ISSN: 2640-4133

Research Article

Advances in Bioengineering & Biomedical Science Research

A Comparison Study on the Postprandial Plasma Glucose Waves and Fluctuations for 65 Fasting Days Versus 65 Non-Fasting Days Applying Time Domain and Frequency Domain Analyses Along with wave Theory and Energy Theory of GH-Method: Math-Physical Medicine (No. 408)

Gerald C Hsu

EclaireMD Foundation, USA

***Corresponding author**
Gerald C Hsu, EclaireMD Foundation, USA

Submitted: 06 Sep 2021; **Accepted:** 10 Sep 2021; **Published:** 28 Sep 2021

Citation:Gerald C Hsu (2021) A Comparison Study on the Postprandial Plasma Glucose Waves and Fluctuations for 65 Fasting Days Versus 65 Non-Fasting Days Applying Time Domain and Frequency Domain Analyses Along with wave Theory and Energy Theory of GH-Method: Math-Physical Medicine (No. 408). Adv Bioeng Biomed Sci Res 4(3): 83-88.

Abstract

This particular investigation includes two parts utilizing the collected data from the period from 10/19/2020 to 3/1/2021. The collected data are segregated into 65 non-fasting breakfasts and 65 intermittent fasting days (~16 fasting hours in a day). The purpose is to study the effect on the author's diabetes control due to the ongoing intermittent fasting.

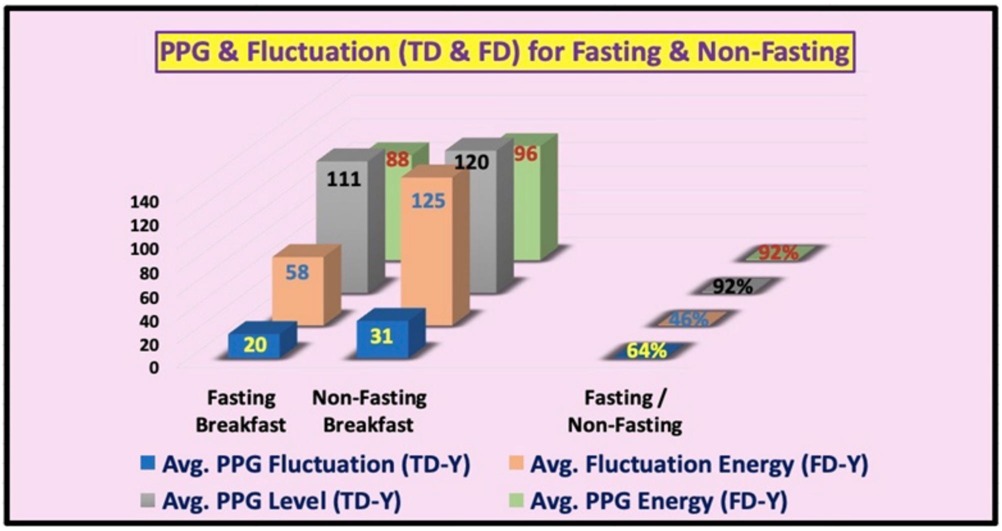
The first part investigates the sensor-collected postprandial plasma glucose (PPG) values and their associated relative energies. The second part focuses on PPG wave fluctuations or glycemic variability (GV), which is the maximum PPG value minus the minimum PPG value of the glucose waves.

At first, the author applies the wave theory to study the mean values of PPG waves i.e., the Y-amplitude of a curve in a time domain (TD). He then utilizes the signal processing techniques and Fast Fourier Transform (FFT) software program to convert these PPG waves into a frequency domain (FD) representation. In his previous research, he has proven that the Y-axis magnitude (Y-amplitude) in FD is directly proportional to the square of the Y-axis magnitude (glucose value) in TD. In this way, he can quickly estimate the "relative" energy levels associated with his glucose levels. The relative energy are generated by glucose and carried by red blood cells circulating in the blood system. Furthermore, in order to have a better understanding of the different degree of organ impact via glucose energies, he then segregated them into the low-frequency energy segment versus the high-frequency energy segment, where he conducted their corresponding analyses.

