The GH-Method

The Relationship Among Key Biomarkers for Diabetes Research Based on 69 Intermittent Fasting Data and 69 Normal Meal Data Using GH-Method: Math-Physical Medicine (No. 410)

Gerald C. Hsu*

eclaireMD Foundation, USA

Abstract

The purpose of this report is to reconfirm the extremely high correlations existing among key biomarkers of diabetes, including weight, fasting plasma glucose (FPG), and postprandial plasma glucose (PPG) which have been demonstrated in the author's previous research papers. However, this is the first study that includes his intermittent fasting (IF) data. There are no sophisticated methodologies utilized in this study other than statistical correlation calculations. The human organs, glucose, and chronic diseases have their natural biochemical interpretations, reasonings, and operational functions. However, their observed physical phenomena follow the basic theories and extended principles of physics which can be further analyzed or solved using mathematical equations or tools. There are a few key observations identified and reconfirmed through this investigation using IF data. In this study, data is extracted from 3 time periods: 69 non-fasting breakfasts, 69 fasting days, and 137 combined total periods. (1) The correlation coefficients (R) of weight vs. sensor FPG from these 3 periods are within the range of 76% to 90%. These three high R values have proven that the amount of body weight determines the level of FPG. (2) The R of sensor PPG vs. sensor FPG from these 3 periods are within the range of 95% to 98%. These three extremely high R values have proven that PPG and FPG have a tight relationship where they fluctuate together. However, there are two caveats. The first is that FPG is one of the indicators of the health state of insulin secretion and insulin quality from the pancreatic beta cells. The second is that a patient's lifestyle, particularly carbs/sugar intake amount and post-meal exercise, must be under strict management. (3) Although a 16 hour-long fasting includes a tea-only breakfast, it is very close to a total fasting situation where the associated PPG wave of the tea-only fasting still has some lower magnitude of vibrations (wave fluctuations with both peaks and nadirs). This is a direct result of the human brain's neuro-scientific interaction with both the liver and pancreas. Nevertheless, the tea-only fasting can still be served as a near baseline for PPG analysis. (4) The data pattern of PPG fluctuations is remarkably similar to the data pattern of the PPG magnitudes in the order of non-fasting period being the highest, the total period being the middle, and fasting period being the lowest.

Keywords: Biomarkers; Diabetes; Intermittent fasting; Weight; Glucose

Abbreviations: FPG: fasting plasma glucose; PPG: postprandial plasma glucose; IF: intermittent fasting; R: correlation coefficients; MPM: math-physical medicine; HbA1C: hemoglobin A1c

Received: 11 August 2021, Accepted: 07 September 2021, Available online: 15 September 2021

*Corresponding author: Gerald C. Hsu, eclaireMD Foundation, USA

1. INTRODUCTION

The purpose of this report is to reconfirm the extremely high correlations existing among key biomarkers of diabetes, including weight, fasting plasma glucose (FPG), and postprandial plasma glucose (PPG) which have been demonstrated in the author's previous research papers. However, this is the first study that includes his intermittent fasting (IF) data. There are no sophisticated methodologies utilized in this study other than statistical correlation calculations.

2. METHODS

2.1 MPM background

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

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

2.2 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 average daily glucose of 250 mg/dL (HbA1C of 10%). During that year, his triglycerides reached 1161 and his albumin-creatinine ratio (ACR) at 116. He also suffered from five cardiac episodes within a decade. In 2010, three independent physicians warned him regarding his need for 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, PPG, FPG, and HbA1C. As a result, from using his developed mathematical metabolism index (MI) model 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), average 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(4–6).

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 dining out frequently, post-meal exercise disruption, jet lag, and 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.

By 2020, his weight was further reduced to 165 lbs. (BMI 24.4) and his HbA1C was at 6.2% without any medication intervention or insulin injection(7–10). Actually, during 2020 with the special COVID-19 quarantined lifestyle, not only has he published approximately 400 medical papers in 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 strong knowledge of chronic diseases, practical lifestyle management experiences, and his development of various high-tech tools contribute to his excellent health status since 1/19/2020(11–13).

