



# **Research Article**

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Using 12-years of Glucoses Including Intermittent Fasting Glucose Data Along with High-Carb Meals Glucose Data to Study The Suitability, Lower-Bound, and Upper-Bound of the Linear Elastic Glucose Theory Based on GH-Method: Math-Physical Medicine, Part 23 (No. 412)

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#### Abstract

The author utilizes his collected finger-piercing measured glucose data starting in 2012 and sensor collected glucose data starting in 2018 to conduct his research on applications of his developed linear elastic glucose theory (LEGT) in 2020. He also segregates his glucose data from the intermittent fasting (IF) experiment (16-hours without food) to use for his lower-bound study (carbs/sugar intake amounts near or equal to zero) and his high-carbs meals (carbs/sugar amount between 40 grams to 200 grams per meal) for his upper-bound study. Furthermore, using old record of his sparse hyperglycemia data (not on a daily or frequent basis) during the earlier years of 2010-2011, he applies LEGT calculation algorithms to re-verify the suitability of his created GH-modulus. He indeed suffered from hyperglycemic conditions which were indicated via fasting plasma glucose (FPG) and postprandial plasma glucose (PPG) from 2010 to 2013. For example, in 2010, his average FPG was at 220 mg/dL and average PPG was at 280 mg/dL with a HbA1C level of 10%.

The purpose of this research is to investigate the relationship between the overall improvement on his diabetes-related health state and his created GH-Modulus of LEGT, especially where the GH.p Modulus connects carbs/sugar intake amount and food induced incremental PPG level. In addition, he also addresses the suitability of LEGT applications on a lower bound case of intermittent fasting (when carbs intake amount is or near zero) along with two upper bound cases of high-carbs meals (40-200 grams of carbs) and high glucoses record during earlier years from 2010 to 2013. The objective is to identify and verify a realistic range of LEGT suitability.

 from mathematics, physics, and engineering. Therefore, the author developed LEGT as a useful tool for patients to understand and control their diabetes conditions.

The most vital and important influential factor for glucose variability is insulin secretion or insulin resistant by the pancreatic beta cells. However, by the time people develop complications due to their insulin problems, they have already become diabetes patients. In order to understand the overall pancreatic health status without a lab test, we can get a quick idea from the FPG reading. Using FPG value via either early morning finger-measured glucose or average glucose collected by a sensor during sleep hours, which lack interventions from food and exercise, the FPG value is actually a good indicator of pancreatic health status. This is the reason the author uses his FPG as the GH.f-Modulus (between 0.6 and 1.0) in order to determine the baseline PPG value in predicting his PPG level.

Any diabetes medication or insulin injection can only suppress the "external" symptoms or expressions of hyperglycemic or hypogly-

cemic situations. Unfortunately, chemical drugs cannot repair the damaged pancreatic beta cells, which is the root cause of diabetes disease. This is the reason why people use the term "control" or "treatment", not "cure", to describe the actions of medication, injection, or surgery for various of endocrinological diseases. When combining a stringent lifestyle management program (diet, exercise, sleep, stress, etc.), not only can it control the diabetes conditions without medications, but it can also "slowly" repair the damaged beta cells; therefore, it can ultimately recover a degree of lost quantity or strength along with the needed quality of insulin secretion and improve the degree of insulin resistance.

In comparison with diet, the subject of exercise is relatively simple and easy to comprehend. The author has a walking exercise routine of 2,000 to 4,000 steps (20 to 40 minutes) after each meal which is enough to decrease his elevated PPG on a downward trend. Using a factor of -5.0 as the GH.w-Modulus, he can reduce his PPG 10 mg/dL by walking 2,000 steps and 20 mg/dL by walking 4,000 steps.

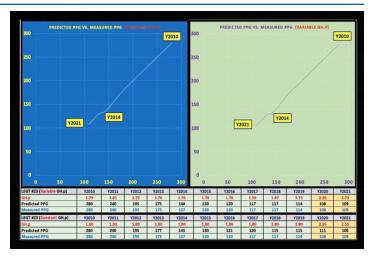
Unfortunately, on the other hand, diet control is not an easy task for most patients. Despite complicated information and practical knowledge regarding the relationship between food nutrition and chronic diseases, it also requires strong willpower and long-term persistence which are not the strong suits for most people. However, these two elements, knowledge and persistence, are the necessary foundations in achieving real benefits on controlling diabetes and complications via a lifestyle management program.

