Opinion

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Diabetes & its Complications

Using Math-Physical Medicine and Artificial Intelligence Technology to Manage Lifestyle and Control Metabolic Conditions of T2D

Gerald C. Hsu*

eclaireMD Foundation, USA.

***Correspondence:**
Gerald C. Hsu, eclaireMD Foundation, USA, E-mail: g.hsu@eclairemd.com.

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Background and Aim

The author received an honorary PhD in mathematics and majored in engineering at MIT. He attended different universities over 17 years and studied seven academic disciplines including mathematics, engineering, computer science, and business administration. He has also worked in various industries including defense, nuclear power, computer-aided-design, computer hardware, software engineering, and semiconductor design.

By 2010, his type-2 diabetes (T2D) and its complications became very serious. Although he never received formal training in medicine, in order to save his life, he launched his own study and research on T2D. First, he studied six metabolic diseases and food nutrition during 2010 - 2013, then conducted research during 2014 - 2018. Thus far, he has spent 20,000 hours on his research and collected, processed, and analyzed ~1.5 million data to examine the relationship between metabolic conditions and lifestyle details. Due to the fact that he has no academic training in biology and chemistry, he could not conduct his research using the traditional "bio-chemical" approach, instead he used a "math-physical medicine" approach which is based on mathematics, physics, engineering modeling, signal processing, computer science, big data analytics, statistics, machine learning, and artificial intelligence. This approach could provide quantitative data proof and precise interpretation of certain biomedical phenomena. His main focus is on preventive medicine for chronic disease control using six prediction tools he developed during the period of 2015 - 2017, i.e. Metabolism, Weight, FPG, PPG, Adjusted Daily Glucose, and Estimated A1C. He believes that the better the prediction, the more control one would have over chronic disease.

Glucose testing is invasive, troublesome, and costly. Most T2D patients are not performing the measurement on a regular basis. There is also an argument on the accuracy of glucose testing methods via either lab-tested A1C or finger piercing and testing strips. Regardless of this argument, he has collected a complete set of FPG and PPG data using both lab-tested A1C and 9,328 finger prick testing strips. The author spent 7.5 years researching and developing an effective way to help himself and other patients with diabetes control by predicting their glucose values, both FPG and PPG, accurately, easily, and instantly based on a math-physical medicine approach and artificial intelligence technology.

This particular paper was prepared to describe his developed metabolism model and glucose prediction tools used to control his metabolic conditions and lower his risk probability of having a heart attack or stroke via an effective daily lifestyle management.

Methods and Materials

Data

All data was collected in its entirety from one patient only, himself, via a customized software over 7.5 years since 2012. His long and consistent education and work has provided practical experience on how important it is to collect and categorize "clean data" from the beginning. Otherwise, for many data analysis projects, research scientists spend 70% to 80% of their time and resources to clean up "dirty or contaminated data" before launching their real research work, which includes data process, analysis, and interpretation. As a result, he started his project by developing a software program since 2010, and by using the program the author was able to collect and process more than 95% of his data as "clean data" and needed very little data cleaning and organizing later on. This project does not need to be concerned with "data interference" and "data contamination" problems due to different sources of genetic conditions, various lifestyles, and contradicting data source interpretations. These data come from a consistent sample source, making it much easier for the author to dive into one variable and extract the buried information.

The author learned an important work ethic from Professor Norman Jones of MIT in the early 1970s about data integrity. In this study, he used his measured data as the base for future data comparison and research. He has safeguarded the integrity of his collected data and has never altered its original content or influenced its integrity. In this way, all results from using his developed prediction tools are compared against the measured glucose and A1C values.