On 5/5/2018, he applied 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 the present day(14–18).

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, and tools from mathematics, physics, engineering, and computer science to conduct his medical research work[19,20]. His medical research work is based on the aim of achieving high precision with quantitative proof in his medical findings[21–23].

2.3 Input data for time domain

During the period from 10/15/2020 to 3/5/2021, he segregated his collected glucose data into two separated groups as follows:

Non-fasting: 69 days, Fasting: 69 days

Furthermore, for the purpose of comparison, he also uses his collected sensor glucose data from 10/15/2020 and 3/5/2021 as a total period of 137 breakfasts in this study. This total period contains an average of both non-fasting and fasting[24,25].

2.4 PPG fluctuation in time domain

He utilizes the maximum PPG minus the minimum PPG as the fluctuation value of the breakfast PPG wave fluctuation data to conduct his TD analysis which is similar to the concept of the defined glycemic variability (GV)[26].

3. RESULTS

Figure 1 shows the input information that contains the selected time frame, the number of breakfasts, carbs/sugar intake in grams, post-breakfast walking steps, and finger-piercing measured PPG.

Figure 2 depicts the comparison of his synthesized PPG waves for the three periods. The following table indicates information in the format of average PPG, starting PPG, peak PPG, and peak minus start PPG:

Non-fasting: 119, 113, 125, 12, Fasting: 111, 107, 114, 7, Total: 115, 109, 119, 10

Once more, the data patterns are in the order of non-fasting period being the highest, total period being in the middle, and fasting period being the lowest.

Figure 3 reflects the comparison of his PPG candlestick results for the three periods using the K-line model. The following table shows information in the format of average PPG, maximum PPG, minimum PPG, and maximum minus minimum PPG:

Non-fasting: 119, 137, 106, 31, Fasting: 111, 123, 102, 21, Total: 115, 130, 104, 26

Again, the data patterns are in the order of non-fasting period being the highest, total period being in the middle, and fasting period being the lowest.

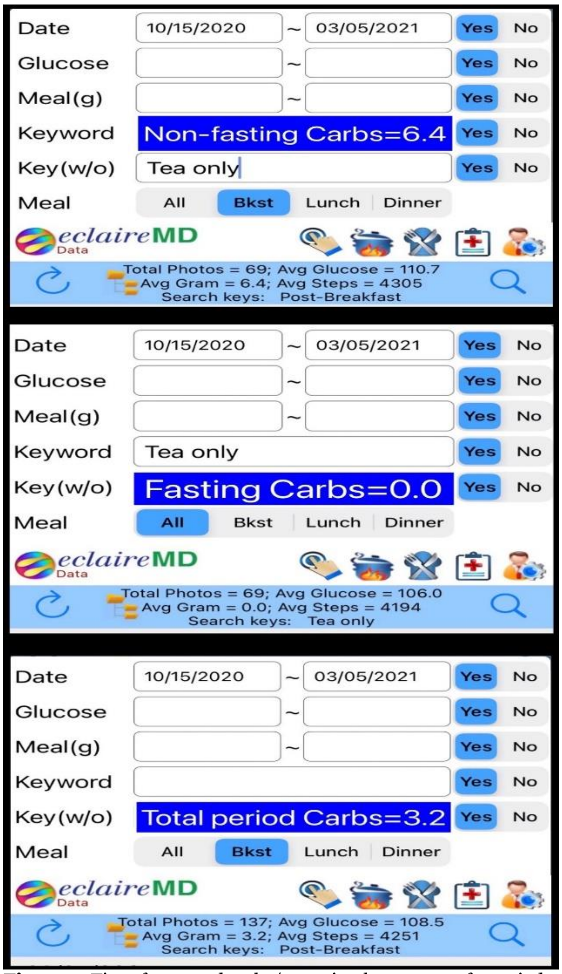


Figure 1: Time-frame and carbs/sugar intake amount of 3 periods.

