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A Summarized Investigation Report of GH.p-Modulus Values using Linear Elastic Glucose Theory of GH-Method: Math-Physical Medicine, Part 17 (No. 371)

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Abstract

This article is Part 17 of the author's linear elastic glucose behavior study. It summarizes key conclusions from the first 16 segments of his research work regarding the data range of GH.p-modulus values [9 through 23].

This research report includes the following:

(1) The author's personal data and GH.p-modulus values;
(2) The data and GH.p-modulus values of three US patients and two Myanmar patients;
(3) The low-bound and high-bound analysis from eight hypothetical standard cases of different carbs/sugar intake amounts and post-meal walking steps;
(4) The data with high quite GH.p-modulus values from a special investigation case using 285 egg meals with neuroscience influences.

The following paragraphs describe his key variable definitions and mathematical operations of obtaining the GH.p-modulus:

*(1) Baseline PPG equals to 97% of fasting plasma glucose (FPG) value, or 97% * (weight * GH.f-Modulus).*
*(2) Baseline PPG plus increased amount of PPG due to food, i.e., plus (carbs/sugar intake amount * GH.p-Modulus).*
*(3) Baseline PPG plus increased PPG due to food, and then subtracts reduction amount of PPG due to exercise, i.e., minus (post-meal walking k-steps * 5).*
(4) The Predicted PPG equals to Baseline PPG plus the food influences, and then subtracts the exercise influences.

The linear elastic glucose equation is:
*Predicted PPG = (0.97 * GH.f-modulus * Weight) +(GH.p-modulus * Carbs&sugar) - (post-meal walking k-steps * 5)*

Where,
(1) Incremental PPG = Predicted PPG - Baseline PPG + Exercise impact
(2) GH.f-modulus = FPG / Weight
(3) GH.p-modulus = Incremental PPG / Carbs intake

Therefore,

GH.p-modulus = (PPG - (0.97 * FPG) + (post-meal walking k-steps * 5)) / (Carbs&Sugar intake)

This study is a summarized report of the author's previous 16 segments of research articles on linear elastic glucose

theory. He focuses on the GH.p-Modulus using four different data groups which cover patients of different nationalities, varying time periods, comparison between pre-virus vs. COVID-19 periods, finger glucoses vs. sensor glucoses, hypothetical boundary analysis (upper bound and lower bound), and a special neuroscience study of egg meals to arrive at the following observed conclusion.

In summary, the author presumes that most patients still having a reasonable normal lifestyles, their GH.p-Modulus value should be located between 1.0 and 6.0. In this study of linear elastic glucose theory, the GH.p-modulus indeed reflects the actual general health conditions and lifestyle details of a patient.

Practical advice of GH.p-Modulus to patients
(1) If you have a record for some of your glucoses, carbs/sugar intake amount, and post-meal walking steps, then you may use this equation to calculate your GH.p-Modulus:

GH.p-Modulus = ((0.97*FPG) + (post-meal k-steps*5)) / (Carbs&sugar amount)

(2) If you don't have your data stored, then you may apply the following suggestions: If your diabetes conditions is moderate (HbA1C ~7.0 & glucose ~150 mg/dL), then use 1.8 to 2.2 for your GH.p-Modulus; and if your diabetes conditions is more serious (HbA1C >8.0 & glucose >180 mg/dL), then use 2.5 to 3.3 for your GH.p-Modulus.

(3) Normally, the GH.p-Modulus should be within 1.5 to 2.5; however, if you want to be more conservative in predicting your PPG, then you may use the GH.p-Modulus greater than 3.0 in the following equation:

Predicted PPG = (0.97 * FPG) + (GH.p-Modulus * carbs& sugar) - (post-meal walking k-steps * 5)

Introduction
This article is Part 17 of the author's linear elastic glucose behavior study. It summarizes key conclusions from the first 16 segments of his research work regarding the data range of GH.p-modulus values [9, 23].

This research report includes the following:

1. The author's personal data and GH.p-modulus values;
2. The data and GH.p-modulus values of three US patients and two Myanmar patients;
3. The low-bound and high-bound analysis from eight hypothetical standard cases of different carbs/sugar intake amounts and post-meal walking steps;
4. The data with quite high GH.p-modulus values from a special investigation case using 285 egg meals with neuroscience influences.

