

## Applying Multiple Regression Analyses and Linear Elastic Glucose Theory to Analyze and Compare the Predicted and Measured Finger-Pierced Postprandial Plasma Glucose using Carbs/Sugar Intake Amount and Post-Meal Walking Steps as Inputs over 2016-2017 Period for a Diabetes Patient Based on GH-Method: Math-Physical Medicine (No. 544)

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### Abstract

In the author's previous research reports, he mainly applied physics theories, engineering models, mathematical equations, computer big data analytics and artificial intelligence (AI) techniques, as well as some statistical approaches. However, the majority of medical research papers he has read thus far are primarily based on statistics. As a result, in this article, he selected some basic statistical tools, such as correlation, variance,  $p$ -values, and multiple regression analyses, to study the predicted finger-piercing postprandial plasma glucose (PPG) as the output (dependent variable) by using his carbs/sugar intake grams and post-meal walking steps as inputs (independent variables).

Since 1/1/2018, the author has been utilizing a finger-pierced device to collect and store his glucose data on the iPhone and Amazon cloud server. He has accumulated 4 glucose data per day over the past 10 years, along with entering his carbs/sugar intake grams and post-meal walking steps after each meal into the database.

This article displays a multiple regression analysis result of the finger-piercing measured PPG data with the predicted finger PPG values (dependent output variables) by using his average daily carbs/sugar intake amounts and daily average post-meal walking steps (independent input variables) over a selected 2-year period from 1/1/2016 to 12/31/2017.

In this study, he will not repeat the detailed introduction of the regression analysis in the Method section because it is available in any statistics textbook. It should be noted that in regression analysis, the correlation coefficient  $R$  should be  $> 0.5$  or 50% to indicate a strong inter-connectivity and the  $p$ -value should be  $< 0.05$  to be considered as statistically significant.

By utilizing his developed linear elastic glucose theory (LEGT), he calculates the predicted finger-piercing PPG using the same inputs of carbs/sugar and walking steps during the same chosen time period.

In summary, there are three specific conclusions worth mentioning:

(1) The multiple regression based predicted finger PPG data (orange curve) and measured finger PPG data (blue curve) have a strong correlation (88%) and variance (79%) with an extremely high 99% prediction accuracy. These findings have proven the usefulness of the predicted dependent variable, PPG, by using multiple regression analysis results of 2 independent variables, carbs/sugar and post-meal walking. However, these findings are associated with the specific case of the finger piercing glucose data type during the selected timeframe of 2016-2017. For a compar-

ison, the author has identified a lower prediction accuracy of 91% using a timeframe of 2020-2021 and continuous glucose monitoring (CGM) sensor glucose data type.

(2) Furthermore, he utilizes his developed LEGT model to calculate the predicted finger PPG which achieved a perfect 100% prediction accuracy, whereas the multiple regression model achieved a 99% prediction accuracy.

(3) Apparently, the key to attain a perfect LEGT predicted PPG is selecting a suitable GH.p Modulus value which is dependent on many influential factors such as patient, diabetes severity, time window selection, and glucose measurement device used. Nevertheless, this particular study offers additional proof to confirm the author's intuition that the physics model is more accurate and superior to the statistics model.

## Introduction

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## Methods

### MPM Background

To learn more about the author's developed GH-Method: math-physical medicine (MPM) methodology, readers can select the following three papers from his ~500 published medical papers.

The first paper, No. 386 describes his MPM methodology in a general conceptual format. The second paper, No. 387 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

depicts a general flow diagram containing ~10 key MPM research methods and different tools.

In particular, paper No. 453 illustrates his GH-Method: math-physical medicine in great details, "Using Topology concept of mathematics and Finite Element method of engineering to develop a mathematical model of Metabolism in medicine in order to control various chronic diseases and their complications via overall health conditions improvement".