The author has drawn five major conclusions from this study:

1. *Within a relative shorter intermittent fasting period, the fasting effort has no significant impacts on his weight change. Weight impact can only be observed over a longer period of time.*
2. *For the strength of PPG, both of its value and energy of non-fasting are 8% higher than fasting. This means that fasting effort offers a better benefit for his diabetes control.*
3. *For the strength of PPG value fluctuations with the maximum minus the minimum, the non-fasting's amount of fluctuation value is about 1/3 higher than the fasting amount. However, the non-fasting's fluctuation energy is about 2x higher than the fasting's fluctuation energy. This means that the PPG fluctuation has a bigger impact and it also reveals more information about his diabetes control than the average glucose level, such as HbA1C.*
4. *Regarding the PPG fluctuation energy, non-fasting (125) is 30% higher than the PPG level's energy of fasting (96). Furthermore, the PPG fluctuation's energy of non-fasting (125) is more than 2x higher than the PPG fluctuation's energy of fasting (58). These phenomena infer that glucose fluctuation is an important factor for diabetes patients to consider.*
5. *In terms of comparison between high-frequency (higher frequency with lower amplitude, selecting 80% of frequency components), and low-frequency (lower frequency with higher amplitude, selecting 20% of frequency components), for the PPG level, the high-frequency has about 2x more energy than the low-frequency; while for the PPG fluctuation, the*

high-frequency has about 3-4x more energy than the low-frequency. This indicates that diabetes patients must be careful with their glucose wave fluctuation.



Introduction

This particular investigation includes two parts utilizing the collected data from the period from 10/19/2020 to 3/1/2021. The collected data are segregated into 65 non-fasting breakfasts and 65 intermittent fasting days (~16 fasting hours in a day). The purpose is to study the effect on the author's diabetes control due to the ongoing intermittent fasting.

The first part investigates the sensor-collected ***postprandial plasma glucose (PPG)*** values and their associated relative energies. The second part focuses on ***PPG wave fluctuations or glycemic variability (GV)***, which is the maximum PPG value minus the minimum PPG value of the glucose waves.

At first, the author applies the wave theory to study the mean values of PPG waves i.e., the Y-amplitude of a curve in a time domain (TD). He then utilizes the signal processing techniques and Fast Fourier Transform (FFT) software program to convert these PPG waves into a frequency domain (FD) representation. In his previous research, he has proven that the Y-axis magnitude (Y-amplitude) in FD is directly proportional to the square of the Y-axis magnitude (glucose value) in TD. In this way, he can quickly estimate the "relative" energy levels associated with his glucose levels. The relative energy are generated by glucose and carried by red blood cells circulating in the blood system. Furthermore, in order to have a better understanding of the different degree of organ impact via glucose energies, he then segregated them into the low-frequency energy segment versus the high-frequency energy segment, where he conducted their corresponding analyses.

Methods and Results

MPM Background

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

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

The Author'S Case of Diabetes

The author was a severe type 2 diabetes patient since 1996. He weighed 220 lb. (100 kg) at that time. By 2010, he still weighed 198 lb. with an average daily glucose of 250 mg/dL (HbA1C of 10%). During that year, his triglycerides reached to 1161 and 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 needs of kidney dialysis treatment and his future high risk of dying from his severe diabetic complications.

In 2010, he decided to self-study endocrinology, diabetes and food nutrition. During 2015 and 2016, he developed four prediction models related to diabetes conditions, i.e., weight, *postprandial plasma glucose (PPG)*, fasting plasma glucose (FPG), and HbA1C (A1C). As a result, from using his developed mathematical metabolism index (MI) model and those four prediction tools, by end of 2016, his weight was reduced from 220 lbs. (100 kg) to 176 lbs. (89 kg), waistline from 44 inches (112 cm) to 33 inches (84 cm), averaged finger glucose from 250 mg/dL to 120 mg/dL, and HbA1C from 10% to ~6.5%. One of his major accomplishments is that he no longer takes any diabetes medications since 12/8/2015.

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

By 2020, his weight was further reduced to 165 lbs. (BMI 24.4) and his HbA1C was at 6.2% without any medications intervention or insulin injection. Actually, during 2020 with the special

COVID-19 quarantined lifestyle, not only has he published approximately 400 medical papers in 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 developed various high-tech tools contribute to his excellent health status since 1/19/2020.

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 present day.