Metabolism Model

Due to his mathematics and engineering background, he views these data curves related to biomedical conditions and lifestyle management as a collection of various nonlinear input and output signal waves of the human body. At first, he applied the "Finite Element" concept of structural engineering modeling to convert this "analog" human system into a "digitized" mathematical system in order to get an approximate solution of a real human system. He spent the entire year of 2014 to develop a mathematical governing equation of metabolism modeling which includes lifestyle input and metabolic output. This equation contains 10 categories that occupied a total length of 14 hand-written pages. Its input includes six lifestyle categories of food, water, exercise, sleep, stress, and life pattern regularity. Its output includes 4 metabolic categories of weight, glucose, blood pressure, and lipid. In addition to food and exercise, he also investigated the impact his traveling patterns, water intake, bowel movement, stress and tension, routine life pattern disturbance, and psychological effect on physiology had on his body health and glucose. Overall, these 10 categories contain ~500 elements and ~1.5 million data over 7.5 years. With such a big volume of data, a computer software program is necessary for handling the data collection and processing.

He also defined two new terms known as the Metabolism Index (MI) and General Health Status Unit (GHSU). MI is a total score reflecting your body health condition (i.e. state of your metabolism) which combines all of those 10 categories. GHSU is a moving average value of your past 90-days daily MI scores. The "health state" is expressed as the "break-even" line which is 73.5%; above this percentage is regarded "unhealthy" and below the break-even line is "healthy".

Glucose Prediction

The author started with a simple task of predicting tomorrow's weight output from the previous 3-days weight and food inputs. The weight prediction is the pre-processor for predicting FPG in the morning. Although there are five influential factors for FPG creation, he discovered that weight is the predominant one.

The prediction of PPG, however, is a much more complicated task since it involves about 15 influential factors that create PPG value. He applied signal processing technology from electronic and communication engineering to decompose the human body's highly nonlinear biomedical signal curves, such as glucose wave, into different sub-waves based on 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 (via Fourier Transform), etc. Finally, he recombined them back to a predicted glucose curve to simulate the real measured one. By developing and analyzing many mathematical models, he was able to identify primary, secondary, and tertiary factors according to their respective contribution margins and importance levels on glucose creation.

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

For example, by the fall of 2016, the accuracy of his predicted PPG reached ~95%. But, in September of 2017, he identified that weather temperature also had an impact on glucose value. Therefore, he selected a 2-year period (6/2015 - 7/2017) to examine his past travel schedule in detail (average air travel every 13 days in the past seven years) and also entered each day's local ambient temperature of the city where he stayed. In this way, he was able to generate a new temperature sub-wave which brought the accuracy of the predicted PPG from ~95% to ~98%.

Another factor was that his glucose was quite high when he was sick with the flu for a month at the end of 2017. After that experience, he further enhanced his prediction model with the inclusion of "physical sickness or wellbeing" which brought the prediction accuracy to 99.8%.

After analyzing each sub-wave in detail, he was ready to reintegrate these sub-waveforms into another nonlinear predicted 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 very high linear accuracy while still maintaining high correlation. High correlation means the trend of predicted curve moves along with the measured curve like its "twin".

A1C Prediction

For A1C estimation, he utilized all of his historical test data to determine a "customized" glucose-to-A1C conversion ratio. He also utilized statistical algorithms to automatically modify it when new test data is available. Finally, he specifically added in a "safety margin" which he learned from his nuclear power work experience. He inserted a +15% margin on top of his originally predicted A1C value for the purpose of providing a numerical safety buffer. This predicted A1C value can serve as a daily "early warning" to T2D patients before they have a chance to get their A1C tested. Both the Adjusted Glucose and Estimated A1C models also utilized another layer of "self-adjusting" machine-learning algorithms in order to correct or compensate for the built-in "error" from chemical process of various lab tests and glucometers.

Risk Probability of Heart Attack and Stroke

In 2014, he researched and built a metabolism model (MI & GHSU) to measure the multiple interactions of four metabolic disease outputs and six lifestyle inputs. In 2017, he noticed the close relationship between chronic diseases and heart attack/stroke; therefore, he extended his math-physical medicine research to cover the risk probability of cardiovascular diseases and stroke.

Initially, he chose age, gender, race, family history, smoking, drinking, substance abuse, personal medical history, and waistline to establish a "static" baseline. He then applied the hemodynamics concept to develop a "dynamic" macro-simulated model for blood blockage and artery rupture.