### The Author'S Case of Diabetes and Complications

The author has been a severe type 2 diabetes (T2D) patient since 1996 and weighed 220 lbs. (100 kg, BMI 32.5) at that time. By 2010, he still weighed 198 lbs. (BMI 29.2) with an average daily glucose of 250 mg/dL (HbA1C of 10%). During that year, his triglycerides reached to 1161 (diabetic retinopathy or DR) and albumin-creatinine ratio (ACR) at 116 (chronic kidney disease or CKD). He also suffered five cardiac episodes within a decade. In 2010, three independent physicians warned him regarding his needs of kidney dialysis treatment and future high risk of dying from severe diabetic complications. Other than cerebrovascular disease (stroke), he has suffered most known diabetic complications, including both macro-vascular and micro-vascular complications.

In 2010, he decided to launch his self-study on endocrinology, diabetes, and food nutrition in order to save his own life. During 2015 and 2016, he developed four prediction models related to diabetes conditions: weight, PPG, fasting plasma glucose (FPG), and A1C. As a result, from using his developed mathematical metabolism index (MI) model in 2014 and the four prediction tools, by end of 2016, his weight was reduced from 220 lbs. (100 kg, BMI 32.5) to 176 lbs. (89 kg, BMI 26.0), waistline from 44 inches (112 cm), nonalcoholic fatty liver disease /NAFLD) to 33 inches (84 cm), average finger glucose reading from 250 mg/dL to 120 mg/dL, and lab-tested A1C 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 has achieved excellent results on all fronts, especially his 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 dining 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 and overall metabolism state were somewhat affected during this two-year heavy travel period.

During 2020 and 2021 with a strict COVID-19 quarantine lifestyle, not only has he written and published ~400 medical papers in 100+ journals, but he has also reached his best health conditions for the past 26 years. By the beginning of 2021, his weight was further reduced to 165 lbs. (BMI 24.4) along with a 6.1% A1C value (daily average glucose at 105 mg/dL), without having any medication interventions or insulin injections. These good results are due to his non-traveling, low-stress, and regular daily life routines. Due to the knowledge of chronic diseases, practical lifestyle management experiences, and his developed various high-tech tools, they contributed to his excellent health status since 1/19/2020, which is the start date of being self-quarantine.

On 5/5/2018, he applied a CGM sensor device on his upper arm and checks glucose measurements every 5 minutes for a total of ~288 times each day. He has maintained the same measurement pattern to present day. In his research work, he uses the CGM sensor glucose at time-interval of 15 minutes (96 data per day). Incidentally, the difference of average sensor glucoses between 5-minute intervals and 15-minute intervals is only 0.4% (average glucose of 114.81 mg/dL for 5-minutes and average glucose of 114.35 mg/dL for 15-minutes with a correlation of 93% between these two sensor glucose curves) during the period from 2/19/20 to 8/13/21.

Therefore, over the past 11 years, he could study and analyze the collected ~3 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 medical research work is based on the aims of achieving both “high precision” with “quantitative proof” in the medical findings.

The following timetable provides a rough sketch of the emphasis of his medical research during each stage:

- 2000-2013: Self-study diabetes and food nutrition, developing a data collection and analysis software.
- 2014: Develop a mathematical model of metabolism, using engineering modeling and advanced mathematics.
- 2015: Weight & FPG prediction models, using neuroscience.
- 2016: PPG & HbA1C prediction models, utilizing optical physics, AI, and neuroscience.
- 2017: Complications due to macro-vascular research such as cardiovascular disease (CVD), coronary heart disease (CHD) and stroke, using pattern analysis and segmentation analysis.
- 2018: Complications due to micro-vascular research such as CKD, bladder, foot, and eye issues such as DR.
- 2019: CGM big data analysis, using wave theory, energy theory, frequency domain analysis, quantum mechanics, and AI.
- 2020: Cancer, dementia, longevity, geriatrics, DR, hypothyroidism, diabetic foot, diabetic fungal infection, linkage between metabolism and immunity, and learning about certain infectious diseases such as COVID-19.
- 2021: Applications of LEGT and perturbation theory from quantum mechanics on medical research subjects, such as chronic diseases and their complications, cancer, and dementia. Using metabolism and immunity as the base, he ex-

pands his research into cancers, dementia, and COVID-19. In addition, he has also developed a few useful analysis methods and tools for his medical research work.

