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Research Article

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An Artificial Intelligence Model Applying Linear Elastic Glucose Theory to Control Type 2 Diabetes Based on GH-Method: Math-Physical Medicine, LEGT Part 27 (No. 416)

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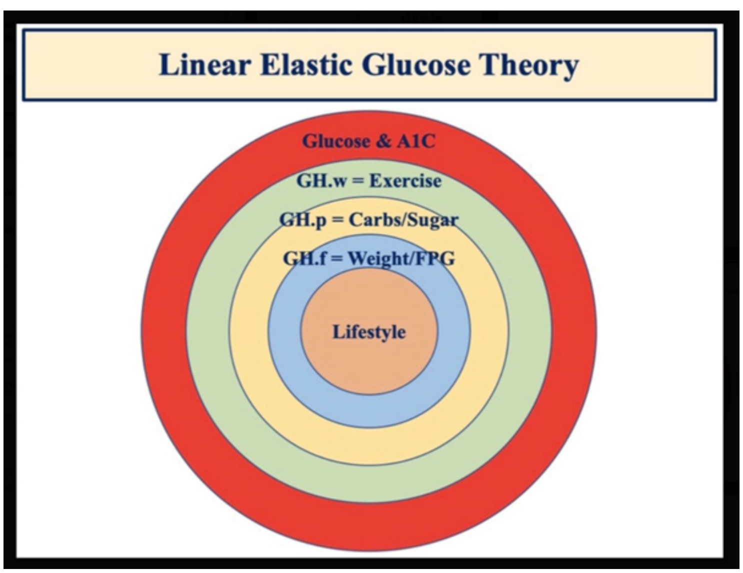
Abstract
On 10/14/2020, the author wrote his first research note on his developed linear elastic glucose theory (LEGT). Over the past 5+ months, he has continuously conducted his research on this subject, where he completed his research note of a summary report, No. 415, LEGT Part 26 on 3/15/2021.

After completing Part 26 of summary report, in the early morning of 3/17/2021, he had an idea on how to develop a software program using artificial intelligence techniques and a few selected key data, without collecting a big dataset or learning complex subjects such as physics or mathematics, to aid in other diabetes patients on their diabetes control.

In summary, similar to Young's modulus of engineering materials, the most important GH-Modulus of biomedicine applications, the GH.p-Modulus for diet, is related to and also dependent on the patient's overall metabolic conditions, physical age, lifestyle, overall health, medical diseases, types of food, amounts of carbs/sugar intake, and to some degree, even the chosen time-window for certain particular analyses. Nevertheless, its linear and elastic behaviors and general glucose characteristics are still quite similar to the Young's modulus of stress and strain in theory of elasticity of engineering. All of the author's collected glucose data thus far still present their behaviors within the defined "elastic" region. Therefore, his developed LEGT with this developed AI program using LEGT would be quite useful for other T2D patients to control their diabetes conditions.



Introduction
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After completing Part 26 of summary report, in the early morning of 3/17/2021, he had an idea on how to develop a software program using artificial intelligence techniques and a few selected key data, without collecting a big dataset or learning complex subjects such as physics or mathematics, to aid in other diabetes patients on their diabetes control.

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.

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 choose 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 is only about 1/3 of PPG, but this is the only factors diabetes patients can take them into their own hands to control. The current diabetes treatments by physicians are mainly trying to stabilize glucose level via medication and/or insulin injection. Unfortunately, this kind of treatment is only trying to alter the external symptom (i.e. output only) of the endocrinological diabetes disease, but not try to cure or even improve the degree of sickness from disease disease at the root cause level. 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 has already had an intuition of 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 his predicted PPG, his first vital task was to identify an accurate but easy way to estimate his carbs/sugar intake amount. Utilizing optical physics (relationship among visible food color, internal wavelength, molecular structure, and nutrition ingredients), big data analytics (~6 million collected food nutrition data and 160 million digits per meal photo), and artificial intelligence (machine learning and self-correction), he has developed a computer software program to predict the carbs/sugar amount of his food or meals via a picture of his food or meal 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 AI tool in order to obtain his incremental PPG induced from food. This observed linear coefficient of 1.8-2.5 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 this synthesized nonlinear system into 3 simpler linear systems or 3 straight-line segments, which are the pancreatic beta cells' insulin, diet for glucose rising, and exercise for glucose declining.

