Advances in Endocrinology and Diabetes

Kosmos Publishers

Research Article

Adv Endo and Dia. AEAD- 101

Using Math-Physical Medicine to Control T2D via Metabolism Monitoring and Glucose Predictions

Gerald C. Hsu*

eclaireMD Foundation, USA

***Corresponding author**: Gerald C. Hsu, eclaireMD Foundation, USA. Tel: +15103315000; Email: g.hsu@eclairemd.com

Citation: Hsu GC (2018) Using Math-Physical Medicine to Control T2D via Metabolism Monitoring and Glucose Predictions. Adv Endo and Dia. AEAD- 106.

Received Date: 15 June, 2018; **Accepted Date:** 21 June, 2018; **Published Date:** 29 June, 2018

1. Introduction

Diabetes is a metabolic disorder in which plasma glucose blood levels are abnormally high and the body cannot produce enough insulin or become insulin-resistant. Unfortunately, people with diabetes have a higher risk of getting cardiovascular disease and stroke. In order to fully understand a particular patient's diabetes condition, the patients and their medical professionals need to have a broad sense of the disease, in-depth knowledge, and quick view of the patient's metabolism status, i.e. overall health state. By having a simple indicator that dynamically demonstrates a general health status on a daily or momentary basis can benefit them.

The basic requirement for patients with type 2 diabetes (T2D) to control their disease is to know what their glucose values are. However, glucose testing is invasive, inconvenient, and costly. Most T2D patients are not performing the measurement on a regular basis for these reasons; therefore, it is important to find an alternative way to achieve a quick, easy, painless, low-cost, effective and accurate testing method available for these patients.

The author was diagnosed with T2D since 1995 and, by 2010; his health was in a "near-collapse" state. He suffered from five episodes of cardiac issues, high possibility of requiring kidney dialysis in the future, bladder problems, foot ulcer, and other medical complications. As a result, he decided to launch his research on diabetes in order to save his own life. He spent nearly 8-years (~20,000 hours) researching an effective way to help himself to control his diabetes condition via a scientific, yet simplified, and effective lifestyle management method. His health condition comparison between 2010 and 2017 can be seen in the following chart **(Table 1)**.

Health Exam Record	2010	2017
A1C (<6.4%)	10.0	6.1
90 Days Average Glucose (<120 mg/ dL)	279	113
ACR (<30)	116.4	12.3
Triglycerides (<150)	1161	67
HDL (>40)	24	48
LDL (<130)	174	74
Total Cholesterol (<200)	253	118
BMI (<25.0)	31	24.7
Weight (lbs.)	210	167
Waistline (inch)	44	34

Table 1: Health Data Comparison between 2010 and 2017.

Since he is a mathematician, engineer, and an industrialist, he launched his efforts by performing the following standard steps:

- phenomena observation
- data collection
- equation development
- statistical analysis
- practical answers for problem-solving
- user-friendly tool to use

This paper describes how he achieved his health goals by monitoring his daily metabolism status and also predicting his daily glucose values automatically via his invented "math-physical medicine" approach and AI tool.

His glucose values include fasting plasma glucose (FPG) measured in the morning before breakfast and postprandial plasma glucose (PPG) measured after the first bite of food two hours later and three times per day.

2. Methods

2.1. Metabolism Monitoring

In the beginning, the author used advanced mathematics, nonlinear engineering modeling, big data analytics to develop a set of mathematical equations to describe the patient's metabolism. He defined "metabolism" as a form of "energy body needs" which is an organic process containing easily measured metabolic conditions (weight, glucose, lipids, blood pressure) and daily lifestyle data (food, water, exercise, stress, sleep, healthy daily routine). This metabolism equation contained a total of 10 categories, 6 inputs and 4 outputs. In addition to the major categories, such as food and exercise, he also investigated the impact on his metabolism by traveling, water intake, bowel movement, urination, stress / tension / anxiety, disturbance on daily life routine pattern and healthy habits, psychological effect on the physiology of his health, etc. Overall, these 10 categories comprised of ~500 elements and ~1.5 million data collected and stored over 7.5 years. With such a big volume of data, a customized computer software program was developed for handling the data collection, processing, and analysis.

He defined two new terms known as the Metabolism Index (MI) and General Health Status Unit (GHSU). MI is the total score reflecting the body's health condition (i.e. state of metabolism), which combined all of the 10 categories. GHSU is a moving average value of the past 90-days daily MI scores. The graph of this data **(Figure 1)** shows a person's "health state". The "break-even" line between a "healthy state" and an "unhealthy state" is 73.5%. A value below this percentage is regarded as healthy and a value above the line is unhealthy.

