells' insulin, diet for rising glucose, and exercise for declining glucose.

After 9-months of struggling during 2015-2016, in the early morning of 3/16/2016, he finally discovered a strong correlation (>80% of R, the correlation coefficient) existing between his body weight and his collected fasting plasma glucose (FPG) by having an "out-of-box" thinking. Since both weight and FPG belong to the output category of the biomedical system, while lifestyle details belong to the input category. As a trained engineer, he was taught to always seek and identify those relationships existing between inputs and outputs, not just among outputs or among inputs.

From 2017 to 2020, he utilized 7 to 8 different research angles to investigate his pancreatic beta cells' "self-repair" situation. Since there is no food or exercise associated with glucose during sleep hours to confuse the equation, by using the FPG data, a long-term record of FPG or weight can serve as a reliable "benchmark indicator" for the pancreatic health state. As a result, he identified his second GH-Modulus, the GH.f-Modulus, to transform either weight or FPG into a baseline PPG.

Relatively speaking, exercise is a much easier subject to be dealt with. Based on his trial-and-error for the linear coefficient between the post-meal walking k-steps (1,000-steps) and reduction amount of PPG, he identified that PPG would be reduced by 5 to 6 mg/dL for every thousand steps after having meals (1000 steps equals to about 10 minutes of walking). Therefore, he chose -5 to -6 as his third GH-Modulus, the GH-w-Modulus.

By combining these three linear models together, he obtained a "pseudo-linear" model (i.e., 3 straight lines) of his predicted PPG waveform as shown in Figure 1. For a better comparison, this pseudo-linear model is then superposed with a synthesized nonlinear PPG wave over 180 minutes from his collected 3,255 meals data over a period of 1,085 days from 5/5/2018 to 3/15/2021.

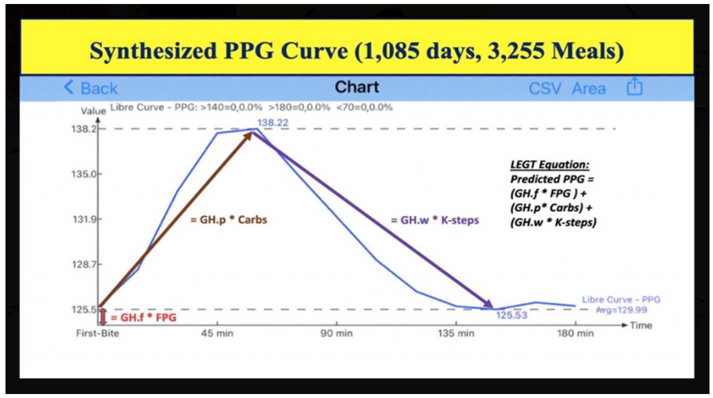

Figure 1: Three linear segments of a synthesized PPG wave using three GH-Moduli of LEGT

If readers are interested in learning his step-by-step development and more detailed explanation of the predicted PPG equation using LEGT, they can read the author's published papers listed in References 4 through 29. He displays his LEGT equation below (also see Figure 1).

The LEGT equation is:

Predicted PPG= Baseline PPG + food induced incremental PPG + exercise induced incremental PPG

or,

Predicted PPG= (FPG * GH.f) + (Carbs/sugar * GH.p) + (post-meal walking k-steps * GH.w)

Based on his experiences on utilizing his GH-Modulus, the GH.f should fall into the range between 0.6 to 1.0 depending upon the choice of weight or FPG. Frequently, for his own case, he choose 0.6 if using Weight; or choose 0.97 / 1.0 if using FPG to start his equation calculation. He also choose the GH.w as -5.0 for most of his exercise cases. Finally, *the GH.p-Modulus, the most important and difficult multiplier defines the food induced incremental PPG, is described again as follows:*

Food induced Incremental PPG= GH.p * carbs/sugar
or
GH.p = incremental PPG / carbs

In comparison with Young's modulus equation:
E = stress / strain

where higher E (stiff material) under the same stress would result into less strain.

If we consider carbs/sugar intake similar to stress and incremental PPG similar to strain, the*n the biomedical GH.p-modulus and engineering E of Young's Modulus would have a* ***"reciprocal"*** *relationship to each other.*

Therefore, a higher E of Young's modulus value is equivalent to a lower GH.p-Modulus value. If a higher E (stiff material) under the same stress level would result in a lower strain. This is similar to a lower GH.p-Modulus under the same carbs/sugar intake amount which would result in a smaller amount of incremental PPG; or the same GH.p-Modulus with the smaller carbs/sugar intake amount which would result in a smaller amount of incremental PPG.