After 9-months of struggling during 2015-2016, in the early morning of 3/16/2016, he had finally discovered a strong correlation (>80% of R, the correlation coefficient) actually existed 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 his biomedical system, while lifestyle details belong to the input category of his biomedical system. As a trained engineer, he was taught during his school years that he should always seek and identify those relationships existed between inputs and outputs, not just among outputs or among inputs.

During years of 2017 to 2020, he utilized 7 to 8 different research angles to investigate his pancreatic beta cells "self-repair" situation. One way was using the FPG data since there is no food or exercise associated with glucose during sleep hours to confuse the equation; therefore, a long-term collected record of FPG or weight can serve as a reliable "benchmark indicator" of 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 (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 which is 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.

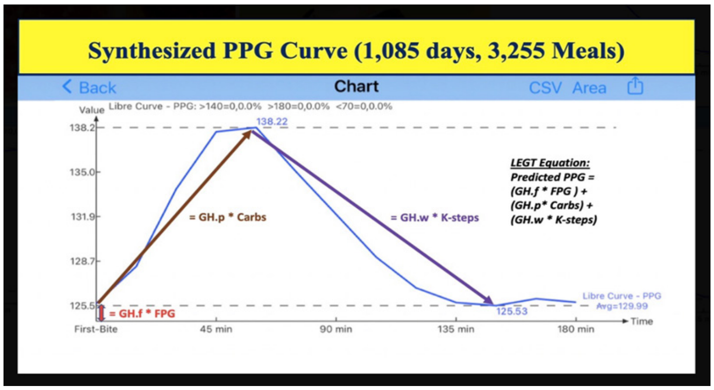

Figure 1: Three linear segments of a synthesized PPG wave using three GH-Moduli

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 at below (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. Frequently, for his own case, he choose 0.6 if using Weight or 0.97 or 1.0 if using FPG to start his equation calculation. He also choose the GH. was -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, then ***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.

Description of the Artificial Intelligence PPG Model

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

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

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

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 developed AI food nutrition program or rely on their own learned knowledge about carbs/sugar amount for each meal for completing the calculation of this second stage of diet.

Third step discusses the PPG value reduction between time instant of 60-minutes to 180-minutes (defined as P3 value). It should've added that in another time instant of 120-minutes (defined as Finger PPG value), the PPG value is corresponding to those common advices by physicians to their diabetes patients of measuring their PPG at two hours after their first-bite of meals using 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. But the selected GH.w value of -5 is 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 via more 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 linear representation with a pretty high accuracy of prediction, but it is a much simpler way to know your PPG situations.

For LEGT PPG case, its averaged glucose values are listed with a geometry equation as below:

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

and

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

Above descriptions, including those important equations and three GH-Modulus, are the building blocks of this AI-based PPG program. For most of Type 2 diabetes (T2D) patients, they just enter their weight or FPG values, averaged carb/sugar intake grams, and post-real walking k-steps, over a selected time period into this AI-based software program, they can then leave their work burden to this AI assistant. Later on, the author plans to continuously augment this AI-based machine-learning capabilities on dealing with variety of health situations and be able to automatically improve its glucose prediction capability.

Results from Examples

Figure 1 shows LEGT equations graphically. It shows the three straight line segments with the corresponding three linearities associated with three GH-Modulus.

