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Research Article

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Analyzing relations among weight, FPG, and PPG using statistical correlation analysis and Linear Elastic Glucose Theory of GH-Method: math-physical medicine, LEGT Part 20 (No. 402)

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Abstract

The author uses collected health and medical data of three clinic cases during a time period from 3/3/2020 to 2/14/2021. At first, he supplied statistical correlation analysis to study the degree of relationships of weight versus FPG and FPG versus PPG. He then applies his developed two moduli, GH-f and GH-p from the linear elastic glucose theory (LEGT) to calculate and evaluate the separated contribution percentages of three contributors within each period. These three contributors are: (1) postprandial plasma glucose (PPG) baseline factor via fasting plasma glucose (FPG) and GH-f Modulus, (2) diet factor via carbs/sugar intake amount and GH-p Modulus, and (3) exercise factor via post-meal walking steps. His purpose is to identify the FPG variance and its contribution on PPG formation due to the hidden strength from the overall health state of pancreatic beta cells.

This study also includes a boundary analysis of FPG's influences on PPG formation. The upper bound of FPG influences is calculated through GH-f value of 0.97, i.e. 97% of FPG as the baseline PPG. The lower bound of FPG influences is calculated through GH-f value of 0.6, i.e. 60% of FPG as the baseline PPG. Therefore, this particular analysis consists of two portions, the upper bound analysis portion versus the lower bound analysis portion.

Regrading correlation results, Case A has a "very high" correlation coefficient (R) of 80% for weight vs. FPG and 93% for FPG vs. PPG. Both of Case B and Case C have two "high enough" correlation coefficients (R) of mid-70% for weight vs. FPG and low-50% for FPG vs. PPG.

The applications of linear elastic glucose theory (LEGT) have two key observations as explained below.

First, when it uses the upper bound of GH-f Modulus 0.97 for FPG to serve as the baseline PPG, then his GH-p Modulus for these three cases becomes a set of "near-constant" values as listed:

Upper-Bound Analysis of GH-p

Case A: 3.1
Case B: 1.7
Case C: 0.6

When it uses the lower bound of GH-f Modulus 0.60 for FPG to serve as the baseline PPG, then his GH-p Modulus for these tree cases becomes another set of "near-constant" value as listed:

Lower-Bound Analysis of GH-p

Case A: 5.8
Case B: 3.8
Case C: 1.8

These two boundary analyses have proved that the linear elastic relationship indeed exist between carbs/sugar intake amount and the diet part of the PPG formation.

Second, this study produced three contribution factors which are "near-constant" percentages in terms of their PPG contribution. For the upper bound analysis using 0.97*FPG as the baseline PPG, the analysis produces the results in the following table for these three cases, in the format of (baseline PPG %, diet on PPG %, and post-meal walking %).

Upper-Bound Analysis

Case A: (82%, 36%, -18%)

Case B: (87%, 26%, -13%)
Case C: (92%, 15%, -7%)