Therefore, during the past 11 years, he could study and analyze his collected ~2 million data regarding his health status, medical conditions, and lifestyle details. He applies his knowledge, models, 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 his medical findings.

Input Data for Time Domain

During the period from 10/19/2020 to 3/1/2021, he segregated his collected glucose data into two separated groups as follows:

Non-fasting: (65days)
Fasting: (65 days)

Frequency Domain of PPG Wave

After conducting the TD analysis, he then utilizes the Fast Fourier Transform (FFT) algorithm-based software program to convert his PPG waves from a TD into a FD to conduct his analysis. Since his data component numbers (on x-axis) for both TD and FD are 65 for both non-fasting and fasting, in order to obtain his "relative" energy associated with glucose, he does not need to include the N (days or frequencies) into his equations.

PPG Fluctuation in TD and FD

He utilizes the maximum PPG minus the minimum PPG, from his breakfast PPG wave fluctuation data, to conduct both TD analysis and FD analysis for the PPG fluctuation which is similar to the concept of a defined Glycemic Variability or GV.

Graphic Results

Figures 1 shows his data collection of number of breakfasts, carbs/sugar intake grams, post-breakfast walking steps, finger-piercing measured PPG, sensor collected PPG, and body weight (lbs.) in the morning. The left portion of Figure 1 is the direct comparison of his weight between non-fasting (167.14 lbs.) and fasting (166.89 lbs.). ***These two measured mean weights are almost identical. The reason is that the weight impact from intermittent fasting (IF) is a slower process which takes a longer period of time to observe its noticeable impact*** (Reference 17).

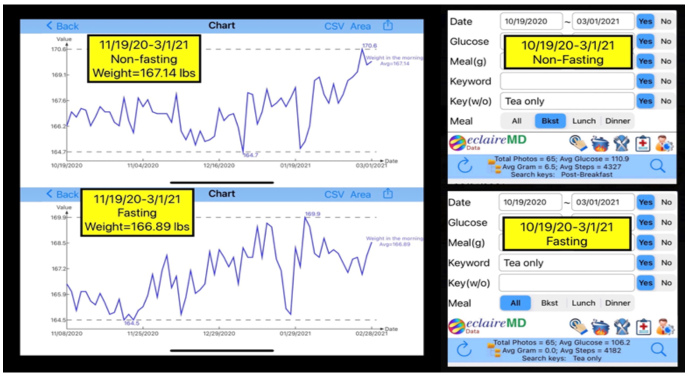


Figure 1: Timeframe selection, Inputs, and Weight comparison of non-fasting vs. fasting

Figure 2 is a data table which depicts his input data, calculated data from his TD and FD analyses for both PPG value and PPG fluctuation.

(10/19/2020 - 3/1/2021)	Fasting Breakfast	Non-Fasting Breakfast	Fasting / Non-Fasting
No. of Meals	65	65	
Avg. Breakfast PPG (Finger)	106.2	110.9	96%
Carbs/Sugar grams	0.0	6.5	
Post-meal Walking Steps	4182	4327	97%
N (Days or Frequencies)	64	64	
Avg. PPG (TD-Y)	111	120	92%
Avg. PPG Energy (FD-Y)	88	96	92%
(1) (Frequey Area)/100	56	61	91%
(2) (Freq-Y * N)/100	57	61	92%
(3)(Time-Y **2)/100	123	143	86%
N (Days or Frequencies)	64	64	
K-line PPG Max	122	137	89%
K-line PPG Min	102	106	96%
K-line Max-Min (Candlestick)	20	31	65%
Avg. Max-Min of PPG (TD-Y)	20	31	64%
Avg. Max-Min Energye (FD-Y)	58	125	46%
(1) (Frequey Area)/100	37	80	46%
(2) (Freq-Y * N)/100	37	80	46%
(3)(Time-Y **2)/100	4	10	42%
(Max-Min) / (Avg. PPG) (TD-Y)	18%	26%	70%
(Max-Min) / (Avg. PPG) (FD-Y)	65%	130%	50%

Figure 2: Input data and Calculated data

Figure 3 reveals the ***average PPG value from a TD analysis for both non-fasting (120 mg/dL) and fasting (111 mg/dL), using synthesized curve. Figure 5 reveals the average PPG K-line Y-amplitude from a TD analysis for both non-fasting (120) and fasting (111) which yields the same results between both synthesized curve model and Candlestick k-line model.***