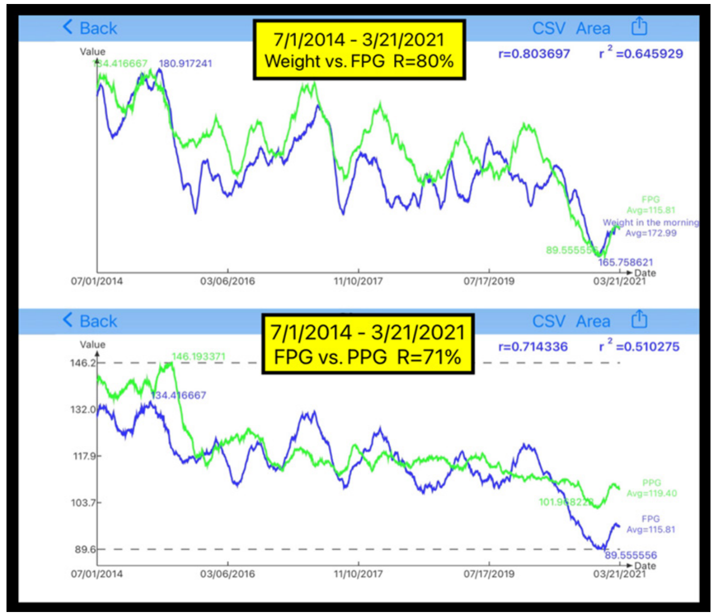

Figure 2: High correlation coefficients of weight vs. FPG and PPG vs. FPG

Figure 2 shows the high correlation coefficients of body weight vs. FPG (80%) and PPG vs. FPG (71%) during the same period from 7/1/2014 to 3/21/2021. This demonstrates that body weight influence FPG; and FPG is highly connected to PPG.

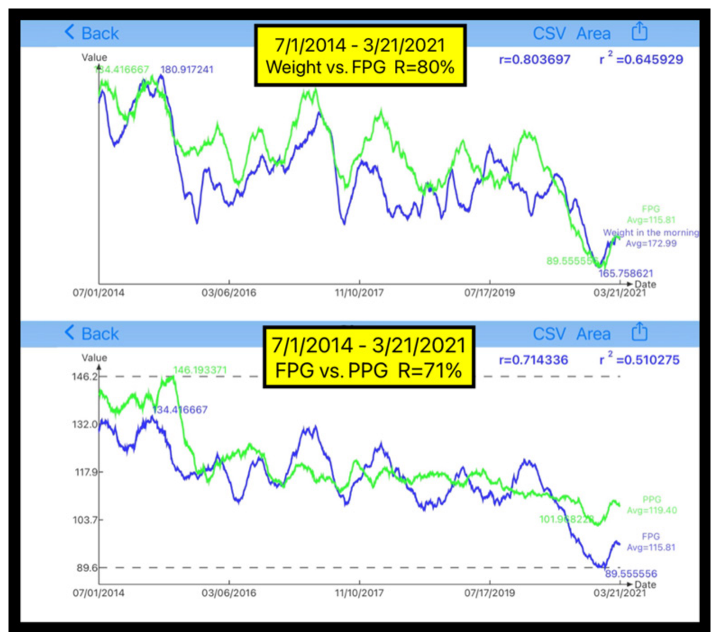

Figure 2: High correlation coefficients of weight vs. FPG and PPG vs. FPG

Figure 3 shows a very high accuracy on Cabs/Sugar amount estimation using both NI (99.5%) and AI (99.0) approaches over the same period of 5/5/2018-3/15/2021. This AI tool combined with optical physics is a powerful tool for the difficult task of knowing your carbs/sugar intake amount for each meal. It is also quite interesting to notice that human eyes and brain (natural intelligence: NI) is still superior to computer software (artificial intelligence: AI).

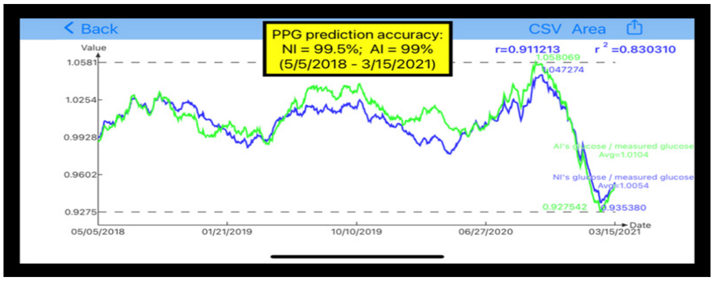

Figure 3: High accuracy on Cabs/Sugar amount estimation via both NI (99.5%) and AI (99.0)

Figures 4 and 5 utilized data of 12- years period from 2010 through 2021 utilizing LEGT calculated PPG versus collected glucoses.