He utilized 368,513 data which included 72,893 metabolic conditions (obesity, diabetes, hypertension, hyperlipidemia) and 295,620 lifestyle conditions (food, exercise, water, sleep, stress, daily life routine) within 2,274 days (1/2012-3/2018) to separately compute three different sets of risk probabilities. Finally, he integrated them into one overall risk probability. He also conducted data sensitivity analyses to cover the probability variance by using a range of different weighting factors.

Results

Metabolism

The results showed in Figure 1: MI & GHSU that he was very unhealthy (MI and GHSU score of 80%-110%) before 2013. The curve went through a sharp decline in 2014 due to the knowledge he learned from his research. After 2015, he was "healthy" (MI and GHSU score of 60%-70%). As of 5/19/2018, his MI is 52.7% and GHSU is 55.6% due to his disciplined lifestyle management. All of his current health examination results also confirmed the fact that his chronic disease conditions are well under control. In 2000, he could not climb more than five steps in a flight of stairs; however, in 2017, he climbed 520 steps without stopping. He completed his first 5K marathon at the end of 2017 in Abu Dhabi and finished a 10K marathon in the spring of 2018 in Silicon Valley.

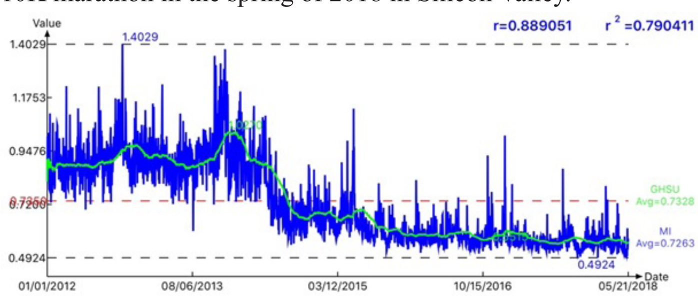

Figure 1: Metabolism Index (MI) and General Health Status Unit (GHSU) from 2012 to 2018.

Glucose - FPG

In 2015-2016, he spent ten months investigating FPG. Initially, he exhausted all avenues to find possible connecting factors, including a very low correlation of ~9% between FPG and PPG. Although his 50-years of engineering training taught him to always look for relationships between input and output, now he must think "out-of-box" to seek for a suitable solution. In the early morning of 3/17/2016, he had a dream about searching for the relationship among different body output categories. He then discovered that there was a high correlation of 84% between FPG and Weight. In the attached Figure 2: FPG and Weight Relationship, he used 26,000 FPG-related data from 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, and the FPG curve followed the Weight curve like its "twin". In the 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.

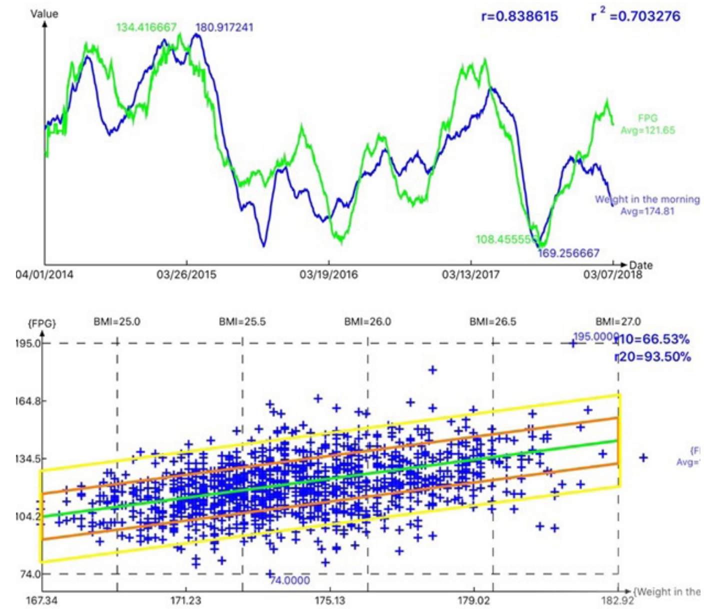

Figure 2: FPG and Weight Relationship (time-series analysis & spatial analysis).