Figure 4 reveals the comparison of correlation coefficients (R) between bodyweight vs. sensor FPG for the three periods. The following table displays the results of R between weight and sensor FPG:

Non-fasting: 76%, Fasting: 90%, Total: 82%

These three high correlations indicate that bodyweight determines the FPG level.

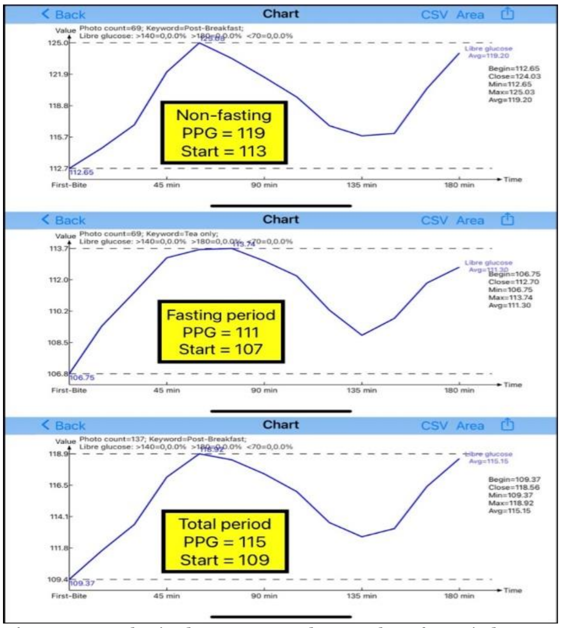


Figure 2: Synthesized PPG wave and PPG value of 3 periods.

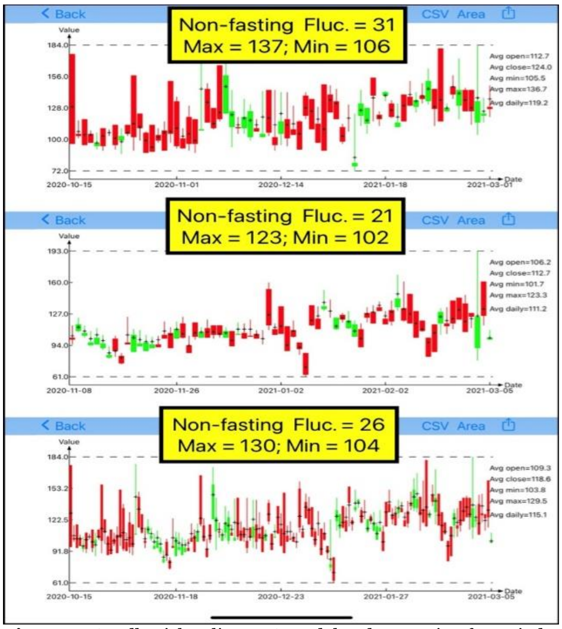


Figure 3: Candlestick K-line PPG model and max-min of 3 periods.

Figure 5 illustrates the comparison of R between sensor PPG vs. sensor FPG for the three periods. The following table shows the results of R between sensor PPG and sensor FPG:

Non-fasting: 95%, Fasting: 98%, Total: 97%

These three extremely high correlations indicate that PPG and FPG have a tight relationship where they fluctuate together.

However, there are two caveats that support this important observation.

The first is that FPG is one of the indicators of the health state of insulin secretion and insulin quality from the pancreatic beta cells. While sleeping, there are no external influential factors that play a role in glucose formation; therefore, insulin is the only key factor. That is why the pancreatic beta cells' health state is the most influential factor for glucose levels, including both FPG and PPG. Of course, either injected or oral medication can alter the hyperglycemic symptoms through insulin intervention.

The second is that if the patients do not take any injected or oral medications, then their lifestyles, particularly carbs/sugar intake amount and post-meal exercise, must be under a stringent management program.