Sensor Data	Y2010	Y2012	Y2021
Weight in TD	220	189	168
FPG in TD = 64% of Weight	141	121	108
PPG (0-min) in TD = FPG +17	158	138	125
PPG (peak) in TD = GH.p*Carbs + PPG (0-min)	283	234	147
PPG (180-min) in TD = PPG (peak)- GH.w*K-steps	280	222	117
PPG in TD	258	132	132
Daily Avg. Glucose in TD	229	129	126
Carbs/Sugar	65.0	50.0	11.7
Walking K-steps	0.5	2.0	4.9
Calculation Data	**Y2010**	**Y2021**	**Y2021**
FPG / Weight	0.64	0.64	0.64
GH.f = PPG (0-min) / Weight	0.72	0.73	0.74
PPG (0-min) - FPG			
PPG (0-min) / FPG	1.1	1.1	1.2
PPG (peak) in TD - PPG (0-min) in TD	125	97	23
GH.p = PPG (peak-0-min) / Carbs	1.93	1.93	1.93
PPG (peak) in TD - PPG (180-min) in TD	3	12	30
GH.w = PPG (peak-180-min) / K-steps	6.2	6.2	6.2
Simulated Sensor PPG	**Y2010**	**Y2012**	**Y2020**
0 min	158	138	125
15 min	189	162	131
30 min	221	186	136
45 min	252	210	142
60 min	283	234	147
75 min	283	233	143
90 min	282	231	140
105 min	282	230	136
120 min	281	228	132
135 min	281	227	128
150 min	281	225	125
165 min	280	224	121
180 min	280	222	117
Average PPG	258	211	132

Figure 4: Data table of Y2010, Y2012, & Y2021

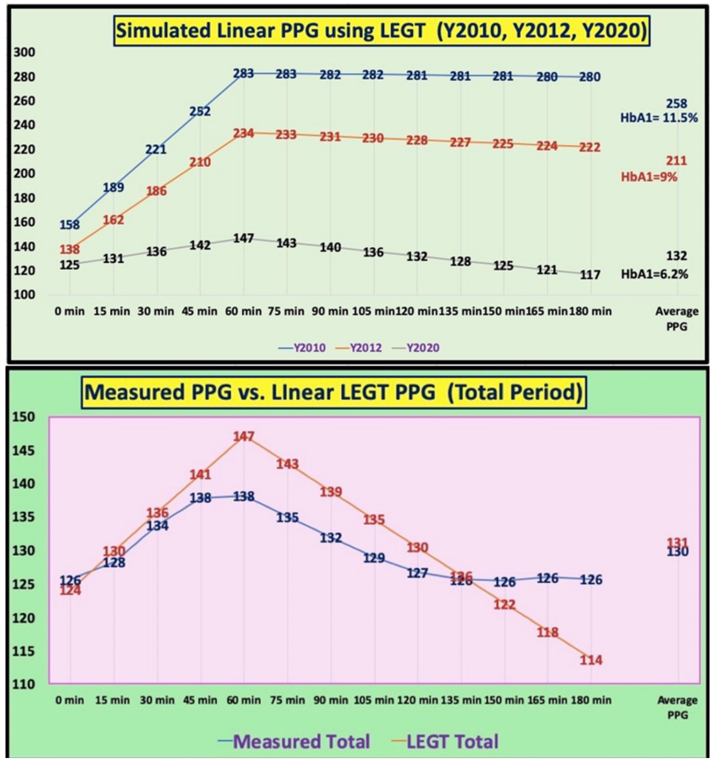

Figure 5: Sensor PPG and LEGT PPG of Y2010, Y2012, Y2021 and total period of pre-virus and virus

Figure 4 is the data table contains years 2010, 2012, and 2021 and Figure 5 is the output results of these three years. The most important three GH-Modulus values are outlined below in the format of (GH.f from weight, GH.p, GH.w):

Y2010: (0.72, 1.93, -6.2)
Y2012: (0.73, 1.93, -6.2)
Y2021: (0.74, 1.93, -6.2)

It looks like for a long 12-years period, the appropriate GH-Modulus are:
GH.f = 0.73
GH.p = 1.93
GH.w = -6.2