Methods
Background
To learn more about the author's GH-Method: math-physical medicine (MPM) methodology, readers can refer to his article to understand his developed MPM analysis method in [1].

Stress, Strain, & Young's Modulus
Prior to his medical research work, he was an engineer in the various fields of structural engineering (aerospace, naval defense, and earthquake engineering), mechanical engineering (nuclear power plant equipments, and computer-aided-design), and electronics engineering (computers, semiconductors, and software robot).

The following excerpts come from the internet public domain, including Google and Wikipedia:

"Strain - ε:
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
ε = dL / L
where
ε = strain (m/m, in/in)
dL = elongation or compression (offset) of object (m, in)
L = length of object (m, in)

Stress - σ:
Stress is force per unit area and can be expressed as
σ = F / A
where
σ = stress (N/m2, lb./in2, psi)
F = applied force (N, lb.)
A = stress area of object (m2, in2)

Stress includes tensile stress, compressible stress, shearing stress, etc.

E, Young's modulus:
It can be expressed as:
E = stress / strain
= σ / ε
= (F / A) / (dL / L)
where
E = Young's Modulus of Elasticity (Pa, N/m2, 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 (Figure 1)

(8/5/18-11/27/20	Finger	Sensor
PPG	113	132
FPG	110	111
Carbs gram	13.6	13.6
Walking k-steps	4.25	4.25
(8/5/18-11/27/20	Finger	Sensor
GH.p (avg. data)	2.0	3.3

Finger	Y2017-2019	Y2020	Y2017-2020
PPG	116	109	114
FPG	116	106	114
Carbs gram	14.3	12.7	13.9
Walking k-steps	4.32	4.37	4.33
Finger	Y2017-2019	Y2020	Y2017-2020
GH.p (avg. data)	1.8	2.2	1.8

Figure 1: The author's case of 3 different time periods and 2 different glucose measuring devices.

Based on various experimental results, the following table lists some of Young's modulus associated with different materials:

Nylon: 2.7 GPa
Concrete: 17-30 GPa
Glass fibers: 72 GPa
Copper: 117 GPa
Steel: 190-215 GPa
Diamond: 1220 GPa

Young's modules in the above table are ranked from soft material (low E) to stiff material (higher E)."

Professor James Andrews taught the author strength of materials and linear elasticity at the University of Iowa and Professor Norman Jones taught him nonlinear and dynamic plastic behaviors of structures at Massachusetts Institute of Technology. These two great academic mentors provided him with the foundational knowledge to understand these two important subjects in engineering.

Highlights of Linear Elastic Glucose Theory

Here is the step-by-step explanation for the predicted PPG equation using linear elastic glucose theory as described in [9, 24]:

1. Baseline PPG equals to 97% of FPG value, or 97% * (weight * GH.f-Modulus).
2. Baseline PPG plus increased amount of PPG due to food, i.e., plus (carbs/sugar intake amount * GH.p-Modulus).
3. Baseline PPG plus increased PPG due to food, and then subtracts reduction amount of PPG due to exercise, i.e., minus (post-meal walking k-steps * 5).
4. The Predicted PPG equals to Baseline PPG plus the food influences, and then subtracts the exercise influences.

The Linear Elastic Glucose Equation is

Predicted PPG = (0.97 * GH.f-modulus * Weight) + (GH.p-modulus * Carbs&sugar) - (post-meal walking k-steps * 5)

Where
1. *Incremental PPG = Predicted PPG - Baseline PPG + Exercise impact*
2. *GH.f-modulus = FPG / Weight*
3. *GH.p-modulus = Incremental PPG / Carbs intake*

Therefore,

GH.p-modulus = (PPG - (0.97 * FPG) + (post-meal walking k-steps * 5)) / (Carbs&Sugar intake)

By using this linear equation, a diabetes patient only needs the input data of body weight, carbs & sugar intake amount, and post-meal walking steps in order to calculate the predicted PPG value without obtaining any measured glucose data.

In early 2014, the author came up with the analogy between theory of elasticity and plasticity and the severity of his diabetes conditions when he was developing his mathematical model of metabolism using topology concept and finite element method.