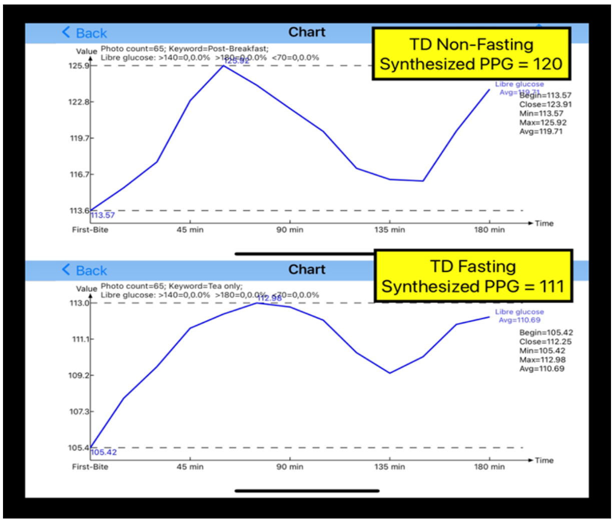


Figure 3: Synthesized PPG waves comparison in TD

A synthesized PPG wave has reduced the extremity for the high-amplitude and low-amplitude of a wave through the process of calculating averaged value. In Figure 4, the author utilizes his created Candlestick K-line model and a TD analysis to calculate ***the PPG fluctuation (max-min) values for non-fasting (31 mg/dL) and fasting (20 mg/dL).*** There is a one-third difference between non-fasting fluctuation and fasting fluctuation.

Figure 4: Candlestick K-line PPG comparison in TD

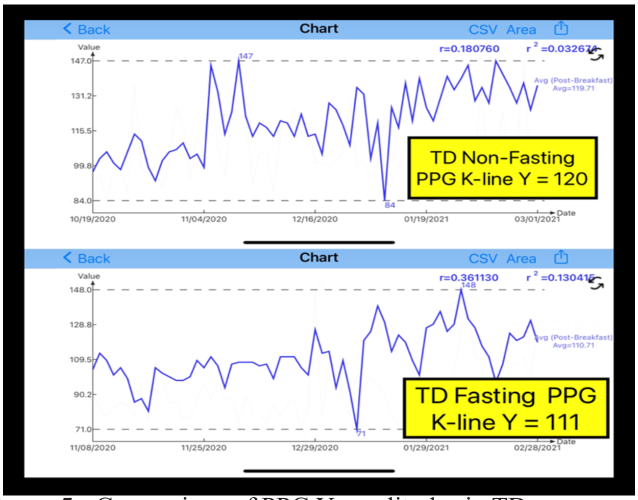


Figure 5: Comparison of PPG Y-amplitudes in TD

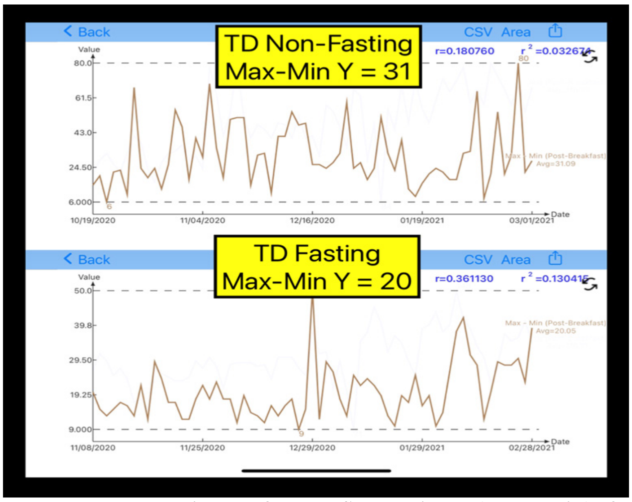


Figure 6: Comparison of PPG fluctuations (Max-Min) from K-Line models

Figure 7 and Figure 8 reflect the FD analysis results after the FFT operations of PPG value associated energy (Y-amplitude of FD) for both non-fasting ***PPG energy (96) and non-fasting PPG fluctuation energy (125) versus fasting PPG energy (88) and fasting PPG fluctuation energy (58).***