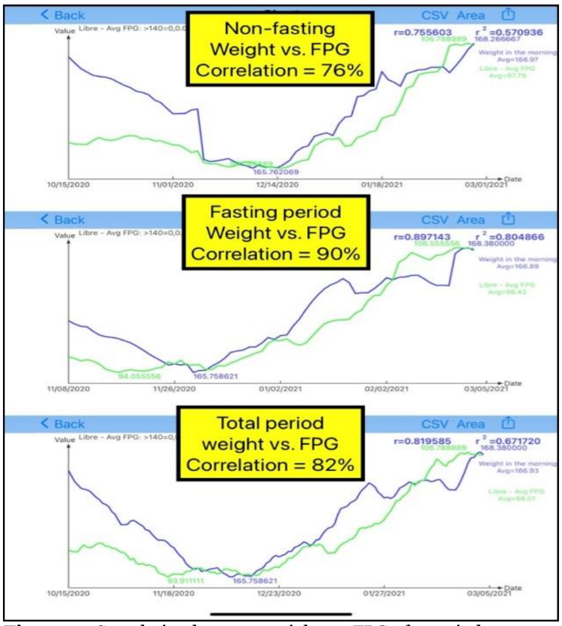


Figure 4: Correlation between weight vs. FPG of 3 periods.

Figure 6 uncovers the PPG fluctuations, max-min for the three periods, where the non-fasting period has 31, the fasting period has 20, and the total period has 26.

The PPG fluctuation can actually reveal additional information and generate a higher impact on the internal organs than the average PPG, or HbA1C.

Figure 7 combines three waves from three periods together. It is obvious that the wave patterns are in the order of the non-fasting period being the highest, the total period being in the middle, and the fasting period being the lowest. Once again, this has demonstrated the power of IF on glucose.

Finally, Figure 8 uses a bar diagram to put both PPG magnitude and PPG fluctuations together. The bar diagram reconfirms most of the conclusions shown in Figures 1 through 7.

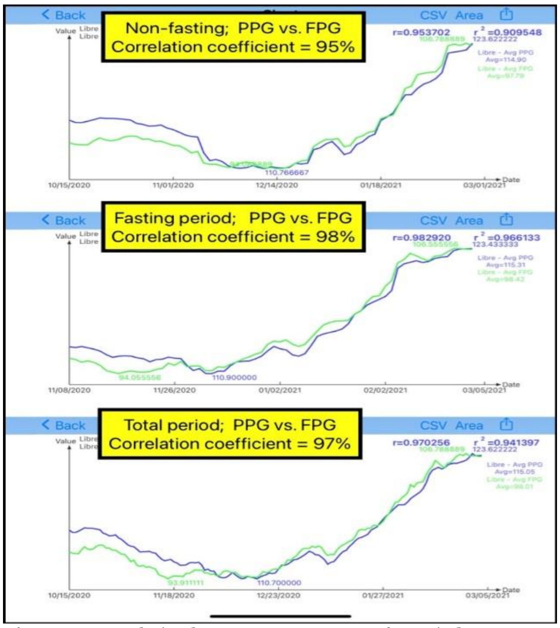


Figure 5: Correlation between PPG vs. FPG of 3 periods.

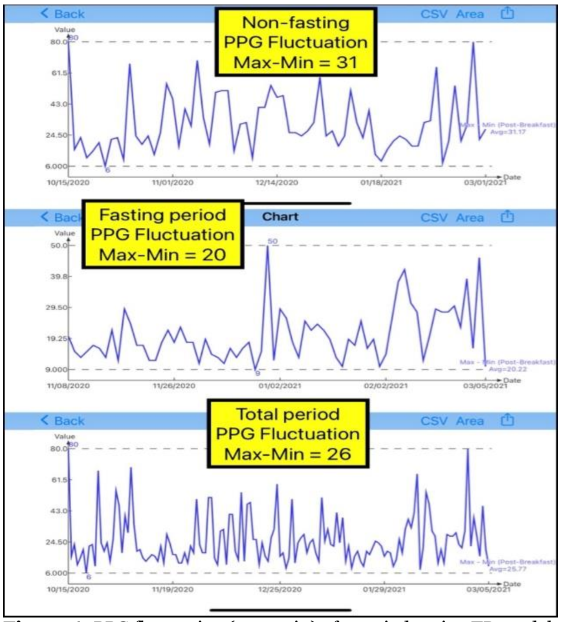
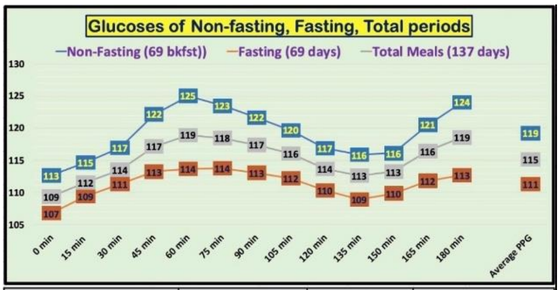