On 10/14/2020, by utilizing the concept of Young's modulus with stress and strain, which was taught in engineering schools, he initiated and engaged this linear elastic glucose behaviors research. The following paragraphs describe his research findings at different stages:

1. He discovered that there is a "pseudo-linear" relationship existing between carbs & sugar intake amount and incremental PPG amount. Based on this finding, he defined the first glucose coefficient of GH.p-modulus for PPG.

2. Similar to Young's modulus relating to stiffness of engineering inorganic materials, he found that the GH.p-modulus is dependent upon the patient's severity level of diabetes, i.e., the patient's glucose sensitivity on carbs/sugar intake amount, which reflects this patient's health state of liver cells and pancreatic beta cells.

3. Comparable to GH.p-modulus for PPG, in 2017, he uncovered a similar pseudo-linear relationship existing between weight and FPG with high correlation coefficient of above 90%. Therefore, he defined the second glucose coefficient of GH.f-modulus as the FPG value divided by the weight value. This GH.f-modulus is related to the severity of combined chronic diseases, including both obesity and diabetes. More than 33 million Americans, about 1 in 10, have diabetes, and

approximately 90% to 95% of them have type 2 diabetes (T2D), where 86% also have problems with being overweight or obese. In other words, 7.7% to 8.2 % of the US population or 25 to 27 million Americans have issues with both obesity and diabetes.

4. He inserted these two glucose coefficients of GH.p-modulus and GH.f-modulus, into the predicted PPG equation to remove the burden of collecting measured glucoses by patients.

5. By experimenting and calculating many predicted PPG values over a variety of time length from different diabetes patients with different health conditions, he finally revealed that GH.p-modulus seems to be "near-constant" or "pseudo-linearized" over a short period of 3 to 4 months. This short period is compatible with the known lifespan of human red blood cells, which are living organic cells. This is quite different from the engineering inorganic materials, such as steel or concrete which can last for an exceptionally long period of time. The same conclusion was observed using his monthly GH.p-modulus data during the COVID-19 period in 2020 when his lifestyle became routine and stabilized.

6. He used three US clinical cases during the 2020 COVID-19 period to delve into the hidden characteristics of the physical parameters and their biomedical relationships. More importantly, through the comparison study in Part 7, he found explainable biomedical interpretations of his two defined glucose coefficients of GH.p-modulus and GH.f-modulus.

7. He conducted a PPG boundary analysis by discovering a lower bound and an upper bound of predicted PPG values for eight hypothetical standard cases and three US specific clinical cases. The derived numerical values of these two boundaries make sense from a biomedical viewpoint and also matched the situations of the three US clinical cases. He conducted two extreme stress tests, i.e., increasing carbs/sugar intake amount to 50 grams per meal and boosting post-meal walking steps to 5k after each meal, to examine the impacts on the lower bound and upper bound of PPG values.

8. Based on six international clinical cases, he further explored the influences from the combination of obesity and diabetes. Using a "lifestyle medicine" approach, he offered recommendations to reduce their PPG from 130-150 mg/dL down to below 120 mg/dL via reducing carbs/sugar intake and increasing exercise level in walking.

9. Based on his neuroscience research work using both 126 solid eggs and 159 liquid eggs with an extremely low carbs/sugar intake amount of ~2.5 grams, producing two totally different sets of PPG data and waveforms based on neurosciences viewpoint. He has also identified a different set of much higher values for GH.p-modulus from the exceptionally low carbs/sugar intake of egg meals. Even though this egg neuroscience research results can be served as a special boundary case, it has also further proven that the GH.p-modulus is influenced directly by the human brain and nervous system.

10. He compared the above two egg meals results, including PPG values and glucose coefficients, in particular the GH.p-modulus, against the total results of his 2,843 meals. He discovered the vast differences of GH.p-modulus magnitudes and also learned the tight relationship between GH.p-modulus value and carbs/sugar intake amount. By distinguishing the GH.p-modulus results from the special boundary cases of 12.7 for liquid egg meals and 20.7 for solid egg meals, his general GH.p-modulus values from his 2,843 total meals are 2.1 using finger PPG and 3.4 using sensor PPG.

11. He used his 365 egg meal data from his neurosciences research papers to further calculate detailed variations of their associated GH.p-modulus.

12. He applied the linear elastic glucose theory to formulate certain guidelines as a part of his practical "lifestyle medicine" approach for the family medicine branch.