The invention of LEGT, particularly the GH.p-Modulus for diet, aims at the objective in controlling diabetes via diet management without medication intervention, and achieving the extra benefit in recovering the damaged pancreatic beta cells functionality at the root-cause level. In the author's case, he used a constant GH.p-Modulus of 1.8 during 2010-2019, he could predict his finger PPG level at a >98% prediction accuracy. During 2020-2021 of COVID-19 quarantine lifestyle without travel and hectic schedule, his slightly elevated GH.p-Modulus of 2.5 can equally predict with a >98% accuracy of his most recently lower finger PPG level as well.

Intermittent fasting provides an interesting lower-bound situation of near zero carbs/sugar intake amount which requires a special numerical treatment in order to obtain an accurate analysis result. However, it is just for academic interest only. IF, a not-so-common practice, can indeed bring down the glucose to a steady state within a short timeframe, and can also reduce body weight over a reasonable longer period.

Regarding his upper-bound analyses using both high-carbs meals (40-200 grams per meal) and higher finger PPG data (2010-2013), he discovered that his LEGT is equally applicable and useful to these cases.

This research note concludes that *LEGT* is useful on predicting *PPG* accurately in order to control diabetes conditions.



## Introduction

The author utilizes his collected finger-piercing measured glucose data starting in 2012 and sensor collected glucose data starting in 2018 to conduct his research on applications of his developed linear elastic glucose theory (LEGT) in 2020. He also segregates his glucose data from the intermittent fasting (IF) experiment (16-hours without food) to use for his lower-bound study (carbs/ sugar intake amounts near or equal to zero) and his high-carbs meals (carbs/sugar amount between 40 grams to 200 grams per meal) for his upper-bound study. Furthermore, using old record of his sparse hyperglycemia data (not on a daily or frequent basis) during the earlier years of 2010-2011, he applies LEGT calculation algorithms to re-verify the suitability of his created GH-modulus. He indeed suffered from hyperglycemic conditions which were indicated via fasting plasma glucose (FPG) and postprandial plasma glucose (PPG) from 2010 to 2013. For example, in 2010, his average FPG was at 220 mg/dL and average PPG was at 280 mg/dL with a HbA1C level of 10%.

The purpose of this research is to investigate the relationship between the overall improvement on his diabetes-related health state and his created GH-Modulus of LEGT, especially where the GH.p Modulus connects carbs/sugar intake amount and food induced incremental PPG level. In addition, he also addresses the suitability of LEGT applications on a lower bound case of intermittent fasting (when carbs intake amount is or near zero) along with two upper bound cases of high-carbs meals (40-200 grams of carbs) and high glucoses record during earlier years from 2010 to 2013. The objective is to identify and verify a realistic range of LEGT suitability.

# 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 (TG for artery) and albumin-creatinine ratio (ACR for kidney) at 116. He also suffered from five cardiac episodes within a decade. In 2010, three independent physicians warned him regarding his needs of kidney dialysis treatment and his future high risk of dying from his severe diabetic complications.

In 2010, he decided to self-study endocrinology, diabetes and food nutrition. During 2015 and 2016, he developed four prediction models related to diabetes conditions, i.e., weight, postprandial plasma glucose (PPG), fasting plasma glucose (FPG), and HbA1C (A1C). As a result, from using his developed mathematical metabolism index (MI) model in 2014 and those four prediction tools, by 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), averaged finger glucose from 250 mg/dL to 120 mg/dL, and HbA1C from 10% to ~6.5%. One of his major accomplishments is that he no longer takes any diabetes medications since 12/8/2015.

In 2017, he had achieved excellent results on all fronts, especially glucose control. However, during the pre-COVID period of 2018 and 2019, he traveled to approximately 50+ international cities to attend 65+ medical conferences and made ~120 oral presentations. This hectic schedule inflicted damage to his diabetes control, through dinning out frequently, post-meal exercise disruption, jet lag, and along with the overall metabolism impact due to his irregular life patterns through a busy travel schedule; therefore, his glucose control was affected during this two-year period with 2019 was worse than 2018.