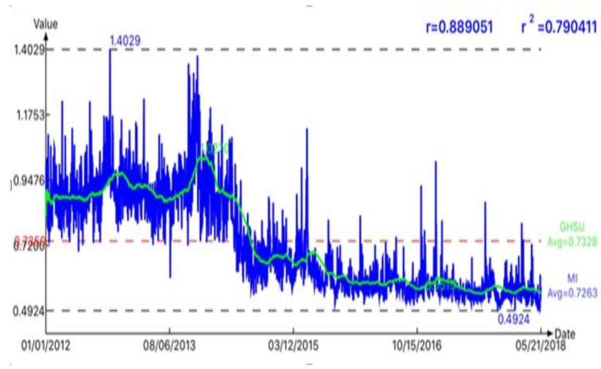

Figure 1: Metabolism Index (MI) and General Health Status Unit (GHSU) from 2012 to 2018.

2.2. Glucose Predictions

The author started with a simple task of predicting tomorrow's weight output from the previous 3-day input of weight, food quantity, and bowel movement. The weight prediction is the pre-processor for predicting FPG in the morning which constitutes a minor part (about 20% - 25%) of A1C formation. Although there are five influential factors for FPG creation, he discovered and proved that weight is the predominant one.

The prediction of PPG, however, is a more complicated task since it involves about 15 influential factors that produce the PPG value. He applied signal processing technology from geophysics and electronic engineering to decompose the human body's highly nonlinear biomedical signal curves, such as the glucose wave, into multiple and different sub-waves created by each influential factor. He carefully checked each sub-signal waveform for its completeness, accuracy, and correlation with other curves, using time-series analysis, spatial analysis, and frequency-domain analysis, etc. Finally, he reintegrated these multiple sub-waveforms back to a predicted glucose curve to simulate the actual measured one. By developing many mathematical equations and analyzing their data using various statistical models, he was able to identify primary, secondary, and tertiary factors according to their respective contribution margins and importance levels on glucose creation. Those factors for FPG and PPG will be discussed in the "Results" section.

Over the past three years, he continuously explored and added some missing influential factors into the formation of the PPG signal. His purpose was to improve the predicted PPG waveform's contents and accuracy while maintaining a high correlation with the measured PPG waveform.

He further improved his model via a "curve-fitting" trial and error engineering method which he learned from his defense work experience. He has continuously compared these two sets of data and improved the accuracy until it reached a high linear accuracy, while still maintaining a high correlation. High correlation means the trend of the predicted curve moving along with the measured curve like its "twin". This predicted PPG also serves as the major part (about 75% - 80%) of his estimated daily A1C.

He also developed a machine-learning statistical algorithm to automatically adjust the conversion value of daily averaged glucose value to a combined daily A1C value. Finally, he specifically added in a "safety margin" which he learned from his nuclear power work experience. The reason for having the safety margin on top of the estimated A1C is to cover the possible variance generated by different chemical process and various environmental factors associated with the A1C testing done in the laboratory. This extra caution can provide a numerical safety buffer to avoid creating unnecessary panic on T2D patients while serving as a daily "early warning" to them before they have a chance to get their A1C tested.

3. Results

The author spent 10 months during 2015-2016 investigating FPG. Initially, he exhausted all avenues to find possible connecting factors, despite finding a low correlation of ~9% between FPG and PPG. On 3/17/2016, he discovered the high correlation of 84% between FPG and Weight. He used 26,000 FPG-related data based on 1,505 days (1/1/2014 - 2/14/2018), to conduct statistical analyses. In the time-series diagram, there are three high periods and three low periods of Weight, along with the FPG curve following the Weight curve like its "twin". In spatial analysis diagram of BMI vs. FPG (without time factor), there is a "quasi-linear" equation existing between two coordinates of BMI and FPG from point A (24.5, 102) to point B (27.0,142). The stochastic (random) distribution of data has two clear "concentration bands" stretched from lower left corner toward upper right corner. The +/- 10% band covers 67% of the total data and the +/- 20% band covers 94% of the total data. Only the remaining 6% of the total data is influenced by other secondary factors. The following graph **(Figure 2)** shows the close relationship between weight and FPG.

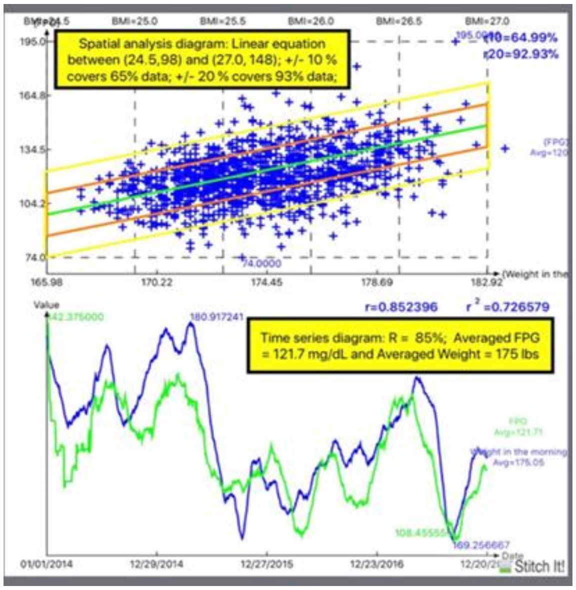

Figure 2: FPG and Weight Relationship (spatial analysis and time-series analysis).