Figure 6: PPG fluctuation (max-min) of 3 periods using TD model.

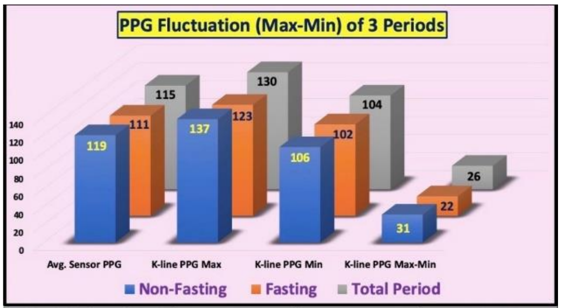
4. CONCLUSION

The human organs, glucose, and chronic diseases have their natural biochemical interpretations, reasonings, and operational functions. However, their observed physical phenomena follow the basic theories and extended principles of physics which can be further analyzed or solved using mathematical equations or tools.



Breakfast (10/15/2020-3/5/2021)	Non-Fasting (69 bkfst))	Fasting (69 days)	Total Meals (137 days)
0 min	113	107	109
15 min	115	109	112
30 min	117	111	114
45 min	122	113	117
60 min	125	114	119
75 min	123	114	118
90 min	122	113	117
105 min	120	112	116
120 min	117	110	114
135 min	116	109	113
150 min	116	110	113
165 min	121	112	116
180 min	124	113	119
Average PPG	119	111	115

Figure 7: Synthesized PPG wave of 3 periods using time-domain analysis.



Breakfast (10/15/2020-3/5/2021)	Non-Fasting	Fasting	Total Period
Avg. Sensor PPG	119	111	115
K-line PPG Max	137	123	130
K-line PPG Min	106	102	104
K-line PPG Max-Min	31	22	26

Figure 8: PPG Fluctuation (max-min) of 3 periods using K-line model.

There are a few key observations identified and reconfirmed through this investigation using IF data. In this study, data are extracted from 3 time periods: 69 non-fasting breakfasts, 69 fasting days, and 137 combined total periods.

(1) The R of weight vs. sensor FPG from these 3 periods are within the range of 76% to 90%. These three high R values have proven that the amount of body weight determines the level of FPG.
(2) The R of sensor PPG vs. sensor FPG from these 3 periods are within the range of 95% to 98%. These three extremely high R values have proven that PPG and FPG have a tight relationship where they fluctuate together. However, there are two caveats. The first is that FPG is one of the indicators of the health state of insulin secretion and insulin quality from the pancreatic beta cells. The second is that a patient's lifestyle, particularly carbs/sugar intake amount and post-meal exercise must be under strict management[27,28].

(3) Although a 16 hour-long fasting includes a tea-only breakfast, it is very close to a total fasting situation where the associated PPG wave of the tea-only fasting still has some lower-magnitude of vibrations (wave fluctuations with both peaks and nadirs). This is a direct result of the human brain's neuro-scientific interaction with both the liver and pancreas. Nevertheless, the tea-only fasting can still be served as a near baseline for PPG analysis[29–31]. The data pattern of PPG fluctuations is remarkably similar to the data pattern of the PPG magnitudes in the order of the non-fasting period being the highest, the total period being the middle, and the fasting period being the lowest.