By 2020, his weight was further reduced to 165 lbs. (BMI 24.4) and his HbA1C was at 6.2% without any medications intervention or insulin injection. Actually, during 2020 with the special COVID-19 quarantined lifestyle, not only has he published approximately 400 medical papers in various journals, but he has also achieved his best health conditions for the past 26 years. These good results are due to his non-traveling, low-stress, and regular daily life routines. Of course, his rich self-learned knowledge of chronic diseases, practical experiences of lifestyle management, and his various developed high-tech tools contribute to his excellent health status since 1/19/2020, the starting day of his COVID-19 self-quarantine life.

On 5/5/2018, he started to apply 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 study and analyze his collected ~2 million data regarding his health status, medical conditions, and lifestyle details. He applies his knowledge, models, equations, and tools from mathematics, physics, engineering, and computer science to conduct his needed medical research work. His continuous effort is primarily aiming at achieving both "high precision" with "quantitative proof" in his medical findings.

## Stress, Strain, & Young's Modulus

Prior to the past 11-years of his self-study in medicine and medical research work, he was an engineer in the fields of structural (aerospace and naval defense), mechanical (nuclear power plants and computer-aided-design), and electronics (computer devices, semiconductors, and software).

The following excerpt comes from the public domain, including Google and Wikipedia:

## Strain - &

Strain is the "deformation of a solid due to stress" - change in dimension divided by the original value of the dimension - and can be expressed as

 $\varepsilon = strain = dL/L$ 

where:

dL = elongation or compression (offset) of object

 $L = length \ of \ object$ 

#### Stress - σ

Stress is force per unit area and can be expressed as  $\sigma = stress \ (lb./in2, psi) = F/A$  where:

F = applied force (lb.)

A = stress area of object (in2)

## E, Young's modulus

It can be expressed as:

 $E = stress / strain = \sigma / \varepsilon$ 

where:

E = Young's Modulus of Elasticity (lb./in2, psi) was named after the 18th-century English physicist Thomas Young.

## **Elasticity**

Elasticity is a property of an object or material indicating how it will restore it to its original shape after distortion. A spring is an example of an elastic object - when stretched, it exerts a restoring force which tends to bring it back to its original length.

## **Plasticity**

When the force is going beyond the elastic limit of material, it is into a "plastic" zone which means even when force is removed, the material will not return back to its original state.

Based on various experimental results, the following table lists some Young's modulus associated with different materials and are ranked from soft material (low E) to stiff material (higher E):

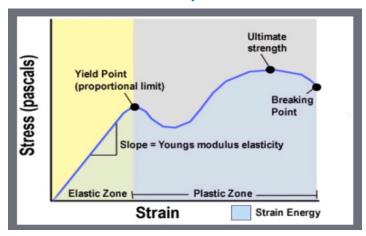
Nylon: 2.7

Concrete: 17-30 & Glass fibers: 72

Copper: 117 & Steel: 190-215

Diamond: 1220

# **Linear Elastic Glucose Theory**



The author defines his LEGT equation as follows:

## 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 the author's experiences on utilizing his GH-Modulus, the GH.f ranges between 0.6 to 1.0 (he uses 0.97 frequently for his own cases) and the GH.w is -5.0 for most cases. Therefore, the GH.p-Modulus is the most important variable which defines the food induced incremental PPG 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 our carbs/sugar intake similar to stress, incremental PPG similar to strain, then *the biomedical GH.p-modulus and engineering E of Young's Modulus would have a reciprocal connection.* 

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 which would result into a lower strain. This is similar to a lower Gh.p-Modulus under the same carbs/sugar intake amount would result into a smaller amount of incremental PPG.

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

# Results 12-years of LEGT Analysis

For consistency reason, the author selected his finger-piercing measured glucose data from 2010 to 2021 to conduct his LEGT analysis. Figure 1 shows the input data and calculated results using LEGT equation which is described again below:

LEGT #23	Y2010	Y2011	Y2012	Y2013	Y2014	Y2015	Y2016	Y2017	Y2018	Y2019	Y2020	Y2021
Weight	198	195	189	183	177	175	173	174	171	173	170	168
FPG	220	180	142	137	128	121	117	120	114	115	101	98
GH.f	0.97	0.97	0.97	0.97	0.97	0.97	0.97	0.97	0.97	0.97	0.97	0.97
PPG Baseline = (GH.f*FPG)	213	175	137	133	124	117	114	116	110	111	98	95
Carbs/Sugar (grams)	40	39	35	30	20	17	15	14	15	13	14	14
GH.p	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.6	1.9	1.7	2.4	2.7
GH.p*Carbs	72	70	63	53	35	29	27	23	29	23	32	38
Walking K-steps	1	1	1	2	3	3	4	4	5	4	4	5
GH.w	-5.0	-5.0	-5.0	-5.0	-5.0	-5.0	-5.0	-5.0	-5.0	-5.0	-5.0	-5.0
K-steps*GH.w	-5	-5	-5	-10	-15	-16	-21	-22	-23	-20	-22	-24
Predicted PPG (mg/dL)	280	240	195	175	144	130	120	117	117	114	108	109
Measured PPG (mg/dL)	280	240	195	175	137	130	120	117	117	114	108	109
Input Data												
input Data	Y2010	Y2011	Y2012	Y2013	Y2014	Y2015	Y2016	Y2017	Y2018	Y2019	Y2020	Y2021
Weight	Y2010 198	Y2011 195	Y2012 189	Y2013 183	Y2014 177	Y2015 175	Y2016 173	Y2017 174	Y2018 171	Y2019 173	Y2020 170	Y2021 168
Weight	198	195	189	183	177	175	173	174	171	173	170	168
Weight FPG	198 220	195 180	189 142	183 137	177 128	175 121	173 117	174 120	171 114	173 115	170 101	168 98
Weight FPG Measured PPG (mg/dL)	198 220 280	195 180 240	189 142 195	183 137 175	177 128 137	175 121 130	173 117 120	174 120 117	171 114 117	173 115 114	170 101 108	168 98 109
Weight FPG Measured PPG (mg/dL) PPG Components	198 220 280 Y2010	195 180 240 Y2011	189 142 195 Y2012	183 137 175 Y2013	177 128 137 Y2014	175 121 130 Y2015	173 117 120 Y2016	174 120 117 Y2017	171 114 117 Y2018	173 115 114 Y2019	170 101 108 Y2020	168 98 109 Y2021
Weight FPG Measured PPG (mg/dL) PPG Components PPG Baseline = (GH.f*FPG)	198 220 280 <b>Y2010</b> 213	195 180 240 Y2011 175	189 142 195 Y2012 137	183 137 175 Y2013 133	177 128 137 Y2014 124	175 121 130 Y2015 117	173 117 120 Y2016 114	174 120 117 Y2017 116	171 114 117 Y2018 110	173 115 114 Y2019 111	170 101 108 Y2020 98	168 98 109 Y2021 95
Weight FPG Measured PPG (mg/dL) PPG Components PPG Baseline = (GH.f*FPG) GH.p*Carbs	198 220 280 Y2010 213 72	195 180 240 Y2011 175 70	189 142 195 Y2012 137 63	183 137 175 Y2013 133 53	177 128 137 Y2014 124 35	175 121 130 Y2015 117 29	173 117 120 Y2016 114 27	174 120 117 Y2017 116 23	171 114 117 Y2018 110 29	173 115 114 Y2019 111 23	170 101 108 Y2020 98 32	168 98 109 Y2021 95 38
Weight FPG Measured PPG (mg/dL) PPG Components PPG Baseline = (GH.f*FPG) GH.p*Carbs K-steps*GH.w	198 220 280 Y2010 213 72 -5	195 180 240 Y2011 175 70 -5	189 142 195 Y2012 137 63 -5	183 137 175 Y2013 133 53 -10	177 128 137 Y2014 124 35 -15	175 121 130 Y2015 117 29 -16	173 117 120 Y2016 114 27 -21	174 120 117 Y2017 116 23 -22	171 114 117 Y2018 110 29 -23	173 115 114 Y2019 111 23 -20	170 101 108 Y2020 98 32 -22	168 98 109 Y2021 95 38 -24
Weight FPG Measured PPG (mg/dL) PPG Components PPG Baseline = (GH.f*FPG) GH.p*Carbs K-steps*GH.w Predicted PPG (mg/dL)	198 220 280 Y2010 213 72 -5 280	195 180 240 Y2011 175 70 -5 240	189 142 195 Y2012 137 63 -5 195	183 137 175 Y2013 133 53 -10 175	177 128 137 Y2014 124 35 -15	175 121 130 Y2015 117 29 -16 130	173 117 120 Y2016 114 27 -21	174 120 117 Y2017 116 23 -22 117	171 114 117 Y2018 110 29 -23 117	173 115 114 Y2019 111 23 -20 114	170 101 108 Y2020 98 32 -22 108	168 98 109 Y2021 95 38 -24 109
Weight FPG Measured PPG (mg/dL) PPG Components PPG Baseline = (GH.f*FPG) GH.p*Carbs K-steps*GH.w Predicted PPG (mg/dL) GH. Modulus	198 220 280 Y2010 213 72 -5 280 Y2010	195 180 240 Y2011 175 70 -5 240 Y2011	189 142 195 Y2012 137 63 -5 195 Y2012	183 137 175 Y2013 133 53 -10 175 Y2013	177 128 137 Y2014 124 35 -15 144 Y2014	175 121 130 Y2015 117 29 -16 130 Y2015	173 117 120 Y2016 114 27 -21 120 Y2016	174 120 117 Y2017 116 23 -22 117	171 114 117 Y2018 110 29 -23 117 Y2018	173 115 114 Y2019 111 23 -20 114 Y2019	170 101 108 Y2020 98 32 -22 108 Y2020	168 98 109 Y2021 95 38 -24 109 Y2021