In Figure 5, both Y2010 and Y2012 have higher starting PPG values at 138-158 mg/dL which were resulted from his heavy body weights of 189 lbs to 220 lbs and poor conditions of damaged pancreas beta cells. Their high peak PPG of 234 mg/dL to 283 mg/dL were resulted from his high carbs/sugar intake amounts of 50 grams to 65 grams per meal. Their relatively flat straight lines between 60-minutes and 180-minutes were resulted from his inactivity after his meals. On contrary, Y2020 curve demonstrates an opposite picture which had a much lower starting PPG value at

125 mg/dL due to his lighter body weight of 168 lbs and healthier or self-repaired to some degree of pancreatic beta cells. His LEGT PPG curve shows his lower peak at 147 mg/dL is resulted from his lower carbs/sugar of 11.7 grams and the declined PPG curvature from his average post-meal walking steps of 4,900 (about 2 miles or 3 kms after each meal).

Figures 6 and 7 utilized data of a near 3-years total period from 5/5/2018 through 3/16/2021 with two almost equal-length sub-periods of pre-virus period of 5/5/2018 - 12/31/2019 and virus period of 1/1/2020 - 3/16/2011. All of these three periods, pre-virus, virus, and total are utilizing LEGT calculated PPG versus collected sensor PPG.

Input Data	5/5/18-12/31/19	1/1/20-3/16/21	5/5/18-3/16/21	
Sensor Data	**Pre-virus**	**Virus**	**Total**	**Average**
Weight	171.90	169.66	172.05	170.78
FPG = 64% of Weight	113.62	103.04	109.17	108.33
PPG (0-min) = FPG +16	128.62	118.04	124.17	123.33
PPG (peak) = GH.p*Carbs + PPG (0-min)	152.79	141.52	147.21	147.16
PPG (120-min)	133.14	117.24	126.44	125.19
PPG (180-min) = PPG (peak)- GH.w*K-steps	129.56	96.76	113.72	113.16
PPG	135.64	121.57	129.71	128.61
Daily Avg. Glucose	130.14	116.94	124.58	123.54
Carbs/Sugar	14.22	13.81	14.05	14.02
Walking K-steps	4.22	4.52	4.35	4.37
Calculation Data	**Y2010**	**Y2021**	**Total**	**Average**
FPG / Weight	0.66	0.61	0.63	0.63
GH.f = PPG (0-min) / Weight	0.75	0.70	0.72	0.72
PPG (0-min) - FPG	15	15	15	15.00
PPG (0-min) / FPG	113%	115%	114%	1.14
PPG (peak) - PPG (0-min)	24	23	23	23.83
GH.p = PPG (peak-0-min) / Carbs	1.70	1.70	1.64	1.70
PPG (peak) - PPG (180-min)	23	45	34	34
GH.w = PPG (peak-180-min) / K-steps	5.5	9.9	7.7	7.7

Sensor PPG	Measured Pre-virus	LEGT Pre-virus	Sensor PPG	Measured Virus	LEGT Virus	Sensor PPG	Measured Total	LEGT Total A
0 min	135	129	0 min	121	118	0 min	126	124
15 min	137	141	15 min	123	126	15 min	128	130
30 min	152	153	30 min	127	134	30 min	134	136
45 min	144	150	45 min	129	142	45 min	138	141
60 min	131	148	60 min	128	137	60 min	138	147
75 min	122	146	75 min	125	132	75 min	135	143
90 min	117	144	90 min	122	127	90 min	132	139
105 min	114	141	105 min	119	122	105 min	129	135
120 min	113	139	120 min	117	117	120 min	127	130
135 min	111	137	135 min	117	112	135 min	126	126
150 min	114	134	150 min	117	107	150 min	126	122
165 min	122	132	165 min	118	102	165 min	126	118
180 min	132	130	180 min	119	97	180 min	126	114
Average PPG	127	140	Average PPG	122	121	Average PPG	130	131