The predicted FPG vs. measured FPG achieved a linear accuracy of 99.8% (118.42 mg/dL vs. 118.62 mg/dL) and 98.6% correlation.

Glucose - PPG

He has collected a complete set of PPG data including his lifestyle detailed data during a period of 1,075 days with 3,225 meals (6/1/2015 - 5/11/2018). This PPG-related data set, size of ~400,000 data, is only a small portion of his entire ~1.5 million data.

As shown in the attached Figure 3: PPG and Its Influential Factors, his average PPG values are:

Predicted PPG: 119.82 mg/dL
Measured PPG: 119.98 mg/dL
with 99.8% linear accuracy and a high correlation of 84%.

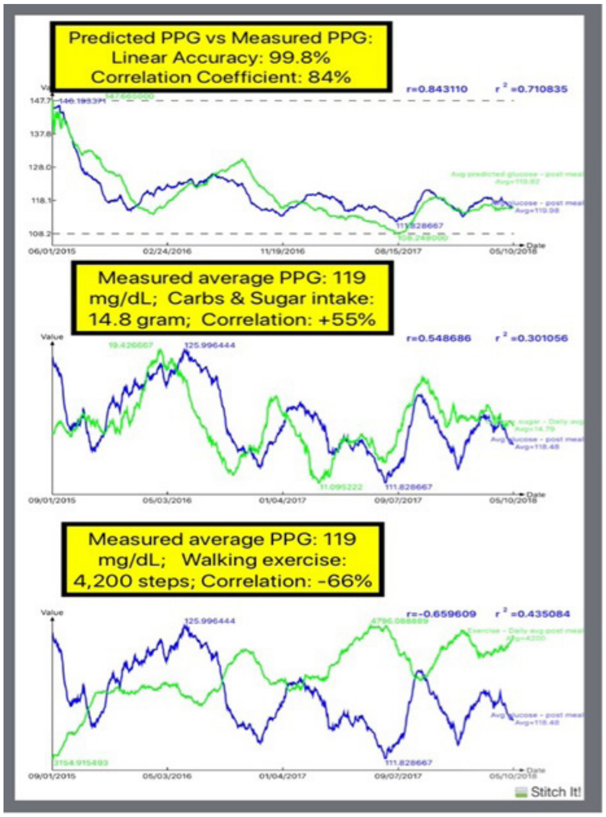

Figure 3: Predicted vs. Measured PPG and Correlation Between Influential Factors and PPG.

It should be noted that an overlapping period of 953 days (10/1/2015 - 5/11/2018) was used for calculating the 90-days moving average for easy viewing of the PPG trend (similar to the concept of "dynamic daily A1C"). The first 90-120 days data were not included in the calculation due to the consideration of data stability.

The daily PPG values contributed amount by each key influential factor and individual contribution margins are listed as follows:

Carbs/Sugar: +14.5 mg/dL, 38%
Post-meal walking: -15.8 mg/dL, 41%
Temperature: +3.7 mg/dL, 10%
All others: +1.9 mg/dL, 11%
Net gain on PPG: +4.3 mg/dL.

In addition, correlation coefficients between key influential factors and measured PPG (119 mg/dL) are:

Carbs/sugar (14.8 gram): +55% (high positive value means higher intake of carbs/sugar pushes PPG higher)
Exercise (4,200 steps): -66% (high negative value means higher amount of exercise brings PPG lower).

Through the continuous use of his AI software program as shown in Figure 4: AI Glucometer and Meal Photos, the author was able to track and analyze all meals using optical physics and signal processing, making meal data collection and PPG prediction much simpler. The 3,225 meal photos were analyzed against 6 million food nutrition content data collected from the US Department of Agriculture (USDA) and stored in a cloud server. All food data were also sorted based on countries, franchise restaurants, individually owned restaurants, home-cooked meals, airline food, etc.

Figure 4: AI Glucometer Screen Design to Predict Glucose via Meal Photos.