5. REFERENCES

1) Hsu GC. Biomedical research using GH-Method: Math-Physical Medicine, version 3. eclaireMD Foundation, USA. No. 386.

2) Hsu GC. From biochemical medicine to Math-Physical Medicine in controlling type 2 diabetes and its complications. eclaireMD Foundation, USA. No. 387.

3) Hsu GC. Methodology of medical research: Using big data analytics, optical physics, artificial intelligence, signal processing, wave theory, energy theory and transforming certain key biomarkers from time domain to frequency domain with spatial analysis to investigate organ impact by relative energy associated with various medical conditions. eclaireMD Foundation, USA. No. 397.

4) Hsu GC. A simplified yet accurate linear equation of PPG prediction model for T2D patients (GH-Method: Math-Physical Medicine). eclaireMD Foundation, USA. No. 97.

5) Hsu GC. Application of linear equation-based PPG prediction model for four T2D clinic cases (GH-Method: Math-Physical Medicine). eclaireMD Foundation, USA. No. 99.

6) Hsu GC. Self-recovery of pancreatic beta cell's insulin secretion based on 10+ years annualized data of food, exercise, weight, and glucose using GH-Method: Math-Physical Medicine. eclaireMD Foundation, USA. No. 339.

7) Hsu GC. A neural communication model between brain and internal organs, specifically stomach, liver, and pancreatic beta cells based on PPG waveforms of 131 liquid egg meals and 124 solid egg meals. eclaireMD Foundation, USA. No. 340.

8) Hsu GC. Using Math-Physics Medicine to Predict FPG. eclaireMD Foundation, USA. No. 349.

9) Hsu GC. Community and Family Medicine via Doctors without distance: Using a simple glucose control card to assist T2D patients in remote rural areas (GH-Method: Math-Physical Medicine). eclaireMD Foundation, USA. No. 264.

10) Hsu GC. Linear relationship between carbohydrates & sugar intake amount and incremental PPG amount via engineering strength of materials using GH-Method: Math-Physical Medicine (Part 1). eclaireMD Foundation, USA. No. 346.

11) Hsu GC. Investigation on GH modulus of linear elastic glucose with two diabetes patients data using GH-Method: Math-Physical Medicine (Part 2). eclaireMD Foundation, USA. No. 349.

12) Hsu GC. Investigation of GH modulus on the linear elastic glucose behavior based on three diabetes patients 'data using the GH-Method: Math-Physical Medicine (Part 3). eclaireMD Foundation, USA. No. 349.

13) Hsu GC. Coefficient of GH.f-modulus in the linear elastic fasting plasma glucose behavior study based on health data of three diabetes patients using the GH-Method: Math-Physical Medicine (Part 4). eclaireMD Foundation, USA. No. 356.

14) Hsu GC. High accuracy of predicted postprandial plasma glucose using two coefficients of GH.f-modulus and GH.p-modulus from linear elastic glucose behavior theory based on GH-Method: Math-Physical Medicine (Part 5). eclaireMD Foundation, USA. No. 357.

15) Hsu GC. Improvement on the prediction accuracy of postprandial plasma glucose using two biomedical coefficients of GH-modulus from linear elastic glucose theory based on GH-Method: Math-Physical Medicine (Part 6). eclaireMD Foundation, USA. No. 358.

16) Hsu GC. High glucose predication accuracy of postprandial plasma glucose and fasting plasma glucose during the COVID-19 period using two glucose coefficients of GH-modulus from linear elastic glucose theory based on GH-Method: Math-Physical Medicine (Part 7). eclaireMD Foundation, USA. No. 359.

17) Hsu GC. Investigation of two glucose coefficients of GH.f-modulus and GH.p-modulus based on data of 3 clinical cases during COVID-19 period using linear elastic glucose theory of GH-Method: Math-Physical Medicine (Part 8). eclaireMD Foundation, USA. No. 360.