To date, he has collected nearly 3 million data regarding his medical conditions and lifestyle details. In addition, he has written 536 medical papers and published 500+ articles in 100+ various medical journals, including 7 special editions with selected 20-25 papers for each edition. Moreover, he has given ~120 presentations at ~65 international medical conferences. He has continuously dedicated time and effort on medical research work to share his findings and knowledge with patients worldwide.

### **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 equipment, 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 -  $\epsilon$ :

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

$$\epsilon = dL / L$$

where

$$\epsilon = \text{strain (m/m, in/in)}$$

dL = elongation or compression (offset) of object (m, in)

L = length of object (m, in)

Stress -  $\sigma$ :

Stress is force per unit area and can be expressed as

$$\sigma = F / A$$

where

$$\sigma = \text{stress (N/m}^2, \text{ lb./in}^2, \text{ psi)}$$

F = applied force (N, lb.)

A = stress area of object (m<sup>2</sup>, in<sup>2</sup>)

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

E, Young's modulus:

It can be expressed as:

$$E = \text{stress} / \text{strain}$$

$$= \sigma / \epsilon$$

$$= (F / A) / (dL / L)$$

where

E = Young's Modulus of Elasticity (Pa, N/m<sup>2</sup>, lb./in<sup>2</sup>, 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 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).”

### Highlights of LEGT

Here is the step-by-step explanation for the predicted PPG equation using the LEGT as described below:

- (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, specifically 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, which is 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:

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

Where

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

For the case of the pre-period’s glucose, the modified equation is as follows:

$$\text{Predicted Pre-period’s glucose} = (\text{FPG} * \text{GH.f}) + (\text{Carbs/sugar} * \text{GH.p}) + (\text{walking k-steps} * \text{GH.w})$$

Where GH.f = 0.97, GH.p = 3.234, GH.w = -5.0

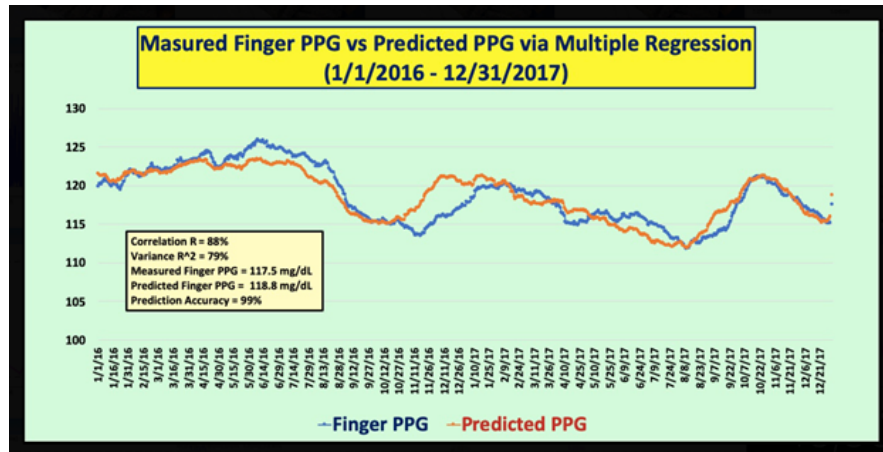
### Results

Figure 1 displays a summarized data table of this multiple regression analysis of finger PPG versus carbs/sugar intake amount and post-meal walking steps during the 2-year period from 1/1/2016 to 12/31/2017. There are 670 observations (days) with the significance F value and 2 p-values of x, which are much lower than 0.05 (near zero); therefore, the results are statistically significant.