and

Lower-Bound Analysis

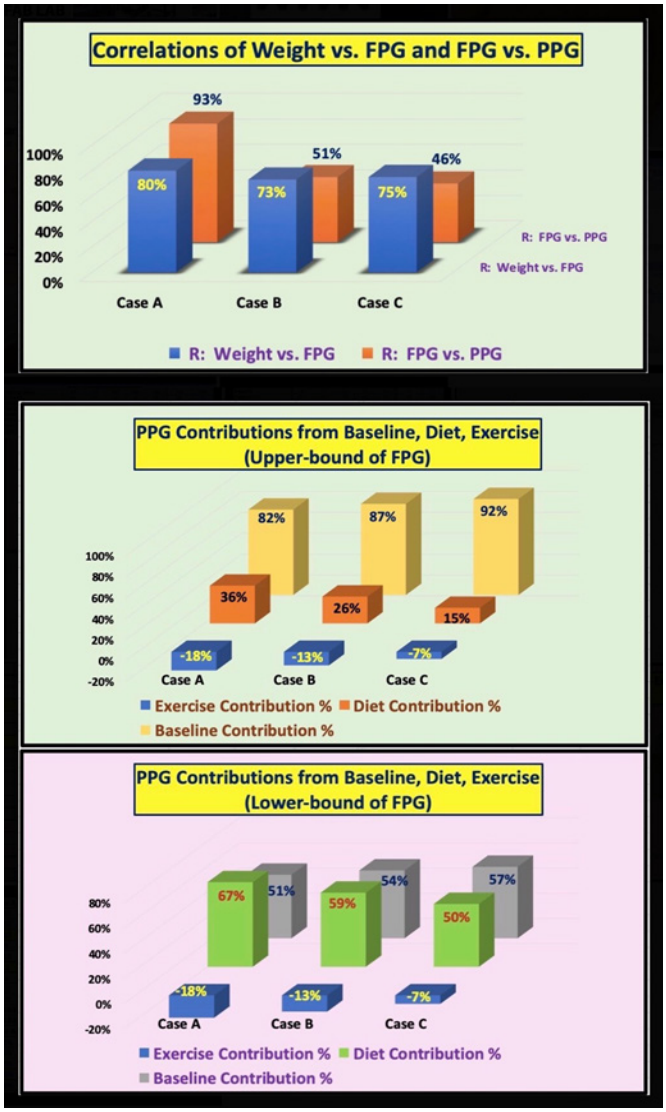
Case A: (51%, 67%, -18%)
Case B: (54%, 59%, -13%)
Case C: (57%, 50%, -7%)

These three "near constant" contribution percentages from both boundary analyses have disclosed that their individual "stabilized" contributions to PPG formation are depending on individual case's health state of pancreatic beta cells. ***The higher GH-p Modulus value, the poor this patient's health status of beta cells insulin secretion and insulin resistance.*** Therefore, in this study, Case A has the worst condition, Case B is in the middle, and Case C has the best condition, in terms of severity of their diabetes conditions, i.e. pancreatic beta cells health status.

From the above first and second observations, it is clear that when GH-f Modulus decreases, then the GH-p Modulus would be increased in order to make the predicted PPG values to match with the measured PPG values. Nevertheless, through moduli of GH-fans GH-p, the linear elastic characters among FPG, carbs/sugar, and PPG are preserved and observed from this study.

In conclusion, the strongest influential factor of PPG is FPG which further discloses the health state of both insulin secretion (insulin quantity) and insulin resistance (insulin quality). As a result, the ability to analyze and interpret FPG and then extend it to connect with PPG is important. It also proves the big data analytics as a power tool and method for identifying hidden biomedical facts of our body and internal organs.

Introduction



The author uses collected health and medical data of three clinic cases during a time period from 3/3/2020 to 2/14/2021. At first, he supplied statistical correlation analysis to study the degree of relationships of weight versus FPG and FPG versus PPG. He then applies his developed two moduli, GH-f and GH-p from the linear elastic glucose theory (LEGT) to calculate and evaluate the separated contribution percentages of three contributors within each period. These three contributors are: (1) postprandial plasma glucose (PPG) baseline factor via fasting plasma glucose (FPG) and GH-f Modulus, (2) diet factor via carbs/sugar intake amount and GH-p Modulus, and (3) exercise factor via post-meal walking steps. His purpose is to identify the FPG variance and its contribution on PPG formation due to the hidden strength from the overall health state of pancreatic beta cells.

This study also includes a boundary analysis of FPG's influences on PPG formation. The upper bound of FPG influences is calculated through GH-f value of 0.97, i.e. 97% of FPG as the baseline PPG. The lower bound of FPG influences is calculated through GH-f value of 0.6, i.e. 60% of FPG as the baseline PPG. Therefore, this particular analysis consists of two portions, the upper bound analysis portion versus the lower bound analysis portion.