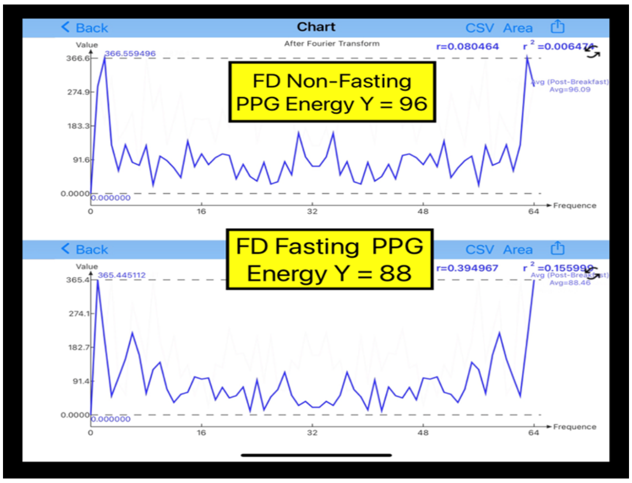


Figure 7: PPG energy comparison from FD analysis

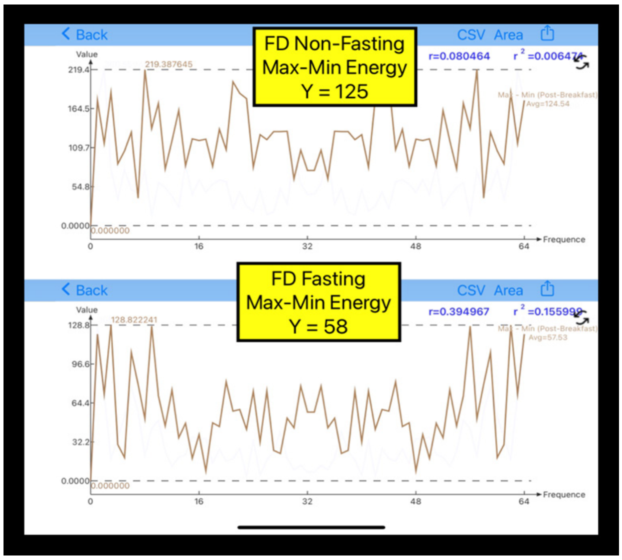


Figure 8: PPG fluctuation (Max - Min) energy comparison

from FD analysis

To distinguish the contribution difference from various frequency segments, to simplify, he only chose 2 frequency segments: the high-frequency (higher frequency with lower amplitude) having 80% of the total frequency components, and low-frequency (lower frequency with higher amplitude) having 20% of the total frequency components.

Figure 9 signifies the *PPG value* associated relative energy result in the format of total frequency area, low frequency energy, and high frequency energy:

Non-fasting: (6101, 1024, 1981)
Fasting: (5567, 982, 1691)

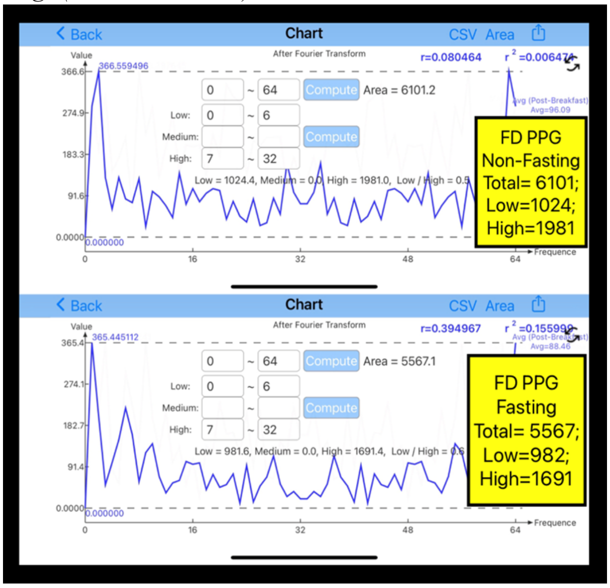


Figure 9: Energy calculations of PPG in FD

Figure 10 indicates the *PPG fluctuation* associated relative energy result in the format of total frequency area, low frequency energy, and high frequency energy:

Non-fasting: (8007, 736, 3188)
Fasting: (3679, 424, 1324)

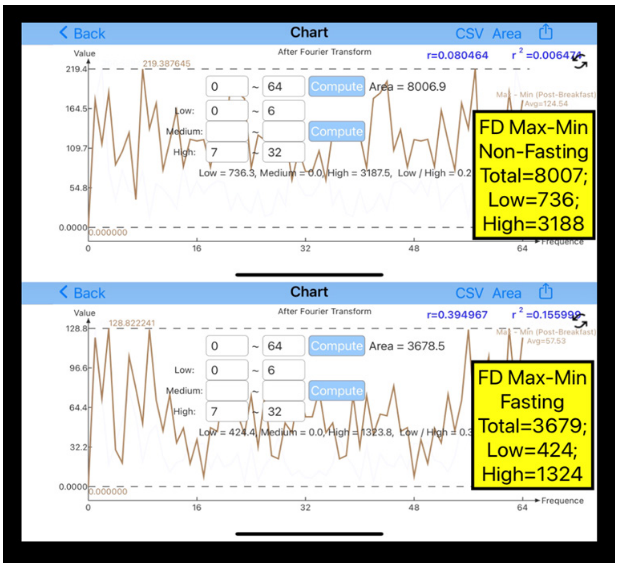
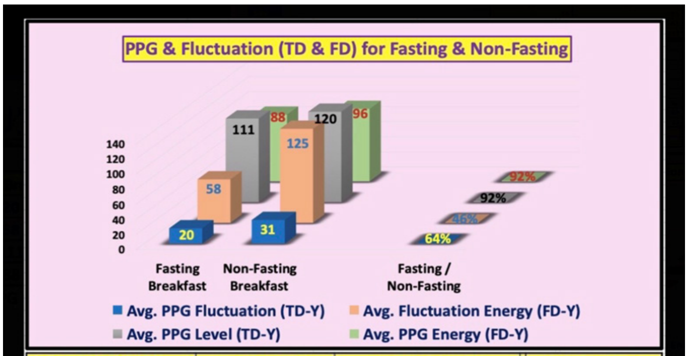


Figure 10: Energy calculations of PPG fluctuations (Max - Min) in FD



(10/19/2020 - 3/1/2021)	Fasting Breakfast	Non-Fasting Breakfast	Fasting / Non-Fasting
Avg. PPG Fluctuation (TD-Y)	20	31	64%
Avg. Fluctuation Energy (FD-Y)	58	125	46%
Avg. PPG Level (TD-Y)	111	120	92%
Avg. PPG Energy (FD-Y)	88	96	92%

Figure 11: Bar diagram and data table of calculation conclusions in both TD and FD

In summary, for the PPG level, the high-frequency has approximately 2x more energy than low-frequency, while for the PPG fluctuation, the high-frequency has about 3-4x more energy than low-frequency.

Conclusions

The author has drawn five major conclusions from this study:

1. ***Within a relative shorter intermittent fasting period, the fasting effort has no significant impacts on his weight change. Weight impact can only be observed over a longer period of time.***
2. For the strength of PPG, both of its value and energy of non-fasting are 8% higher than fasting. This means that fasting ***effort offers a better benefit for his diabetes control.***
3. For the strength of ***PPG value fluctuations*** with the maximum minus the minimum, the non-fasting's amount of fluctuation value is about ***1/3 higher*** than the fasting amount. However, the non-fasting's fluctuation energy is about ***2x higher*** than the fasting's fluctuation energy. This means that the ***PPG fluctuation has a bigger impact and it also reveals more information about his diabetes control than the average glucose level, such as HbA1C.***
4. Regarding the PPG fluctuation energy, non-fasting (125) is 30% higher than the PPG level's energy of fasting (96). Furthermore, the PPG fluctuation's energy of non-fasting (125) is ***more than 2x higher*** than the PPG fluctuation's energy of fasting (58). These phenomena infer that ***glucose fluctuation is an important factor for diabetes patients to consider.***
5. In terms of comparison between high-frequency (higher frequency with lower amplitude, selecting 80% of frequency components), and low-frequency (lower frequency with higher amplitude, selecting 20% of frequency components), for the PPG level, the high-frequency has about 2x more energy than the low-frequency; while ***for the PPG fluctuation, the high-frequency has about 3-4x more energy than the low-frequency. This indicates that diabetes patients must be careful with their glucose wave fluctuation.***