Figure 1: Data table for LEGT analysis (2010-2021)

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

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

Where GH.f = 0.97 and GH.w = -5.0; therefore,

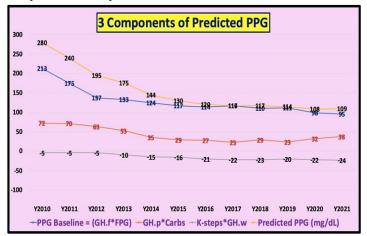
Predicted PPG = (FPG \* 0.97) + (Carbs/sugar \* GH.p) + (post-meal walking k-steps \* (-5.0))

Figure 2 depicts his weight, Finger FPG, and Finger PPG over 12 years.



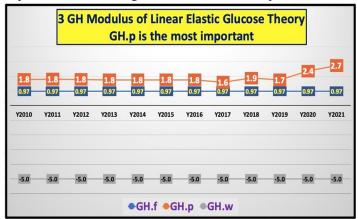
**Figure 2:** Weight, Finger measured FPG, and Finger measured PPG (2010-2021)

Figure 3 illustrates four curves of his baseline PPG (97% of FPG), carbs/sugar induced incremental PPG, exercise reduced PPG, and his predicted PPG. All of these values are glucoses with the same unit of mg/dL. In this figure, we can see the three PPG forming components of the predicted PPG.



**Figure 3:** Three components of Predicted PPG, i.e. baseline PPG, food induced incremental PPG, and exercise reduced PPG

When adjusting the value of GH.p each year to get the predicted PPG to perfectly match with the measured PPG, we can obtain a final determined GH.p-Modulus with variable value each year. Figure 4 reveals three curves of GH.f, GH.p, and GH.w. Since the GH.f (0.97) and GH.w (-5.0) are horizontal straight lines, the only important and interesting GH-modulus is the GH.p-Modulus.



**Figure 4:** Variable GH.p-Modulus between 1.8 and 2.7 (2010-2021) and two other constant GH.f (0.97) and GH.w (-5.0)

First, at below, he summarizes his important findings from Figure 1 through Figure 4.

The GH.p-Modulus is ~1.8 from 2010 throughout 2019, except it has higher values of 2.4 in 2020 and 2.7 in 2021. It should be pointed out that the carbs/sugar intake amounts are around 14 grams during the period of 2016-2021, even including the specific COVID-19 period of 2020-2021. Therefore, the higher GH.p-modulus in 2020-2021 would produce slightly higher incremental PPG than 2016-2019. However, the baseline PPG (97% of FPG) is lower in 2020-2021 (~100 mg/dL) than 2016-2019 (114-120 mg/dL), therefore, the PPG in 2020-2021 (~108 mg/dL) is lower than the PPG in 2016-2019 (114-120 mg/dL). FPG is a good indicator of insulin state, reflecting the health state of pancreatic beta cells for insulin secretion and insulin resistance. The baseline PPG, i.e. FOG, is the strongest and primary influential factor for the PPG formation, while diet and exercise in lifestyle management are the next two important influential factors for the PPG formation. When body weight is reduced, then FPG would also decrease (>90% correlation). Under normal circumstances, when FPG is reduced, then PPG would also be lower (>80% correlation). In addition, diet has about +40% correlation with PPG and exercise has approximately -40% correlation with PPG.