Figure 6: Data table of pre-virus, virus, and total periods

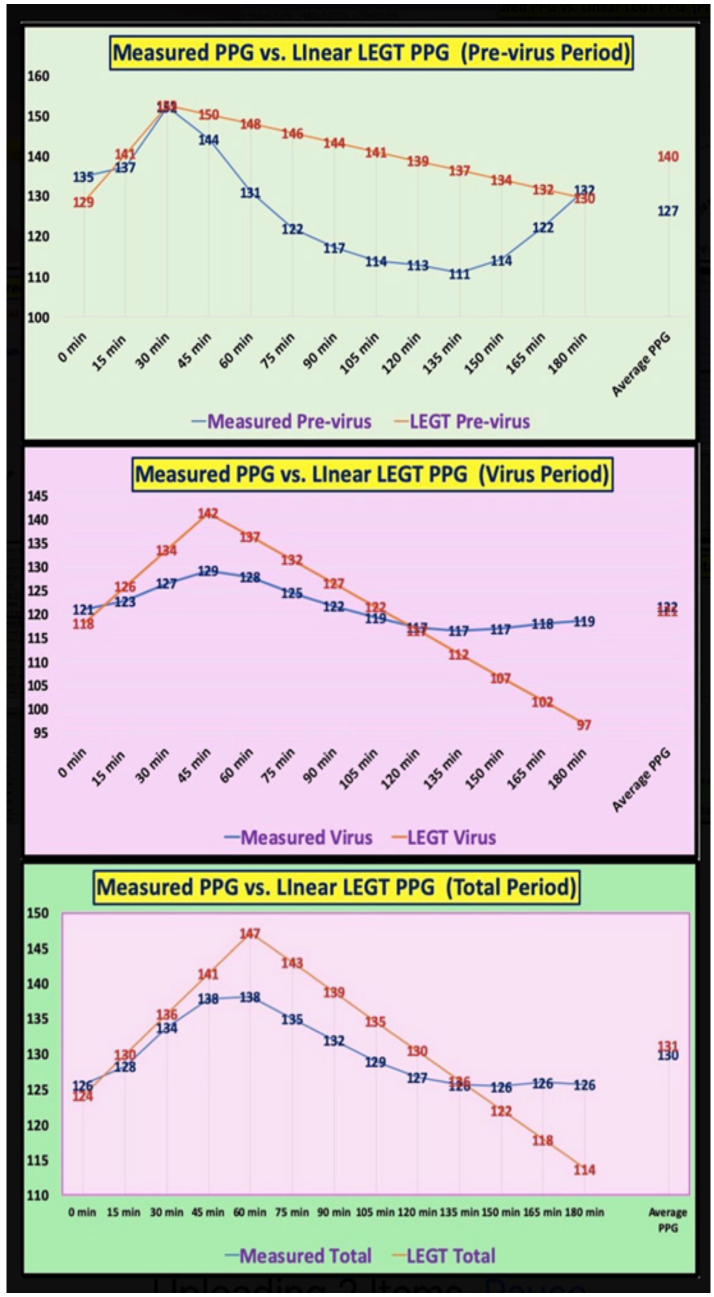

Figure 7: Sensor PPG and LEGT PPG of pre-virus, virus, and total periods

Figure 6 is the data table contains three periods and Figure 7 is the output results of these three periods. *The most important three GH-Modulus values are outlined below in the format of (GH.f from weight, GH.p, GH.w):*

Pre-virus: *(0.75, 1.70, -5.5)*
Virus: *(0.70, 1.70, -9.9)*
Total: ***(0.72, 1.64, -7.7)***

The total periods of three GH-Modulus,
GH.f = 0.72,
GH.p = 1.64,
GH.w = -7.7,
fit better with his shorter recent period.

However, those two sub-periods of pre-virus and virus have shown their distinctive characteristics of health conditions, diet and exercise situations would influence the value of GH-Modulus.