During the 989 days (6/1/2015 - 2/14/2018), he had 2,967 meals and collected about 60,000 PPG-related data.

The findings of PPG and its corresponding influential factors are as follows:

- **Primary factor No.1, Carbs/sugar intake:**
  - average 14.7 grams per meal
  - +60% correlation
  - 38% contribution rate

- **Primary factor No.2, Walking exercise:**
  - average post-meal 4,300 steps
  - -64% correlation
  - 41% contribution rate

Secondary factor, Temperature	:	10%
Combined 12 tertiary factors	:	11%

The following chart **(Figure 3)** shows the decomposition of PPG waveform into 4 major Sub-Waveforms; whereas, the other graph (**Figure 4)** displays the positive impact of carbs/sugar intake on PPG and negative impact of walking exercises on PPG as well as a what-if analysis.

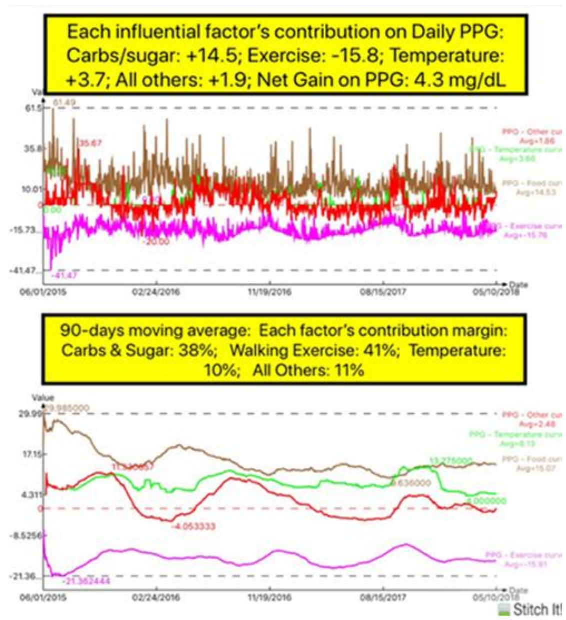

Figure 3: Decomposition of 4 Sub-Waveforms of PPG.

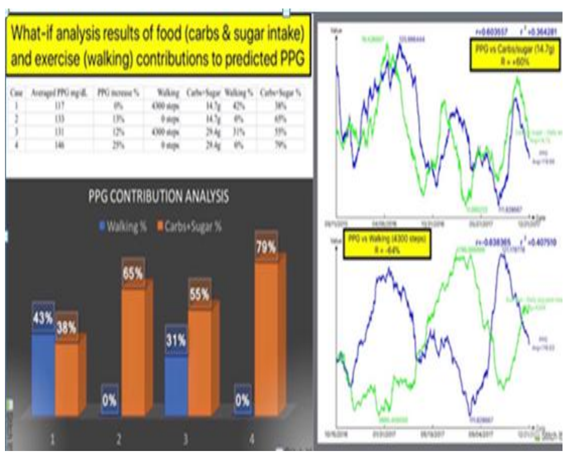

Figure 4: Impact of Carbs/Sugar Intake and Exercise on PPG and What-If Analysis.

The ~3,000 meal photos were analyzed against six million food data collected from the United States Department of Agriculture (USDA) and stored in a cloud server. All food data were sorted based on country, franchise restaurants, individual cafes, home-cooked meals, and airline food.

Here are some comparison results:

Airline food	:	136 mg/dL
Restaurant food	:	127 mg/dL
Home Cooking	:	111 mg/dL

The concluding results of high accuracy and correlations for two glucose predictions are as follows:

(1) The predicted FPG vs. measured FPG achieved a linear accuracy 99.8% (118.42 mg/dL vs. 118.62 mg/dL) and 98.6% correlation.
(2) The predicted PPG vs. measured PPG achieved a linear accuracy 99.3% (119.37 mg/dL vs. 120.16 mg/dL) and 71.3% correlation.

Please see the diagram **(Figure 5)** of the comparison of his estimated Daily A1C vs. lab-tested A1C values.