The above explanation provides an analogy of LEGT in biomedicine with the theory of elasticity in engineering.

More Detailed Description of LEGT based PPG Prediction

This section will illustrate the step-by-step development of his developed LEGT model.

The first step discusses the baseline PPG which is the PPG level at the time instant of 0-minute i.e., the first bite of meal. As mentioned above, the early morning glucose level after waking up is a good "benchmark indicator" for the pancreatic health state. The FPG value has a different mechanism from the insulin generating capability, but it is directly proportional to the health state of the pancreatic beta cells insulin. Furthermore, FPG and weight have an extremely high correlation coefficient (>80%) between them (see Figure 2). Most diabetes patients know their daily weight, where some of them monitor their FPG on a regular basis. Therefore, depending on the data availability for either weight or FPG, patients may choose one of the following two equations to use:

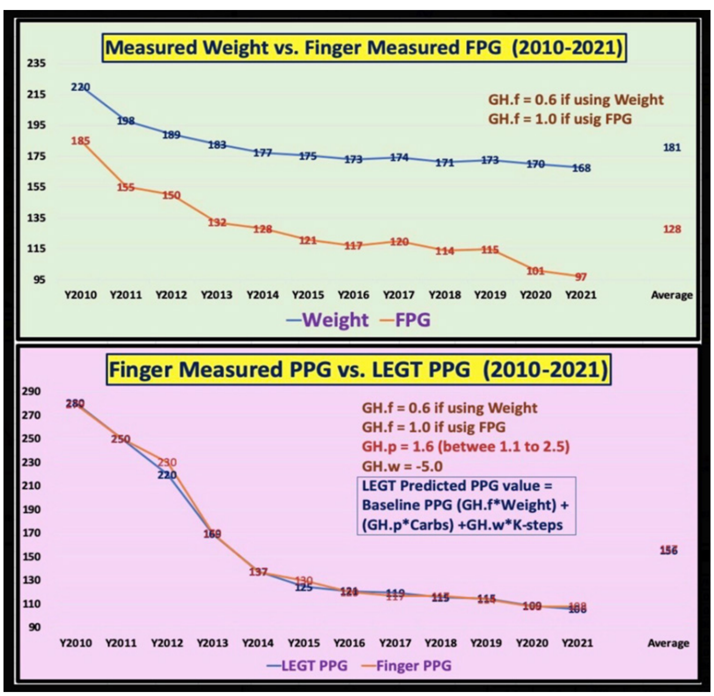

Figure 2: Weight vs. FPG; measured PPG vs. LEGT PPG

Baseline PPG = (0.6 - 0.7) * weight
Baseline PPG = (0.9 - 1.0) * FPG

The second step discusses the rising of PPG values from the starting time at 0-minute (defined as P1 value) to its peak at 45-minutes to 75-minutes. Let us assume the PPG value reaches to its peat at 60-minutes (defined as P2 value). During this time frame, the major fuel for this action of PPG rising is resulted from carbs/sugar intake with meal. Therefore, the second segment of LEGT PPG equation can be listed below:

Incremental PPG amount= P2 -P1= (carbs/sugar intake grams) * GH.p

Where GH.p-Modulus range is between 1.0 and 6.0. But the narrower range of 1.8-2.5 is suitable for many patients under normal diet situations.

During this second step, patients could utilize the author's developed AI food nutrition program or rely on their own learned knowledge about carbs/sugar amount for each meal to complete the calculation.

The third step examines the PPG value reduction between time instant of 60-minutes to 180-minutes (defined as P3 value). It should add another time instant of 120-minutes (defined as Finger PPG value), where the PPG value corresponds to the advice of physicians to diabetes patients on measuring their PPG at two hours after the first bite of meals using the finger-piercing method. The PPG reduction amount can be calculated using the following equation:

PPG reduction amount= P2-P3= (post-meal walking k-steps) * GH.w

Where GH.w-Modulus range is between -5 and -6, the selected GH.w value of -5 is suitable for many patients under normal walking conditions. Other types of exercise are also acceptable but its related GH.w value must be re-evaluated carefully in additional experiments.