In Figure 7, pre-virus period has a higher starting PPG values at 139 mg/dL than 121 mg/dL of virus period. This was due to his virus period's body weights was 2 lbs lighter than pre-virus period and with a better conditions of pancreas beta cells insulin situation. Their higher peak PPG of 131 mg/dL for pre-virus than the peak of 128 mg/dL of virus period is a combination of his higher starting PPG with higher carbs/sugar intake. In addition, his walking steps was higher during the virus period than the pre-virus period as well. However, the most significant observation is shown through the nonlinear biomedical PPG waveform comparison between pre-virus and virus. During pre-virus period, his nonlinear biomedical sensor PPG waveform was influenced by the combination of heavier weight, poorer insulin from beta cells, higher carbs, and lower walking steps. Even though the magnitude is relatively smaller in comparison with Y2010-Y2012 versus Y2020. *However, from viewpoint of energy theory, during pre-virus period, the author did not burn off all of his generated energy before the 120-minutes time instant, therefore, after 135-minutes time instant, his PPG wave was then tilted upward. This significant curvature change was difficult to be compensated using a linear straight LEGT line. That was why their average PPG has a difference of 13 mg/dL between the nonlinear wave (average of 127 mg/dL) and the LEGT linear lines (average of 140 mg/dL).*

Luckily, for virus period waveform, it did not have this phenomenon (i.e. nonlinear wave did not tilt upward significantly). Therefore, the average PPG values are very close to each other (nonlinear 122 mg/dL and LEGT linear 121 mg/dL). In the combined total period, from the contribution of the good behavior from the virus period, it makes the total period average PPG value at 130 mg/dL for nonlinear and 131 mg/dL for LEGT linear.

Figure 8 is a conceptual diagram of linear elastic glucose theory.

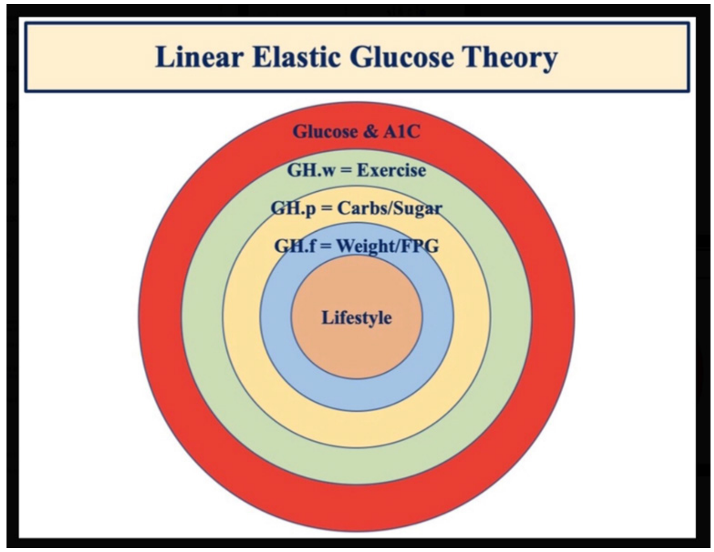

Figure 8: Conceptual diagram of LEGT

Figure 9 demonstrates the high accuracy of his developed geometry equations application for both average sensor LEGT PPG and Finger LEGT PPG at 120-minutes. Therefore, diabetes patients could utilize the following two geometry equations to know his PPG status quickly.

	Y2010	Y2012	Y2020
P1	158	138	125
P2	283	234	147
P3	280	222	117
Total	3353	2748	1721
Avg. LEGT Sensor	258	211	132
120-min Finger	282	228	132

	Pre-virus	Virus	Total
P1	129	118	124
P2	148	137	147
P3	130	97	114
Total	1793	1550	1705
Avg. LEGT Sensor	138	119	131
120-min Finger	139	117	130

Figure 9: Average LEGT PPG and Finger LEGT PPG at 120-minutes using Geometry equations

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

and

Finger LEGT PPG = 0.87 * (P2+P3)/2

Conclusions

In summary, similar to Young's modulus of engineering materials, the most important GH-Modulus of biomedicine applications, the GH.p-Modulus for diet, is related to and also dependent on the patient's overall metabolic conditions, physical age, lifestyle, overall health, medical diseases, types of food, amounts of carbs/sugar intake, and to some degree, even the chosen time-window for certain particular analyses. Nevertheless, its linear and elastic behaviors and general glucose characteristics are still quite similar to the Young's modulus of stress and strain in theory of elasticity of engineering. All of the author's collected glucose data thus far still present their behaviors within the defined "elastic" region. Therefore, his developed LEGT with this developed AI program using LEGT would be quite useful for other T2D patients to control their diabetes conditions [1-29].

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