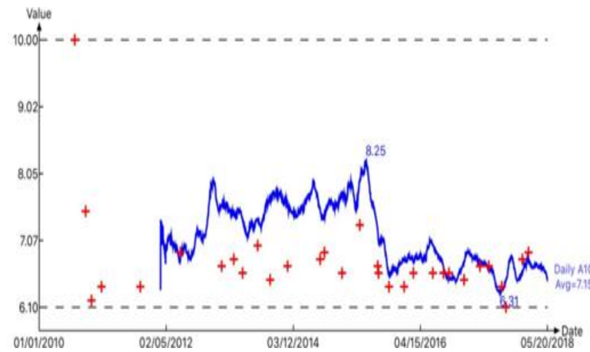

Figure 5: Estimated Daily A1C Curve (with 15% safety margin) and Lab-Tested A1C Data Since 2010.

All of these concluding results have been programmed into a practical and AI software tool by himself. The requirements for the program were to measure his morning body weight and to take his three meal photos before starting his meal to store into the software. This AI tool can then immediately display his predicted fasting glucose as well as his three post-meal glucose values on the iPhone screen. If one particular predicted PPG value is too high, he can then decrease his carbs/sugar intake amount or rearrange his meal's portion to get a new meal photo which reduces to a lower predicted PPG reading. The glucose prediction technology and tool were developed entirely based on his research, using optical physics, signal processing, and all of the mathematics and engineering techniques mentioned in this article.

4. Conclusion

The highly accurate predicted glucose values, both FPG and PPG, can provide an effective tool for T2D patients to control their diabetes condition. In addition, the sophisticated and dynamic metabolism index (MI) prediction can provide a snapshot of their daily overall health state. Other than this full-length article, an abstract is also available for an overview. In addition, the author also displayed a table of summary of different points between existing knowledge domain and math-physical medicine; see the following table **(Table 2)**.

	Subject	Points from Existing Knowledge Domain	Points from MPM (Math-Physical Medicine)
1	Metabolism	The definition of metabolism is generally understood; however, it does not have a clear definition and quantitative measurement in relationship to diabetes.	Both MI and GHSU values must be <73.5% to be healthy; otherwise, it's unhealthy (>73.5%). Using AI software can give you a daily and momentary reading of MI & GHSU values.
2	Glucose(FPG & PPG)	FPG & PPG are measured at different times but the knowledge to the extent of their differences are limited.	Weight (from quantity of food) controls FPG while crabs/sugar (from quality of food) controls PPG. Each gram of crabs/sugar generates around 1.7 mg/dL to 2 mg/dL glucose. Exercise (41% contribution) is as important as food (38% contribution), but the most effective way of exercise is doing it within 2 hours after the first bite of meal.
3	A1C	A1C tests can only be performed at laboratories.	Using AI software, patients can find out their A1C value on a daily or momentary basis within >95% accuracy of lab test results.

Table 2: Different Points between Existing Knowledge Domain and Math-Physical Medicine Approach.

5. Limitation of Research

This article is based on data collected from one T2D patient's 8-years metabolic conditions and lifestyle details (i.e. his own data). It does not cover genetic conditions and life style details of other diabetes patients. His BMI was >31 (obese) in 2000. However, during the period of 2010 - 2018, he has reduced his BMI from 29.5 to 24.5 (overweight). Therefore, his conclusions and findings should be reverified for patients who are either underweight or obese. The author believes in his own work's results, findings, and conclusions, which are based on a solid academic background and a careful and thorough process of identifying the system's basic characters, developing various mathematical equations and statistical models, using modern computer science tools and sophisticated AI techniques. However, other T2D patients need to be cautious about applying his finding, results, and conclusions under different metabolic conditions.

6. Acknowledgment and Other Declaration

First and foremost, I wish to express my sincere appreciation to a very important person in my life, Professor Norman Jones at MIT. Not only did he give me the opportunity to study at MIT, but he also trained me extensively on how to solve problems and conduct scientific research.

I would also like to thank Professor James Andrews at the University of Iowa. He helped and supported me tremendously when I first came to the United States. He believed in me and prepared me to build my engineering foundation during my undergraduate and master's degree work.

He has never hired any research assistant or associate to help with his work except for a part-time computer programmer (~3 working hours per day). He applied his own invention of a “Software Robot” created during 2001 - 2009 and artificial intelligence knowledge he learned in the past to produce his needed computer software for his research project on diabetes control.

This project was self-funded by using his own money that was earned from a successful high-tech venture in Silicon Valley. He did not receive any financial assistance or grants from any institution or organization.

References

The author created this math-physical medicine approach by himself in order to save his own life. Although he has read many medical books, journals, articles, and papers, he did not specifically utilize any data or methodology from other medical work. All of his research is his original work based on data he collected from his own body using computer software he developed during the past 8-years. Therefore, no major problems were associated with data interference or data contamination. In addition, his knowledge, information, technique, and methodology of mathematics, physics, engineering, and computer science came from his lifelong learning from schools and industries and should not be listed as references in this medical article. This is the reason the author does not have a reference section in his article.