Here are some summarized post-meal glucose results:
Airline food PPG - 136 mg/dL
Restaurant food PPG - 127 mg/dL
Home cooking PPG - 111 mg/dL

From the attached Figure 5: PPG and Temperature Record, the temperature impact on PPG is quite obvious, especially in warmer weather >77°F. PPG value would increase 0.9 mg/dL due to temperature increase of each degree above 77°F. This phenomenon is due to increased energy demand and metabolism creation. It should be noted that the FPG value would decrease 0.3 mg/dL due to temperature decrease of each degree below 67°F. This phenomenon is due to "hibernation" effect.

For an overweight patient (BMI 25 - 30), the correlation coefficient between PPG and Weight is a low 11% in time-series analysis. In the spatial analysis diagram, Figures 6 and 7: PPG and Weight, his PPG values stay within a "constant band" regardless of his weight reduction. These two diagrams prove that PPG is not influenced by Weight. Also shown in the same Figure 06, the correlation coefficient between PPG and FPG is a mere 0.9% which means they are not related at all.

In summary, both FPG and Weight have no relationship and influence on PPG. On the other hand, Weight is the primary factor of FPG. Weight is directly proportional to the total quantity of food consumption while PPG is directly related to food quality, specifically the intake amount of carbs and sugar. Of course, a person who eats a large quantity of food will likely take in more carbs and sugar. However, a knowledgeable and well-disciplined T2D patient can control both quantity and quality of food. The above conclusion should be re-verified for light-weight and obese patients. Nevertheless, a strict weight reduction will be a very effective way for obese patients to put their glucose (both FPG and PPG) under control.

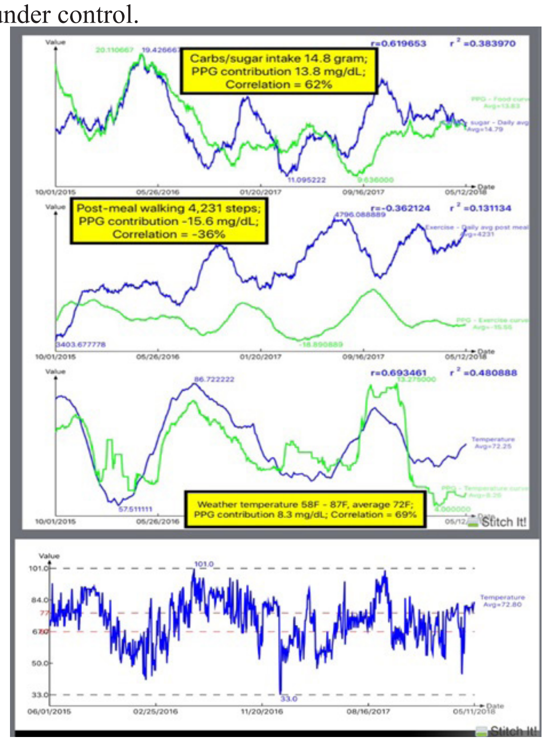

Figure 5: Influential Factor's Contribution to PPG and Temperature Record.

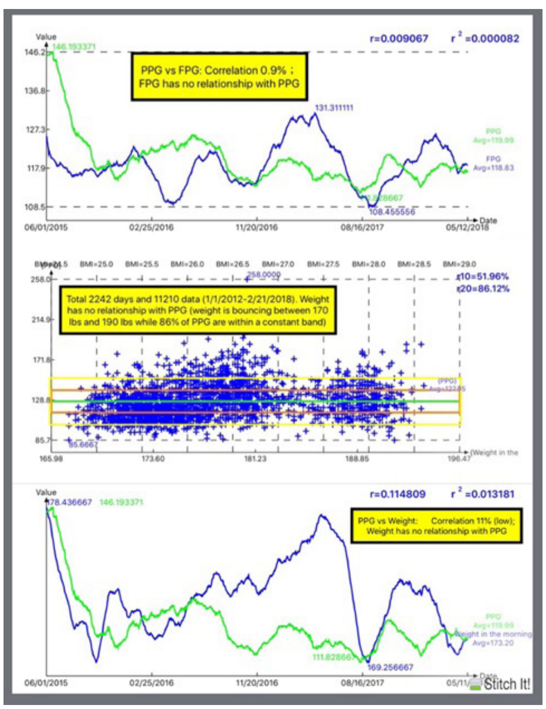

Figure 6: FPG and Weight Relationship (time-series analysis & spatial analysis).