13. He calculates three GH.p-modulus values, 1.8, 2.2, and 1.8, for three different periods, i.e., pre-virus period, COVID-19 period, and total period, respectively. This data range of between 1.8 to 2.2 matches with his observed personal lifestyle and acquired biomedical knowledge through his medical research work during the past 9 years.

14. He calculates two GH.p-modulus values, 2.0 and 3.3, for two different measured glucoses, i.e., finger-piercing measured glucoses and CGM sensor collected glucoses, respectively. This GH.p-Modulus difference between 2.0 and 3.3 mainly reflects the average sensor PPG value is 17% higher than the average finger PPG value.

Results
Figures 1, 2, 3 and 4 show the calculated GH.p-Modulus values based on different input data of FPG, PPG, Carbs/sugar intake amount, and post-meal walking steps for the following four different data groups with a variety of situations:
1. The author's personal data and GH.p-modulus values;
2. The data and GH.p-modulus values of three US patients and two Myanmar patients;
3. The low-bound and high-bound analysis from eight hypothetical standard cases of different carbs/sugar intake amounts and post-meal walking steps;
4. The data with quite high GH.p-modulus values from a special investigation case using 285 egg meals with neuroscience influences.

	Case A	Case B	Case C
Obesity	Male	Female	Young
Diabetes	T2D	T2D	Obesity
Avg. Height (")	69	64	71
BMI	25	27	41
Weight (lbs)	171	155	292
FPG (mg/dL)	101	103	105
GH.f-modulus	0.59	0.66	0.36
Baseline PPG	98	100	102
GH.p-modulus	3.6	2.6	1.0
Carbs/Sugar (g)	12.34	9.81	12.38
Carbs * GH.p	44	26	12
	Case A	Case B	Case C
Carbs/Sugar (g)	12.34	9.81	12.38
Baseline + Carbs	142	125	114
Walking K-steps	4.35	2.13	1.04
- PPG from Walk	-22	-11	-5
Predicted PPG	121	115	109

T2D Patients	Case M1	Case M2	Case U1	Case U2	Case U3	Improved M1	Improved M2
Weight (pound)	150	237	167	157	273	150	200
FPG (mg/dL)	141	137	101	103	105	120	120
GH.f-modulus	0.94	0.58	0.60	0.66	0.38	0.80	0.60
Baseline PPG 9mg/dL)	137	133	98	100	102	116	116
GH.p-modulus	1.4	1.6	3.6	2.6	1.0	1.4	1.6
Carbs/Sugar (standard gram)	15.42	15.35	12.34	9.81	12.38	13.00	13.00
Carbs *GH.p-modulus	22	25	44	26	12	18	21
Walking (standard k-steps)	1.0	2.5	4.4	2.1	1.0	2.5	2.5
T2D Patients	Case M1	Case M2	Case U1	Case U2	Case U3	Improved M1	Improved M2
Predicted PPG	153.4	145.0	120.6	114.8	109.0	122.1	124.7
Measured PPG	153.0	145.6	120.8	113.9	109.9	121.6	123.5
T2D Patients	Case M1	Case M2	Case U1	Case U2	Case U3	Improved M1	Improved M2
Accuracy of Predicted PPG	100%	100%	100%	101%	99%	100%	101%

Figure 2: Clinic cases of 3 US and 2 Myanmar patients

Resuts of Boundary Analysis	Lower-Bound	Upper-Bound
BMI	25	35
Height (inch)	64	69
Weight (pound)	146	237
FPG (mg/dL)	100	150
GH.f-modulus	0.42	1.03
Baseline PPG 9mg/dL)	97	146
GH.p-modulus	2.0	6.0
Carbs/Sugar (standard gram)	10	25
Carbs/Sugar (extreme gram)	10	50
Carbs *GH.p (standard gram)	20	150
Carbs *GH.p (extreme gram)	20	300
Walking (standard k-steps)	1	4
Walking (extreme k-steps)	1	5
Predicted PPG (standard case)	97	276
Predicted PPG (extreme case)	92	475