18) Hsu GC. Postprandial plasma glucose lower and upper boundary study using two glucose coefficients of GH-modulus from linear elastic glucose theory based on GH-Method: Math-Physical Medicine (Part 9). eclaireMD Foundation, USA. No. 361.

19) Hsu GC. Six international clinical cases demonstrating prediction accuracies of postprandial plasma glucoses and suggested methods for improvements using linear elastic glucose theory of GH-Method: Math-Physical Medicine (Part 10). eclaireMD Foundation, USA. No. 362.

20) Hsu GC. A special Neuro-communication influences on GH.p-modulus of linear elastic glucose theory based on data from 159 liquid egg and 126 solid egg meals using GH-Method: Math-Physical Medicine (Part 11). eclaireMD Foundation, USA. No. 363.

21) Hsu GC. GH.p-modulus study of linear elastic glucose theory based on data from 159 liquid egg meals, 126 solid egg meals, and 2,843 total meals using GH-Method: Math-Physical Medicine (Part 12). eclaireMD Foundation, USA. No. 364.

22) Hsu GC. Detailed GH.p-modulus values at 15-minute time intervals for a synthesized sensor PPG waveform of 159 liquid egg meals, and 126 solid egg meals using linear elastic glucose theory of GH-Method: Math-Physical Medicine (Part 13). eclaireMD Foundation, USA. No. 365.

23) Hsu GC. A lifestyle medicine model for family medical practices based on 9-years of clinical data including food, weight, glucose, carbs/sugar, and walking using linear elastic glucose theory and GH-Method: Math-Physical Medicine (Part 14). eclaireMD Foundation, USA. No. 367.

24) Hsu GC. GH.p-modulus study during 3 periods using finger-piercing glucoses and linear elastic glucose theory of GH-Method: Math-Physical Medicine (Part 15). eclaireMD Foundation, USA. No. 369.

25) Hsu GC. GH.p-modulus study using both finger and sensor glucoses and linear elastic glucose theory (Part 16) of GH-Method: Math-Physical Medicine (No. 370). eclaireMD Foundation, USA. No. 370.

26) Hsu GC. Analyzing roles and contributions of fasting plasma glucose, carbs/sugar intake amount, and post-meal walking steps on the formation of postprandial plasma glucose using Linear Elastic Glucose Theory of GH-Method: Math-

Physical Medicine, LEGT, Part 19 (No. 401). eclaireMD Foundation, USA. No. 370.

27) Hsu GC. 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). eclaireMD Foundation, USA. No. 370.

28) Hsu GC. Estimating cardiovascular disease risk and insulin resistance via transforming glucose wave fluctuations from time domain into associated energy in frequency domain and applying the linear elastic glucose theory of GH-Method: Math-Physical Medicine, LEGT, Part 21 (No. 403). eclaireMD Foundation, USA. No. 370.

29) Hsu GC. A study of the postprandial plasma glucose waves and fluctuations of both 65 fasting days and 65 non-fasting breakfasts using time and frequency domains plus wave and energy theories of GH-Method: Math-Physical Medicine (No. 408). eclaireMD Foundation, USA. No. 370.

30) Hsu GC. A study of the postprandial plasma glucose waves and fluctuations of 63 fasting and 43 non-fasting meals at breakfast using time and frequency domains plus wave along with energy theories of GH-Method: Math-Physical Medicine (No. 405). eclaireMD Foundation, USA. No. 370.

31) Hsu GC. Intermittent fasting study of glucose characteristics of 65 non-fasting breakfasts, 65 fasting days, and 1023 breakfasts using time-domain (wave theory) and frequency domain (energy theory) analyses of GH-Method: Math-Physical Medicine (No. 409). eclaireMD Foundation, USA. No. 370.

Special Issue | Issue No. 2

The GH-Method

Advances In Biomedical Research Using GH-Method: Math-Physical Medicine

Gerald C. Hsu

https://www.theghmethod.com

2021