At this stage, a natural biomedical nonlinear PPG wave can then be replaced by three straight-lines and converts the nonlinear real PPG wave into a "pseudo-linear" representation with a high accuracy of prediction, but it is definitely a simpler way to distinguish PPG situations.

For the LEGT PPG case, its average glucose values are listed with a *"geometry equation"* below:

Averaged LEGT PPG= (2.5*P1+6.0*P2+4.5*P3)/13

and

Finger PPG= 0.87 * LEGT PPG at 120-minutes= 0.87 * (P2+P3)/2

The above descriptions include the important equations and three

GH-Modulus, which are the building blocks of the AI-based PPG program. For most T2D patients, they enter their weight or FPG values, average carb/sugar intake grams, and post-meal walking k-steps over a selected time period into the software program. Then, this AI assistant tool will perform the rest of necessary calculations. In the future, the author will continuously augment more AI-based machine-learning capabilities into it in order to deal with a variety of health situations and be able to automatically improve its glucose prediction capability.

Results

Figure 1 shows LEGT equations graphically. It shows three straight line segments of the LEGT PPG model with three associated GH-Moduli.

Figures 2 through 4 utilize the annual data, from 2010 through 2021, during a 12-years long period.

Figure 2 depicts the high correlation between his annual weight and annual FPG. It also demonstrates that the LEGT predicted PPG curve is almost identical to the measured average Finger PPG curve. Although the data used are based on the annual average values, the applicability of this linear elastic concept and its approximation method is still amazing and powerful.

Figure 3 reflects the measured daily average glucose and calculated daily average glucose almost identically, where:

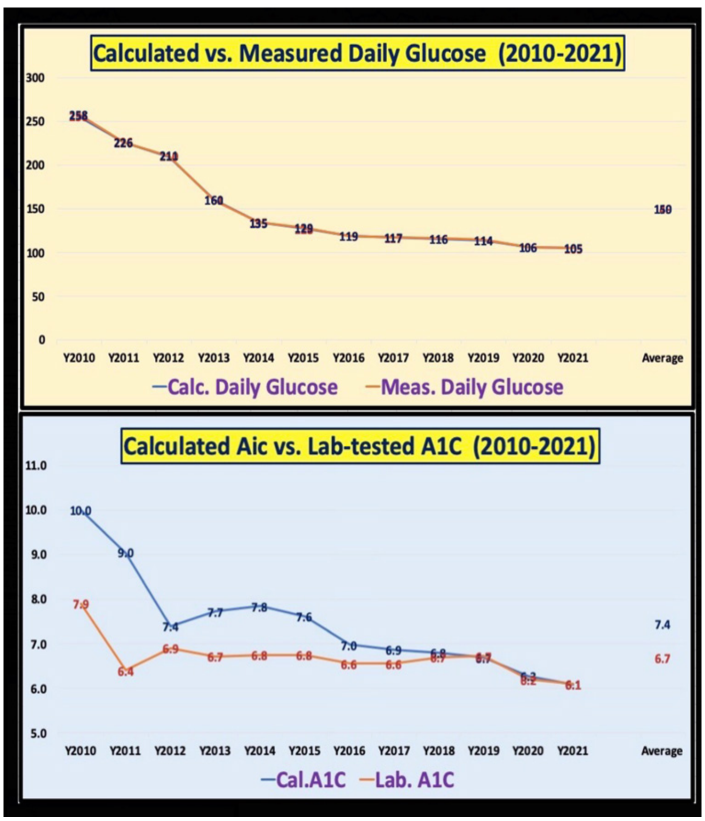

Figure 3: Calculated daily glucose vs. measured daily glucose; Calculated HbA1C vs. lab-tested A1C

*The calculated daily glucose= (1*FPG+3*PPG)/4*

However, the difference between the measured and calculated HbA1C is significant enough to warrant some more explanation below. The lab-tested HbA1C is performed on an irregular basis, while the calculated HbA1C values are based on a summarized conversion table from multiple sources. Currently, there is no universally agreed upon conversion table or equation available for Glucose and A1C. The significant A1C difference is mainly due to the unevenly distributed and irregular lab testing. However, when the author focused on his nine 5-month sub-periods during the period of 2017-2020 having 45 months data, he identified a near 100% accuracy on predicted lab-tested HbA1C using this LEGT approach.