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Methods

MPM Background

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

The first paper, No. 386 (Reference 1) describes his MPM methodology in a general conceptual format. The second paper, No. 387 (Reference 2) outlines the history of his personalized diabetes research, various application tools, and the differences between biochemical medicine (BCM) approach versus the MPM approach. The third paper, No. 397 (Reference 3) depicts a general flow diagram containing ~10 key MPM research methods and different tools.

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

$\varepsilon = dL / L$

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

$\sigma = F / A$

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:

$E = \text{stress} / \text{strain}$
$= \sigma / \varepsilon$
$= (F / A) / (dL / L)$

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).

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 Linear Elastic Glucose Theory

Here is the step-by-step explanation for the predicted PPG equation using linear elastic glucose theory as described in References 10 through 25:

(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. 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. 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. 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. 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. 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. 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. 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. 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. 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. 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. 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. 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. 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. 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.

Pancreatic Beta-Cells Study

The author focuses on his continuous medical research work for the "self-recovery" of his pancreatic beta cells. He uses "self-recovery" because he has kept his carbs/sugar intake amount less than 15 grams per meal and his post-meal walking exercise more than 4,000 steps over the past 5 years. Since 12/8/2015, he has also ceased taking any diabetes medication, which is the strongest influential factor for the phenomena of glucose fluctuations. Therefore, his body is totally free of any external chemical intervention that may alter the internal organ's biochemical process and reactions. Under this strict controlled lifestyle and environment, his damaged pancreatic beta cells must go through the self-repairing process in order to show any meaningful improvement signs of his diabetes conditions. This is his chosen approach in "fixing his diabetes conditions from their root causes via a stringent lifestyle management".

Furthermore, during FPG period, e.g., between 00:00 midnight through 07:00 next morning, glucose is not under any influence from external factors, mainly food and exercise. However, the FPG values still fluctuate through the hours of sleep. Of course, there are some other factors, such as sleep conditions, stress, illness, room environments, etc. that can alter FPG. However, these are secondary influential factors. The major influential factor is insulin, which is produced by pancreatic beta cells; therefore, the ability to analyze and interpret FPG and then extend it to connect with PPG is important.

Results

In this study, Case A is a 74 years old male with 26 years history of type 2 diabetes (T2D). Case B is a 73 years old female with 21 years history of T2D. Case C is a 48 years old male with 5 years history of T2D. All of these three patients have not taken any diabetes medication or insulin injection during the selected time period from 3/1/2020 to 2/14/2021. All of their glucose data were collected via a self-monitored glucose device (SMGD) at 15-minutes time interval. This gives them ~96 glucose data per day. Their FPG value is defined as the average glucose between 00:00 and 07:00, and PPG value is defined as the average glucose between fist-bite of meal and 180-minutes after the first-bite of food.

Figures 1, 2, and 3 show the results of statistical correlation analysis between two curves, e.g. weight vs. FPG, FPG vs. PPG for Case A, Case B, and Case C. Figure 4 using a bar chart to demonstrate the summarized correlation coefficients (R). The following table re-lists the conclusions of R in the format of (R between weight vs. FPG, R between FPG vs. PPG).

Correlation Study

Case A: (80%, 93%)
Case B: (73%, 51%)
Case C: (75%, 46%)

In summary, Case A has a "very high" correlation coefficient (R) of 80% for weight vs. FPG and 93% for FPG vs. PPG. Both of Case B and Case C have "high enough" correlation coefficients of mid-70% for weight vs. FPG and low-50% for FPG vs. PPG. ***The message we get from this analysis is that weight controls FPG and FPG is related to PPG.***