References

1. Gerald C Hsu (2021) Biomedical research using GH-Method: math-physical medicine, version 3 (No. 386).
2. Gerald C Hsu (2021) From biochemical medicine to math-physical medicine in controlling type 2 diabetes and

its complications (No. 387).
3. Gerald C Hsu (2021) 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 (No. 397).
4. Sunghwan Suh and Jae Hyeon Kim (2015) Glycemic Variability: How Do We Measure It and Why Is It Important? Diabetes & Metabolism Journal 39: 273-282.
5. Dorota Czerwoniuk, Wojciech Fendler, Lukasz Walenciak, Wojciech Mlynarski (2011) GlyCulator: A Glycemic Variability Calculation Tool for Continuous Glucose Monitoring Data. Journal of Diabetes Sci Technol 5: 447-451.
6. Klaus Dieter Kohnert, Petra Augstein, Eckhard Zander, Peter Heinke, Karolina Peterson, et al. (2009) Glycemic Variability Correlates Strongly With Postprandialβ-Cell Dysfunction in a Segment of Type 2 Diabetic Patients Using Oral Hypoglycemic Agents. Diabetes Care 32: 1058-1062.
7. F. John Service Glucose (2013) Glucose Variability. ADA, Diabetes 62: 1398-1404.
8. Xuefei Yu, Liangzhuo Lin, Jie Shen, Zhi Chen, Jun Jian, et al. (2018) Calculating the Mean Amplitude of Glycemic Excursions from Continuous Glucose Data Using an Open-Code Programmable Algorithm Based on the Integer Nonlinear Methode. Computational and Mathematical Methods in Medicine
9. Gerald C Hsu (2020) 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 (No. 339). Journal of Diabetes Research Reviews & Reports 2: 1-5.
10. Gerald C Hsu (2020) Self-recovery of pancreatic beta cell's insulin secretion based on annualized fasting plasma glucose, baseline postprandial plasma glucose, and baseline daily glucose data using GH-Method: math-physical medicine (No. 297).
11. Gerald C Hsu (2020) Relationship between metabolism and risk of cardiovascular disease and stroke, risk of chronic kidney disease, and probability of pancreatic beta cells self-recovery using GH-Method: Math-Physical Medicine (No. 259).
12. Gerald C Hsu (2020) Guesstimate probable partial self-recovery of pancreatic beta cells using calculations of annualized glucose data using GH-Method: math-physical medicine (No. 139). Medical & Clinical Research 5: 73-75.
13. Gerald C Hsu (2020) Probable partial self-recovery of pancreatic beta cells using calculations of annualized fasting plasma glucose using GH-Method: math-physical medicine (No. 138). Archives of Infectious Diseases & Therapy 4: 31-33.
14. Gerald C Hsu (2020) Probable partial recovery of pancreatic beta cells insulin regeneration using annualized fasting plasma glucose (GH-Method: math-physical medicine) No. 133.
15. Gerald C Hsu (2020) Changes in relative health state of pancreas beta cells over eleven years using GH-Method: math-physical medicine (No. 112).
16. Gerald C Hsu (2021) Applying the concept of glycemic variability (glucose fluctuation) for an extended study on the self-recovery of pancreatic beta cells and risk probability of having a cardiovascular disease or stroke using GH-Method: math-physical medicine (No. 390).
17. Hsu Gerald C (2021) An evidence-based study of 16-hours intermittent fasting effect on both glucose and weight control using GH-Method: math-physical medicine, Part 2 (No. 398).
18. Gerald C Hsu (2021) Analyzing postprandial plasma glucose wave fluctuations using GH-Method: math-physical medicine (No. 400).
19. Hsu Gerald C (2021) 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).
20. Hsu Gerald C (2021) A study of the postprandial plasma glucose waves of three time periods using time and frequency domains plus wave and energy theories of GH-Method: math-physical medicine (No. 406).
21. Hsu Gerald C (2021) A study of the glucose waves and fluctuations of both pre-virus and COVID-19 periods using time and frequency domains plus wave and energy theories of GH-Method: math-physical medicine (No. 407).