	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8	Case A	Case B	Case C
Gender	Man	Man	Man	Man	Woman	Woman	Woman	Woman	Male	Female	Young
Obesity	No Obesity	No Obesity	Obesity	Obesity	No Obesity	No Obesity	Obesity	Obesity	No Obesity	No Obesity	Obesity
Diabetes	No Diabetes	Diabetes	No Diabetes	Diabetes	No Diabetes	Diabetes	No Diabetes	Diabetes	Pre-Diabetes	Pre-Diabetes	Pre-Diabetes
Weight (lbs)	169	169	237	237	146	146	204	204	171	155	292
FPG (mg/dL)	100	150	100	150	100	150	100	150	101	103	105
Carbs/Sugar (g)	10	10	15	15	20	20	25	25	12.34	9.81	12.38
	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8	Case A	Case B	Case C
Predicted PPG (1K)	112	201	122	231	132	261	142	291	121	115	109
Predicted PPG (2K)	107	196	117	226	127	256	137	286	121	115	109
Predicted PPG (4K)	97	186	107	216	117	246	127	276	121	115	109
	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8	Case A	Case B	Case C
Predicted PPG (2.3K)	105	194	115	224	125	254	135	284	121	115	109
	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8	Case A	Case B	Case C
GH.f-modulus	0.6	0.9	0.4	0.6	0.7	1.0	0.5	0.7	0.59	0.66	0.36
GH.p-modulus	2.0	6.0	2.0	6.0	2.0	6.0	2.0	6.0	3.6	2.6	1.0

Figure 3: 8 Hypothetical standard cases to study upper-bound and lower-bound of GH.p-Modulus

Total: 5/5/2018-11/7/2020	Meals:	159	126	2843	2843
	The Author	Liquid Eggs	Solid Eggs	All Meals - Sensor	All Meals -Finger
	GH.f-modulus (%)	59	64	64	64
	Sensor FPG (mg/dL)	100	109	110	110
Formula	Weight (pound)	170	172	171	171
= FPG / Weight	GH.f-modulus	0.59	0.64	0.64	0.64
= 0.97 * Weight * GH.f-modulus	Baseline PPG (mg/dL)	97	106	106	106
	GH.p-modulus	12.7	20.7	3.4	2.1
	Carbs&Sugar (gram)	2.8	2.2	13.8	13.8
	Carbs *GH.p-modulus	35	46	46	28
	Walking (k-steps)	4.2	4.7	4.3	4.3
= Baseline+Carbs*GH.p-Walk*5	Predicted PPG	111.3	128.3	131.0	113.0
	Measured PPG (mg/dL)	111.3	128.3	131.0	113.0
= Predicted PPG / Measured PPG	Accuracy of Predicted PPG	100%	100%	100%	100%
	The Author	Liquid Eggs	Solid Eggs	All Meals - Sensor	All Meals -Finger
	Carbs&Sugar (gram)	2.8	2.2	13.8	13.8
= predcted PPG - Baseline PPG + K-steps*5	Incremental PPG (mg/dL)	35.4	45.6	46.3	28.3
= Incremental PPG / Carbs&Sugar	GH.p-modulus	12.7	20.7	3.4	2.1

Figure 4: Special case of quite high GH.p-Modulus values from 285 egg experimental meals to demonstrate the brain and neuro-scientific influences on GH.p-Modulus

Here again is the step-by-step explanation for the predicted PPG equation:

(1) Baseline PPG equals to 97% of FPG value, or 97% * (weight * GH.f-Modulus).
(2) Baseline PPG plus increased amount of PPG due to food, i.e., plus (carbs/sugar intake amount * GH.p-Modulus).
(3) Baseline PPG plus increased PPG due to food, and then subtracts reduction amount of PPG due to exercise, i.e., minus (post-meal walking k-steps * 5).
(4) The Predicted PPG equals to Baseline PPG plus the food influences, and then subtracts the exercise influences.