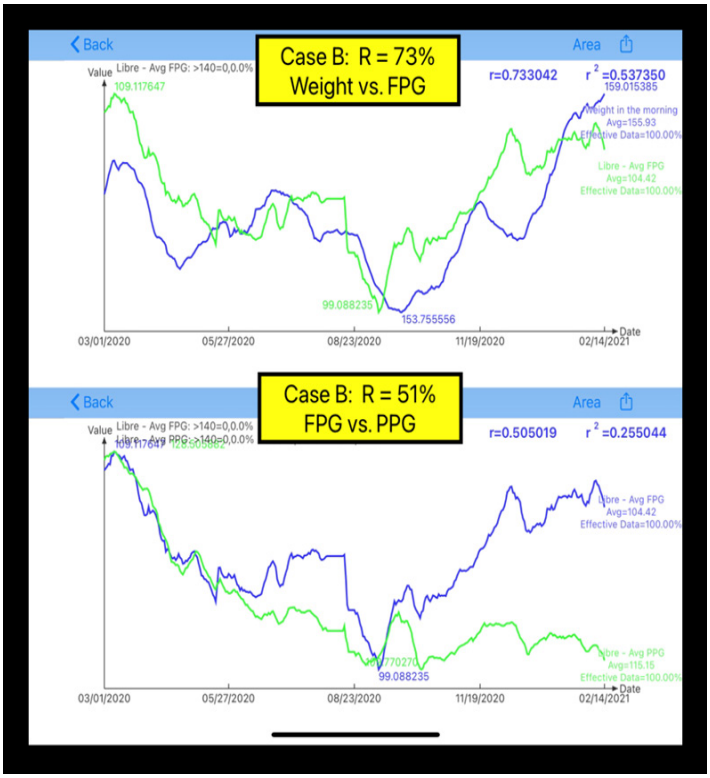

Figure 1: R of Case A for weight vs. FPG and FPG vs. PPG

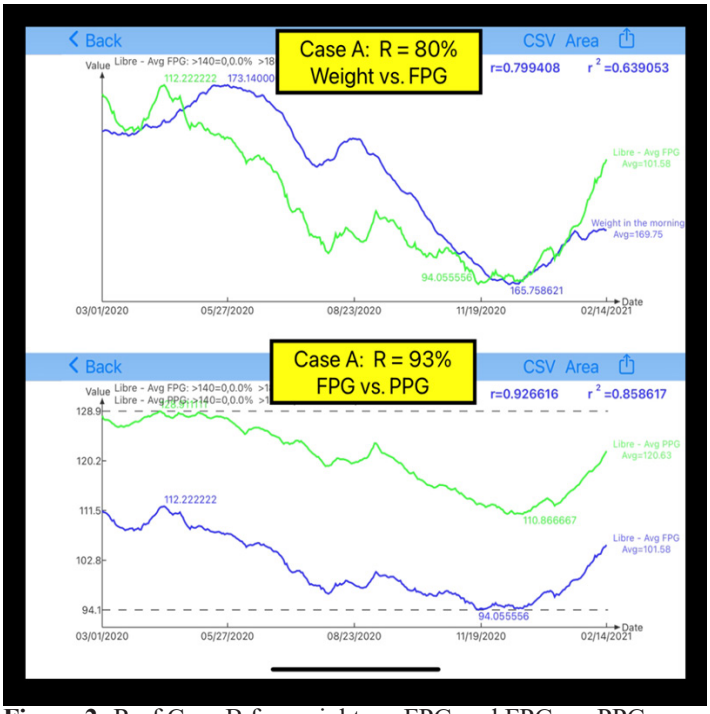

Figure 2: R of Case B for weight vs. FPG and FPG vs. PPG

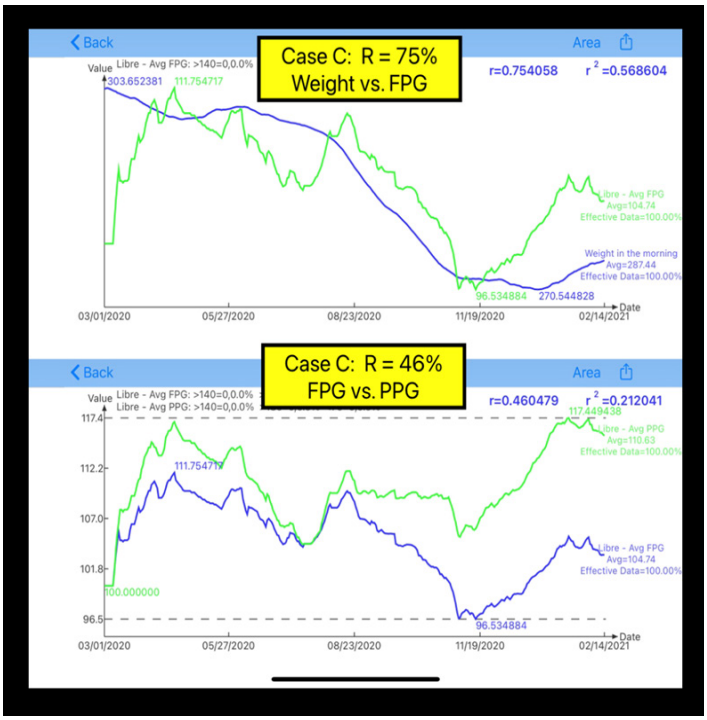

Figure 3: R of Case C for weight vs. FPG and FPG vs. PPG

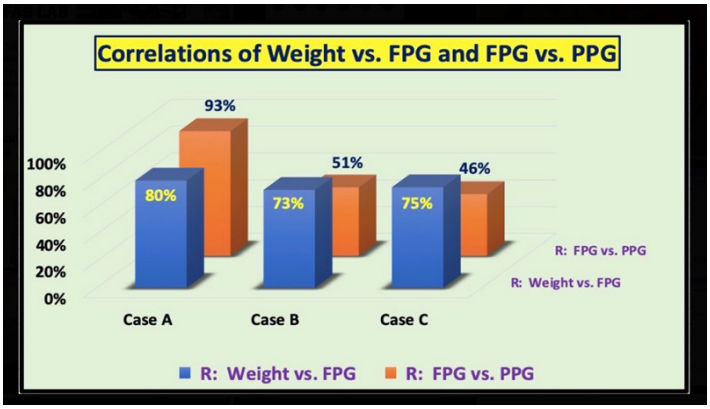

Figure 4: Summarize diagram of R for weight vs. FPG and FPG vs. PPG for Case A, Case B, and C

Correlation Study

Case A: (80%, 93%)
Case B: (73%, 51%)
Case C: (75%, 46%)

In summary, Case A has a "very high" correlation coefficient (R) of 80% for weight vs. FPG and 93% for FPG vs. PPG. Both of Case B and Case C have "high enough" correlation coefficients of mid-70% for weight vs. FPG and low-50% for FPG vs. PPG. ***The message we get from this analysis is that weight controls FPG and FPG is related to PPG.***

Figure 5 shows a table containing both input data and calculated data for two boundary analyses regarding the FPG's influences on PPG's formation. The upper-bound analysis of FPG influences is using GH-f value of 0.97, i.e. 97% of FPG as the baseline PPG. The lower-bound analysis of FPG influences is using GH-f value of 0.6, i.e. 60% of FPG as the baseline PPG. Therefore, this particular analysis consists of two portions, the upper-bound analysis portion versus the lower-bound analysis portion. These two boundary analysis results are displayed through Figure 6 for the upper-bound analysis and Figure 6 for the lower-bound analysis. The calculation follows the procedures as outlined in LEGT and in the author's 19 reference papers.