Average =	15.120	4269	118	Average	117.5	118.8	-1.2
Correlation =	61%	-85%	100%	Correlation =	88%		
R Square =	38%	72%	100%	R Square =	78%		
Slope =	0.53	-0.01					
Y-intercept =	153.13	153.13					
<b>SUMMARY OUTPUT 11/7/21</b>							
<b>(1/1/2016-12/31/2017) PPG vs. Carbs &amp; Steps</b>							
Regression Statistics							
Multiple R	0.89						
R Square	79%						
Adjusted R Square	0.79						
Standard Error	1.66						
Observations	730						
ANOVA							
	df	SS	MS	F	Significance F		
Regression	2	7616	3808	1378	0.000000000		
Residual	727	2009	3				
Total	729	9625					
	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	
Intercept	153.13	1.40	109.24	0.000	150.38	155.88	
Carbs/Sugar	0.53	0.03	15.95	0.000	0.47	0.60	
Walking Steps	-0.01	0.00	-38.04	0.000	-0.01	-0.01	

Figure 1: Data table of multiple regression analysis results of finger PPG versus both carbs/sugar and walking steps (2016-2017)

Figure 2 illustrates the comparison of multiple regression analysis PPG (orange curve) versus measured finger PPG (blue curve).



**Figure 2:** Measured finger PPG versus Multiple regression based Predicted PPG using carb/sugar intake amount and post-meal walking steps as inputs (2016-2017)

The 5 key data are listed below:

*Correlation (R) = 88%*

*Variance (R<sup>2</sup>) = 79%*

*Measured finger PPG = 117.5 mg/dL*

*Predicted finger PPG = 118.8 mg/dL*

*Prediction accuracy = 99%*

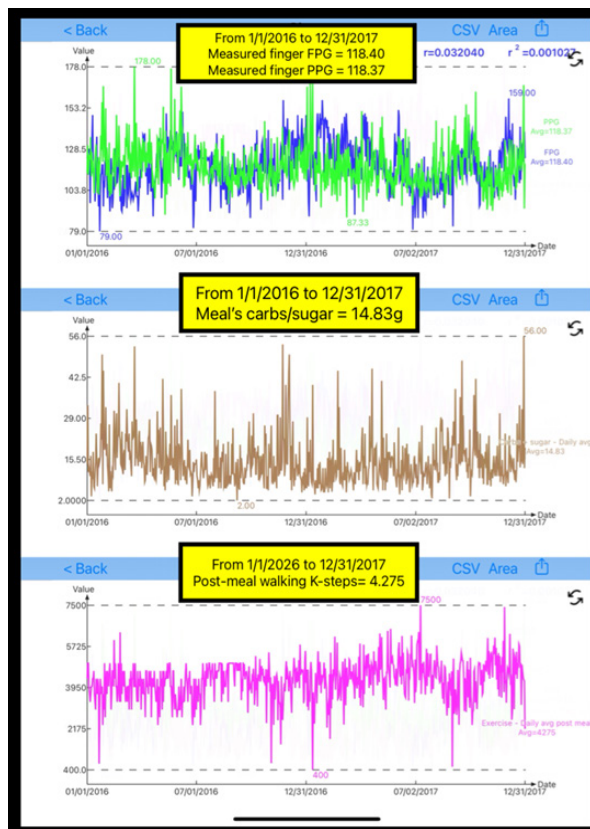
*Prediction Accuracy*

*= 1-(predicted-measured)/measured*

*=99%*

Figure 4 shows his LEGT equation (top diagram) based on physics and engineering.

Figure 3 offers his LEGT calculation with the required background measurement diagrams for the sensor PPG (118.4 mg/dL), carbs/sugar intake (14.83 grams), and post-meal walking (4,275 steps). Within his selected time period of 730 days, he has utilized a total of 7,300 data for this particular study.



**Figure 3:** Input data curves of LEGT model

Figure 4 shows his LEGT equation (top diagram) based on physics and engineering.