In order to provide more information regarding HbA1C, Figure 4 presents the data table with the HbA1C comparison between the daily calculated A1C and Lab-tested A1C results over the past 12 years. Again, an extremely high HbA1C prediction accuracy is observed during the sub-period of 2017-2020 in Figure 4.

Finger (3/20/21)		FPG/Weight					LEGT			Average				
Year	Weight	FPG	GH.f	Carbs	K-steps	GH.p	Pred. PPG	Meas. PPG	Pred/Meas %	Calc. Glu	Meas. Glu	Calc/Meas %	Cal.A1C	Lab. A1C
Y2010	220	185	0.8	93.0	0.3	1.1	280	279	100%	256	258	99%	10.0	7.9
Y2011	198	155	0.8	93.0	0.5	1.1	250	250	100%	226	226	100%	9.0	6.4
Y2012	189	150	0.8	80.0	2.7	1.1	220	230	96%	210	211	100%	7.4	6.9
Y2013	183	132	0.7	50.0	2.7	1.1	169	170	100%	161	160	100%	7.7	6.7
Y2014	177	128	0.7	28.0	3.5	1.1	137	137	100%	135	135	100%	7.8	6.8
Y2015	175	121	0.7	14.5	3.7	1.8	125	130	96%	128	129	99%	7.6	6.8
Y2016	173	117	0.7	15.5	4.1	1.8	121	120	101%	119	119	100%	7.0	6.6
Y2017	174	120	0.7	14.2	4.4	1.8	119	117	103%	117	117	100%	6.9	6.6
Y2018	171	114	0.7	15.5	4.5	1.8	115	117	99%	116	116	100%	6.8	6.7
Y2019	173	115	0.7	13.2	4.0	1.8	115	114	101%	114	114	100%	6.7	6.7
Y2020	170	101	0.6	13.7	4.5	2.4	109	108	101%	106	106	100%	6.3	6.2
Y2021	168	97	0.6	14.1	4.8	2.5	106	108	98%	105	105	100%	6.1	6.1
Average	181	128	0.7	37.1	3.3	1.6	156	157	99%	149	150	100%	7.4	6.7

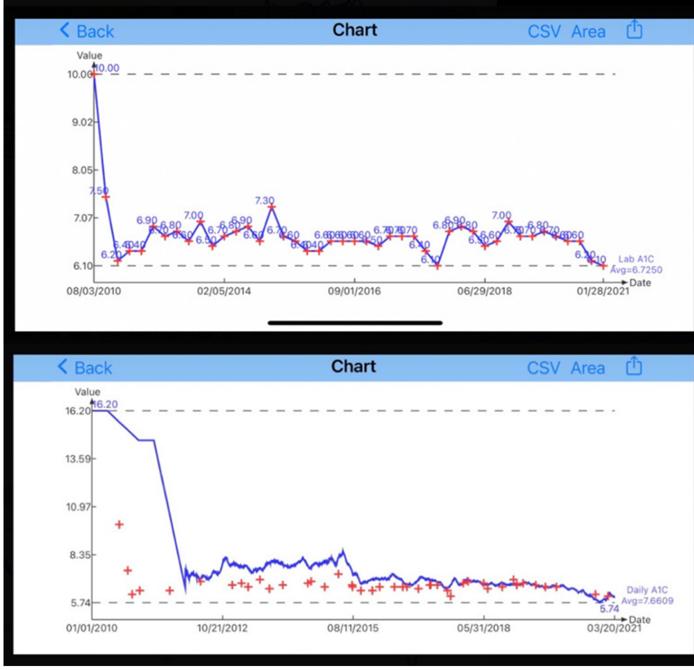

Figure 4: Data table and HbA1C comparisons

Conclusions

In summary, similar to the Young's modulus of engineering materials, the GH.p-Modulus for diet is the most important and complicated biomedical GH-modulus of those three defined GH-Moduli by the author. This GH.p is related to and also dependent on the patient's overall metabolic conditions, age, lifestyle, health, medical diseases, types of food, amount of carbs/sugar intake, and to some degree the chosen time-window for certain analyses. Nevertheless, its linear and elastic behaviors and general glucose characteristics are quite comparable to the Young's modulus of stress and strain in theory of elasticity of engineering. Thus far, all of the author's collected glucose data and behaviors appeared are very well within the defined "elastic" region. Therefore, his developed LEGT should be useful for other type 2 diabetes (T2D) patients to control their diabetes conditions [1-30].

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