The identified conclusions using finger glucoses (4 data per day) for 12 years (Y2010-Y2021) can also be observed with the results using sensor glucoses (96 data per day) for 3 years (5/5/2018-3/10/2021).

From Figure 2, both weight and FPG are sharply decreasing during 2010-2015. As a result, his PPG reached to a stabilized glucose range <120 mg/dL after Y2016 with a stabilized GH.p-Modulus of ~1.8 until his healthiest period during 2020-2021. Due to the COVID-19 quarantine non-travel and stabilized lifestyle period, this resulted in a higher GH.p-Modulus between 2.4 and 2.7 during 2020-2021.

Second, he investigates the lower bound of an extremely low carbs/sugar intake amount, near zero gram of carbs intake, which should correspond to a very high GH.p-Modulus in theory.

Recently, the author has conducted an experiment of >70 IF days by not having any food or meal within a period of 15 to 16 hours (from 20:00 of previous day to 12:00 noon of present day). His normal breakfast is replaced by a big cup (~500 cc) of green tea or black tea. Figure 5 reflects the intake amount of ~0.4 gram with either green tea or black tea and 0 gram with Lipton tea bags. These 70-days of on-going IF experiment's sensor glucose data have brought both surprises and puzzles to him in term of its ultra-high GH.p-Modulus value.

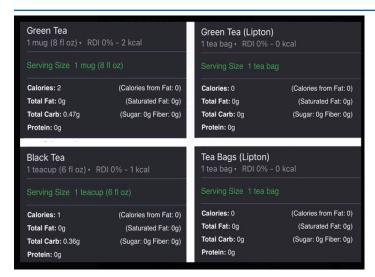


Figure 5: Green and Black Teas (0.4g cabs) and Tea bags (0g carbs)

Figure 6 demonstrates his calculation results of using 12.92 for GH.p for 0.4 gram of carbs intake which still cannot reach to a converge of his predicted PPG with his measured PPG. If using 0 gram of carbs of Lipton tea bags, the infinite number of GH.p-Modulus value would still bring in a zero incremental PPG and also cannot reach to a converge of his predicted PPG with his measured PPG. This extremely low or zero carbs/sugar intake amount has created a challenge to his lower-bound LEGT analysis. Fortunately, nobody could or should take a continuous "long" period with a "complete" fasting condition which is very dangerous to the person's health and life. Fortunately, from using his combined 70 fasting and 70 non-fasting period result, a 12.92 of GH.p-Modulus value for the total combined period and a 7.17 GH.p-Modulus value for the non-fasting period could still yield the same predicted and measured PPG values at 115-119 mg/dL. Therefore, in conclusion, the case of zero carbs and infinite GH.p are truly the lowest boundary case which offers only some academic interest with no practical usage.