(2/15/2021) Upper Bound	Case A	Case B	Case C
Weight	170	156	287
FPG	102	104	105
GH.f	0.97	0.97	0.97
PPG Baseline = (GH.f*FPG)	99	101	102
Carbs/Sugar	14.0	18.0	30.0
GH.p	3.1	1.7	0.6
GH.p*Carbs	44	30	17
Walking K-steps	4.3	3.0	1.5
-(K-steps*5)	-22	-15	-8
Predicted PPG	120.63	116.15	110.63
Measured PPG	120.63	116.15	110.63
Upper-Bound Analysis	Case A	Case B	Case C
Exercise Contribution %	-18%	-13%	-7%
Diet Contribution %	36%	26%	15%
Baseline Contribution %	82%	87%	92%
Total %	100%	100%	100%
Pancreatic Beta Cells	100%	53%	18%

(2/15/2021) Lower Bound	Case A	Case B	Case C
Weight	170	156	287
FPG	102	104	105
GH.f	0.60	0.60	0.60
PPG Baseline = (GH.f*FPG)	61	63	63
Carbs/Sugar	14.0	18.0	30.0
GH.p	5.8	3.8	1.8
GH.p*Carbs	81	68	55
Walking K-steps	4.3	3.0	1.5
-(K-steps*5)	-22	-15	-8
Predicted PPG	120.63	116.15	110.63
Measured PPG	120.63	116.15	110.63
Lower-Bound Analysis	Case A	Case B	Case C
Exercise Contribution %	-18%	-13%	-7%
Diet Contribution %	67%	59%	50%
Baseline Contribution %	51%	54%	57%
Total %	100%	100%	100%
Pancreatic Beta Cells	100%	66%	32%

Figure 5: Input data and Calculated data of LEGT for Case A, Case B, and Case C

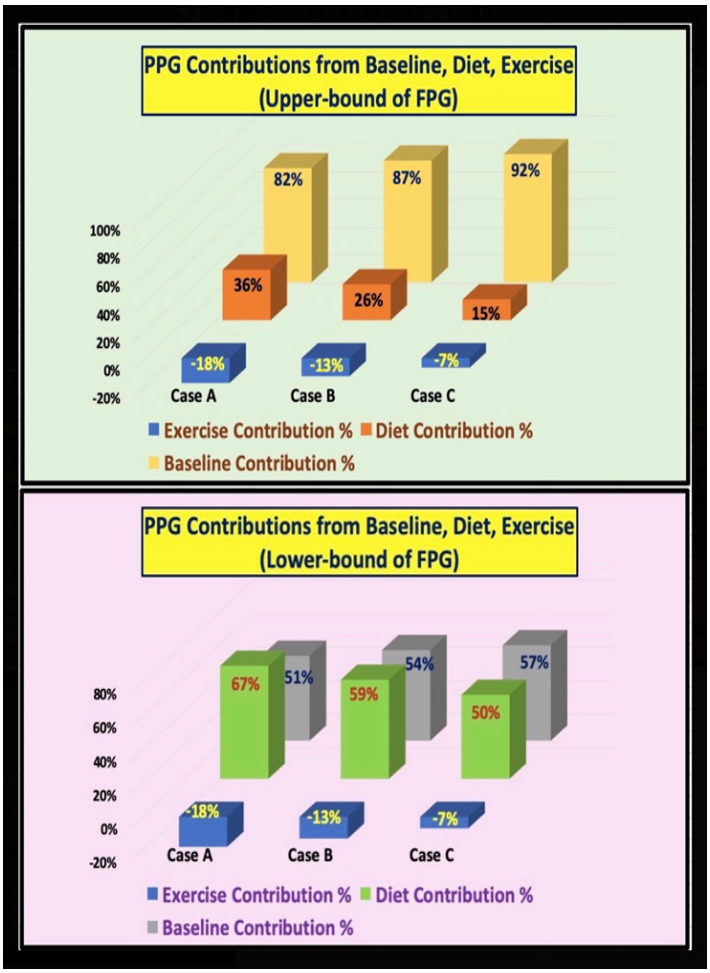

Figure 6: Upper-bound (GH-f: 0.97, GH-p: Case A: 3.1, Case B: 1.7, and Case C: 0.6). Lower-bound (GH-f: 0.60, GH-p: Case A: 5.8, Case B: 3.8, and Case C: 1.8).