The linear elastic glucose equation is:

*Predicted PPG = (0.97 * GH.f-modulus * Weight) +(GH.p-modulus * Carbs&sugar) - (post-meal walking k-steps * 5)*

Where
(1) Incremental PPG = Predicted PPG - Baseline PPG + Exercise impact
(2) GH.f-modulus = FPG / Weight
(3) GH.p-modulus = Incremental PPG / Carbs intake

Therefore,

GH.p-modulus = (PPG - (0.97 * FPG) + (post-meal walking k-steps * 5)) / (Carbs&Sugar intake)

The following is the list of the GH.p-Modulus values for the four groups in the form of (low-end of GH.p, and high-end of GH.p):

Group 1, the author: (1.8, 3.3)
Group 2, clinical cases: (1.0, 3.6)
Group 3, standard cases: (2.0, 6.0)
Group 4, neuroscience: (13, 21)

Figure 1 depicts the data analysis results from the author himself. Using three different time periods, it shows the GH.p data range of 1.8 to 2.2. However, if using two different glucose measurement devices, it depicts the GH.p data range of 2.0 for finger glucoses and 3.3 for sensor glucoses. Group 1 has a GH.p data range between 1.8 and 3.3.

Figure 2 reflects the data analysis results from three US patients and two Myanmar patients. Group 2 with five different patients have a GH.p data range between 1.0 and 3.6.

Figure 3 illustrates the data analysis results from eight "hypothetical standard cases" with different amounts of carbs/sugar intake and post-meal exercise. Group 3 with the eight hypothetical standard cases have a GH.p data range between 2.0 and 6.0.

Figure 4 represents the data analysis results from 285 "neuroscience investigation meals" having the same food ingredients of one large egg with an extremely low carbs/sugar intake amount of 0.76 gram from egg alone for each meal while always maintaining ~4.3k post-meal walking steps. These 285 experimental results show that solid egg meals (135 mg/dL at peak PPG) is 31 mg/dL higher than liquid egg meals (104 mg/dL at peak PPG). This strange and unique physical phenomenon cannot be explained clearly or satisfactorily using the traditional knowledge of internal medicine and food nutrition. It is a result from the biomedical neural communication model between the brain and internal organs, specifically stomach, intestine, liver, and pancreas. The calculated values of GH.p-Modulus in Group 4 is 12.7 for liquid egg meals and 20.7 for solid egg meals. Therefore, Group 4 of the special neuroscience experiment indeed demonstrates a special case of high-end GH.p-Modulus values.

The GH.p-modulus value coordinates with a patient's weight, FPG, PPG, carbs/sugar intake, and post-meal exercise that fluctuates within a reasonable numerical range. When the author combines the results from Groups 1, 2, and 3, he obtains a data range for GH.p-Modulus values between 1.0 and 6.0.

Conclusions

This study is a summarized report of the author's previous 16 segments of research articles on linear elastic glucose theory. He focuses on the GH.p-Modulus using four different data groups which cover patients of different nationalities, varying time periods, comparison between pre-virus vs. COVID-19 periods with different lifestyles, finger glucoses vs. sensor glucoses, hypothetical boundary analysis (upper bound and lower bound), and a special neuroscience study of 285 egg meals to arrive at the following observed conclusion [1-24].

In summary, the author presumes that most patients having a reasonable normal lifestyles, their GH.p-Modulus value should be located between 1.0 and 6.0. In this study, the GH.p-modulus indeed reflects the actual general health conditions and lifestyle details of a patient.

Practical Advice of GH.p-Modulus to Patients

(1) If you have a record for some of your glucoses, carbs/sugar intake amount, and post-meal walking steps, then you may use this equation to calculate your GH.p-Modulus:

GH.p-Modulus = ((0.97*FPG) + (post-meal k-steps*5)) / (Carbs&sugar amount)

(2) If you don't have your data stored, then you may apply the following suggestions: *If your diabetes conditions is moderate (HbA1C ~7.0 & glucose ~150 mg/dL), then use 1.8 to 2.2 for your GH.p-Modulus; and if your diabetes conditions is more serious (HbA1C >8.0 & glucose >180 mg/dL), then use 2.5 to 3.3 for your GH.p-Modulus.*

(3) Normally, the GH.p-Modulus should be within 1.5 to 2.5; however, *if you want to be more conservative in predicting your PPG, then you may use the GH.p-Modulus greater than 3.0 in the following equation:*

Predicted PPG = (0.97 * FPG) + (GH.p-Modulus * carbs& sugar) - (post-meal walking k-steps * 5)

Acknowledgement

Foremost, I would like to express my deep appreciation to my former professors: professor James Andrews at the University of lowa, who helped develop my foundation in basic engineering and computer science, and professor Norman Jones at the Massachusetts Institute of Technology, who taught me how to solve tough scientific problem through the right attitude and methodology.

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