Meals (5/5/2018-3/7/2021)	High Carbs	Low Carbs	High / Low	Comments:	(Linear Extented Results)	Y2010 would-be
No. of Meals	176	2760	6%	High meals 6% of Low meals	No. of Meals	
Finger PPG	141	111	127%	Higher carbs = Higher Finger PPG	Finger PPG (= 280)	283
Carbs/Sugar grams	56.9	12.9	441%	High carbs 4X	Carbs/Sugar grams	56.9
Post-meal Walking Steps	4459	4372	102%	Same Walking steps	Post-meal Walking Steps	4459
Sensor FPG	113	113	99%	same FPG	Finger FPG (=220)	226
Sensor PPG	152.34	129.90	117%	High PPG 18% higher	Sensor PPG	306
Sensor (PPG-FPG)	40	16	242%	Higher carbs = Higher (PPg-FPG)	Sensor (PPG-FPG)	80
K-line Max	185	163	114%		K-line Max	
K-line Min	119	105	113%		K-line Min	
K-line PPG Fluc.	67	58	115%	High PPG fluc. 15% higher	K-line PPG Fluc.	
Libre PPG TD-Y	152	130	117%			
Libre PPG Max-Min TD-Y	50	44	114%			
Libre PPG FD-Y	181	380	48%			
Libre PPG Max-Min FD-Y	188	421	45%			
Libre PPG FD Area	28713	387195	7%			
Libre PPG Max-Min FD Area	30020	430697	7%			
Meals (5/5/2018-3/7/2021)	High Carbs	Low Carbs	High / Low	Comments:	(Linear Extented Results)	Y2010 would-be
Weight	170	171	99%	Same Weight	Weight	220
Sensor FPG	109	109	99%	Same FPG	Sensor FPG	141
GH.f	1.00	1.00	100%	GH.f uses 1.0	GH.f	1.00
PPG Baseline = (GH.f*FPG)	109	109	99%	Same Baseline PPG	PPG Baseline = (GH.f*FPG)	141
Carbs/Sugar (grams)	56.9	12.9	441%		Carbs/Sugar (grams)	56.9
GH.p	1.16	3.29	35%	High GH.p is 1/3 of Low GH.p	GH.p	3.29
GH.p*Carbs	66	42	155%	(1.16<3.25 due to beta cells)	GH.p*Carbs	187
Walking K-steps	4.5	4.4	102%		Walking K-steps	4.5
GH.w	-5.0	-5.0	100%	GH.w uses -5.0	GH.w	-5.0
K-steps*(-5)	-22	-22	102%		K-steps*(-5)	-22
Predicted PPG (mg/dL)	152.10	129.90	117%		Predicted PPG (mg/dL)	305.69
Measured PPG (mg/dL)	152.34	129.90	117%		Measured PPG (mg/dL)	

**Figure 6:** Lower-bound carbs (near or zero gram) analysis from fasting data

Third, he examines two realistic upper bounds of carbs/sugar intake amount which correspond to a lower GH.p-modulus.

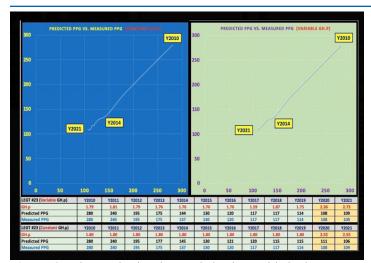
Figure 7 entails his analysis results of 176 high-carbs meals (40 grams to 200 grams per meal) and 2,760 low-carbs meals (1 gram to 39 grams per meal). For these 179 high-carbs meals, his average PPG at 152 mg/dL with a corresponding GH.p-Modulus of 1.16 which is lower than his 10-years' average GH.p of 1.8 during the period of 2010-2019. Interestingly, his carbs (1 gram to 39 grams per meal) of 2,760 low-carbs meals during 5/5/2018 to 3/7/2021 has a lower PPG of 130 mg/dL with a corresponding higher GH.p-Modulus of 3.29. These slightly higher GH.p-Modulus values have pointed out a direction towards better lifestyle and health results.

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Breakfast (10/15/2020-3/5/2021)	Non-Fasting Breakfast	Fasting Day	Total Period Breakfast
No. of Meals	69	69	137
Avg. Breakfast PPG (Finger)	111	106	109
Carbs/Sugar grams	6.4	0.0	3.2
Post-meal Walking Steps	4305	4194	4251
Avg. PPG (TD-Y)	119.20	111.30	115.15
Weight	167	167	167
Sensor FPG	98	98	98
GH.f	0.97	0.97	0.97
PPG Baseline = (GH.f*FPG)	95	95	95
Carbs/Sugar (grams)	6.4	0.4	3.2
GH.p	7.17	12.92	12.92
GH.p*Carbs	46	5	41
Walking K-steps	4.3	4.2	4.3
K-steps*(-5)	-22	-21	-21
Predicted PPG (mg/dL)	119.20	79.66	115.15
Measured PPG (mg/dL)	119.20	111.30	115.15
Carbs/Sugar	6.4	0.0	3.2
GH.p	7.17	Even if GH.p = infinite	12.92
GH.p*Carbs	46	0	41
Walking K-steps	4.3	4.2	4.3
K-steps*(-5)	-22	-21	-21
Predicted PPG	119.20	74.50	115.15
Measured PPG	119.20	111.30	115.15

**Figure 7:** Upper-bound carbs (greater than 40 grams) analysis using 176 meals data (6% of a total of 2936 meals within 3 years)

Let us also explore the higher PPG and higher carbs data during the period of 2010-2013 based on his sparse data collected in Figure 1. His PPG was within the range of 175-280 mg/dL but using a GH.p of 1.8 could still converge his predicted PPG with his measured PPG. This fact has demonstrated that all of his collected glucose data within the 12-year timeframe of 2010 through 2021 are falling very well within the range of "elasticity" with an applicable elastic modulus of GH.p between two constant of 1.8 and 2.6.