He will repeat below his developed predicted PPG equation based on linear elastic glucose theory (LEGT).

Predicted PPG = baseline PPG (i.e. GH-f * FPG) +(GH-p * carbs/sugar intake grams) - (post-meal walking k-steps * 5)

The following table lists the key findings in the format of (Baseline PPG, diet increased PPG, exercise decreased PPG, and predicted and measured PPG):

Upper-Bound Analysis

Case A: (99, 44, -22, 121)
Case B: (101, 30, -15, 116)
Case C: (102, 17, -8, 111)

and

Lower-Bound Analysis

Case A: (61, 81, -22, 121)
Case B: (63, 68, -15, 116)
Case C: (63, 55, -8, 111)

Comparing both baseline PPG and Diet generated PPG values, we can see that the lost amount of mg/dL from baseline PPG between upper-bound and lower-bound would be compensated by the increased amount of mg/dL from diet generated PPG. This is due to the LEGT calculation's objective in matching the predicted PPG with the measured PPG. However, this calculation process would alter the GH-p Modulus value with the higher GH-p, then the worse pancreatic conditions would be, and vice versa.

Conclusions

Regrading correlation results, Case A has a "very high" correlation coefficient (R) of 80% for weight vs. FPG and 93% for FPG vs. PPG. Both of Case B and Case C have two "high enough" correlation coefficients (R) of mid-70% for weight vs. FPG and low-50% for FPG vs. PPG.

The applications of linear elastic glucose theory (LEGT) have two key observations as explained below.

First, when it uses the upper bound of GH-f Modulus 0.97 for FPG to serve as the baseline PPG, then his GH-p Modulus for these three cases becomes a set of "near-constant" values as listed:

Upper-Bound Analysis of GH-p

Case A: 3.1
Case B: 1.7
Case C: 0.6

When it uses the lower bound of GH-f Modulus 0.60 for FPG to serve as the baseline PPG, then his GH-p Modulus for these tree cases becomes another set of "near-constant" value as listed:

Lower-Bound Analysis of GH-p

Case A: 5.8
Case B: 3.8
Case C: 1.8

These two boundary analyses have proved that the linear elastic relationship indeed exist between carbs/sugar intake amount and the diet part of the PPG formation.

Second, this study produced three contribution factors which are "near-constant" percentages in terms of their PPG contribution. For the upper bound analysis using 0.97*FPG as the baseline PPG, the analysis produces the results in the following table for these three cases, in the format of (baseline PPG %, diet on PPG %, and post-meal walking %).

Upper-Bound Analysis

Case A: (82%, 36%, -18%)
Case B: (87%, 26%, -13%)
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Lower-Bound Analysis

Case A: (51%, 67%, -18%)
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Case C: (57%, 50%, -7%)

These three "near constant" contribution percentages from both boundary analyses have disclosed that their individual "stabilized" contributions to PPG formation are depending on individual case's health state of pancreatic beta cells. ***The higher GH-p Modulus value, the poor this patient's health status of beta cells insulin secretion and insulin resistance***. Therefore, in this study, Case A has the worst condition, Case B is in the middle, and Case C has the best condition, in terms of severity of their diabetes conditions, i.e. pancreatic beta cells health status.

From the above first and second observations, it is clear that when GH-f Modulus decreases, then the GH-p Modulus would be increased in order to make the predicted PPG values to match with the measured PPG values. Nevertheless, through moduli of GH-fans GH-p, the linear elastic characters among FPG, carbs/sugar, and PPG are preserved and observed from this study.

In conclusion, the strongest influential factor of PPG is FPG which further discloses the health state of both insulin secretion (insulin quantity) and insulin resistance (insulin quality). As a result, the ability to analyze and interpret FPG and then extend it to connect with PPG is important. It also proves the big data analytics as a power tool and method for identifying hidden biomedical facts of our body and internal organs [1-26].

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