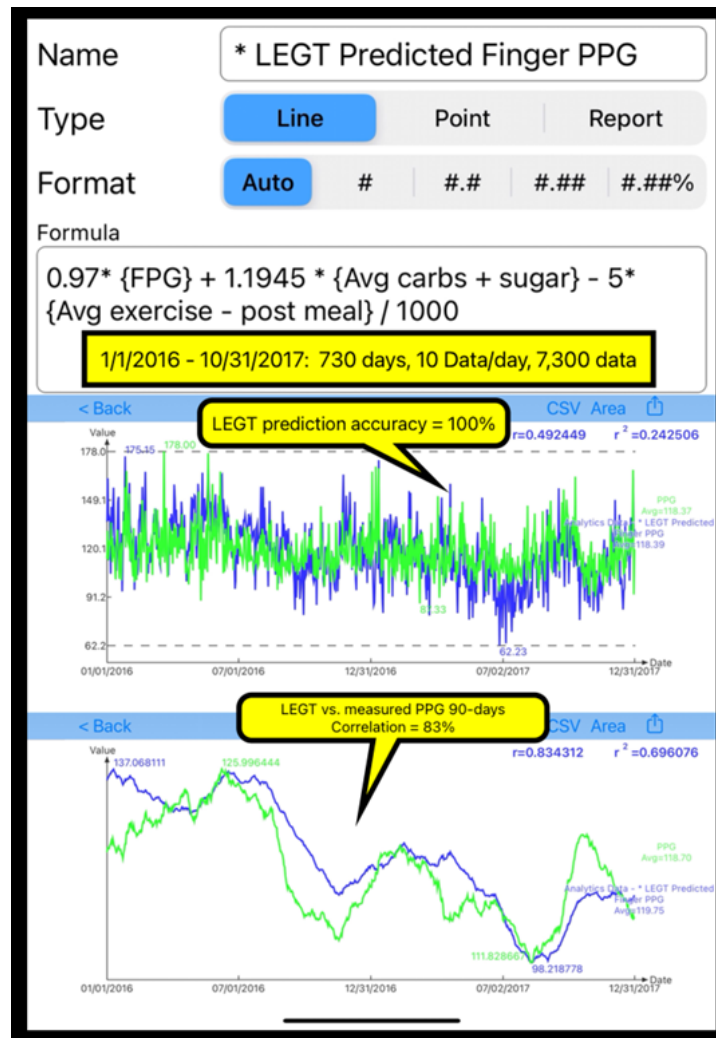


Figure 4: LEGT equation and Output data curves

Here is the equation:

$$\begin{aligned}
 & \text{Predicted PPG} \\
 & = \text{Baseline PPG} + \text{energy influx via food} - \text{energy consumption} \\
 & \text{via exercise} \\
 & = GH.f * FPG + GH.p * carbs/sugar + GH.w * walking\ k\ steps \\
 & = 0.97 * FPG + 1.1945 * carbs/sugar + (-5.0) * walking\ k\ steps \\
 & = 0.97 * 118.4 + 1.1945 * 14.83 + (-5.0) * 4.275 \\
 & = 118.75\ mg/dL
 \end{aligned}$$

### Conclusions

In summary, there are three specific conclusions worth mentioning:

(1) The multiple regression based predicted finger PPG data (orange curve) and measured finger PPG data (blue curve) have a strong correlation (88%) and variance (79%) with an extremely high 99% prediction accuracy. These findings have proven the usefulness of the predicted dependent variable, PPG, by using

multiple regression analysis results of 2 independent variables, carbs/sugar and post-meal walking. However, these findings are associated with the specific case of the finger piercing glucose data type during the selected timeframe of 2016-2017. For a comparison, the author has identified a lower prediction accuracy of 91% using a timeframe of 2020-2021 and CGM sensor glucose data type.

(2) Furthermore, he utilizes his developed LEGT model to calculate the predicted finger PPG which achieved a perfect 100% prediction accuracy, whereas the multiple regression model achieved a 99% prediction accuracy.

(3) Apparently, the key to attain a perfect LEGT predicted PPG is selecting a suitable GH.p Modulus value which is dependent on many influential factors such as patient, diabetes severity, time window selection, and glucose measurement device used. Nevertheless, this particular study offers additional proof to confirm the author's intuition that the *physics model is more accurate and superior to the statistics model*.

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## References

For editing purposes, majority of the references in this paper, which are self-references, have been removed for this article. Only references from other authors' published sources remain. The bibliography of the author's original self-references can be viewed at [www.eclairemd.com](http://www.eclairemd.com).

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