Figure 8 summarizes the conclusion of this linear elastic glucose behavior study for both *constant GH.p values* (1.8 during 2010-2019 and 2.6 during 2020-2021) and variable GH.p values between 1.59 and 2.73 for each year. By using these two slightly different GH.p-Modulus (constant and variable), the linearity between predicted PPG and measured PPG are preserved via two skewed straight lines as shown in Figure 8.



**Figure 8:** Linear elastic glucose behaviors with both constant GH.p and variable GH.p using 12-years data from Y2010 through Y2021

## **Conclusions**

The most vital and important influential factor for glucose variability is insulin secretion or insulin resistant by the pancreatic beta cells. However, by the time people develop complications due to their insulin problems, they have already become diabetes patients. In order to understand the overall pancreatic health status without a lab test, we can get a quick idea from the FPG reading. Using FPG value via either early morning finger-measured glucose or average glucose collected by a sensor during sleep hours, which lack interventions from food and exercise, the FPG value is actually a good indicator of pancreatic health status. This is the reason the author uses his FPG as the GH.f-Modulus (between 0.6 and 1.0) in order to determine the baseline PPG value in predicting his PPG level.

Any diabetes medication or insulin injection can only suppress the "external" symptoms or expressions of hyperglycemic or hypoglycemic situations. Unfortunately, chemical drugs cannot repair the damaged pancreatic beta cells, which is the root cause of diabetes disease. This is the reason why people use the term "control" or "treatment", not "cure", to describe the actions of medication, injection, or surgery for various of endocrinological diseases. When combining a stringent lifestyle management program (diet, exercise, sleep, stress, etc.), not only can it control the diabetes conditions without medications, but it can also "slowly" repair the

damaged beta cells; therefore, it can ultimately recover a degree of lost quantity or strength along with the needed quality of insulin secretion and improve the degree of insulin resistance.

In comparison with diet, the subject of exercise is relatively simple and easy to comprehend. The author has a walking exercise routine of 2,000 to 4,000 steps (20 to 40 minutes) after each meal which is enough to decrease his elevated PPG on a downward trend. Using a factor of -5.0 as the GH.w-Modulus, he can reduce his PPG 10 mg/dL by walking 2,000 steps and 20 mg/dL by walking 4,000 steps.

Unfortunately, on the other hand, diet control is not an easy task for most patients. Despite complicated information and practical knowledge regarding the relationship between food nutrition and chronic diseases, it also requires strong willpower and long-term persistence which are not the strong suits for most people. However, these two elements, knowledge and persistence, are the necessary foundations in achieving real benefits on controlling diabetes and complications via a lifestyle management program.

The invention of LEGT, particularly the GH.p-Modulus for diet, aims at the objective in controlling diabetes via diet management without medication intervention, and achieving the extra benefit in recovering the damaged pancreatic beta cells functionality at the root-cause level. In the author's case, he used a constant GH.p-Modulus of 1.8 during 2010-2019, he could predict his finger PPG level at a >98% prediction accuracy. During 2020-2021 of COVID-19 quarantine lifestyle without travel and hectic schedule, his slightly elevated GH.p-Modulus of 2.5 can equally predict with a >98% accuracy of his most recently lower finger PPG level as well.

Intermittent fasting provides an interesting lower-bound situation of near zero carbs/sugar intake amount which requires a special numerical treatment in order to obtain an accurate analysis result. However, it is just for academic interest only. IF, a not-so-common practice, can indeed bring down the glucose to a steady state within a short timeframe, and can also reduce body weight over a reasonable longer period.

Regarding his upper-bound analyses using both high-carbs meals (40-200 grams per meal) and higher finger PPG data (2010-2013), he discovered that his LEGT is equally applicable and useful to these cases.

This research note concludes that *LEGT* is useful on predicting *PPG* accurately in order to control diabetes conditions [1-37].

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