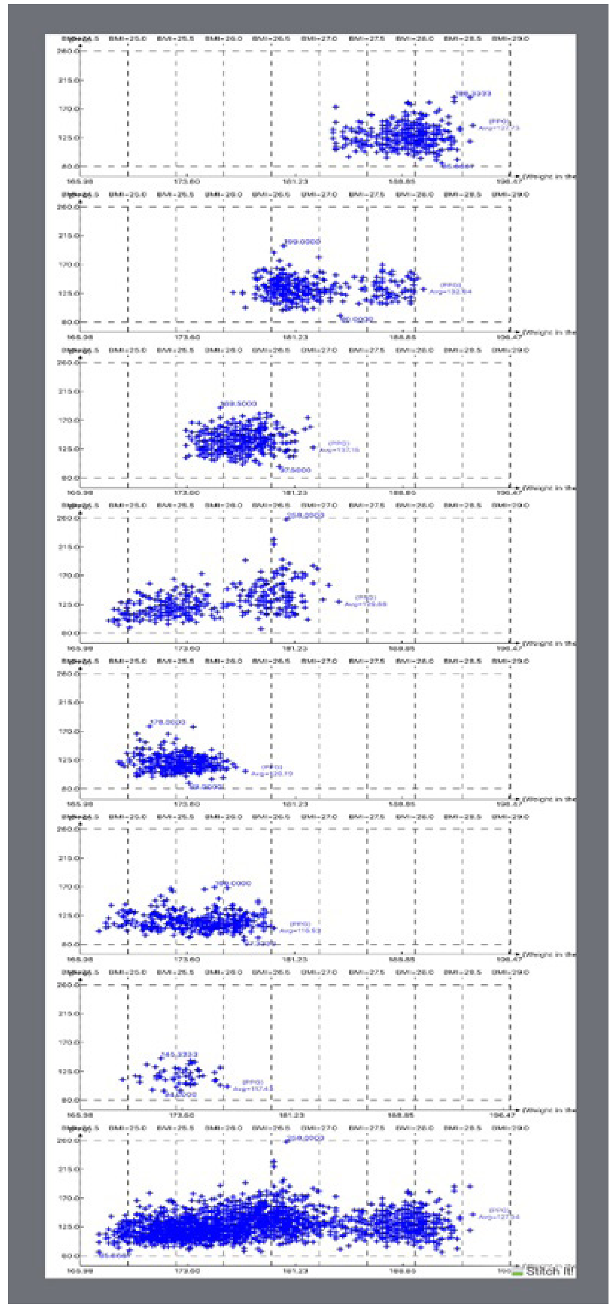

Figure 7: Weight Reduction vs. Constant PPG from 2012 to 2018.

A1C

He utilized optical physics, signal processing, big data analytics, statistics, machine learning, and AI to create prediction models for FPG and PPG, achieving >99% linear accuracy with >80% correlation between predicted and measured glucose. He also developed an easy-to-use AI tool for T2D patients to instantly predict and control their glucose conditions. A screen shot of this AI tool is attached in Figure 4: AI Glucometer.

Combining the knowledge gained from his research, convenience from his AI prediction tools, and persistent lifestyle maintenance efforts, he has brought his A1C value from 10.0% in 2010 to 6.5% in 2018, as shown in Figure 8: Health Data Comparison.

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
Triglyceride (<150)	1161	67
HDL (>40)	24	48
LDL (<130)	174	74
Total Cholesterol (<200)	253	118
BMI (<25.0)	31.0	24.7
Weight (lbs.)	210	167
Waistline (inch)	44	34

Figure 8: Health Data Comparison Between 2010 and 2017.

It is not surprising to notice that his diabetes is under control, and at the same time, his other two chronic conditions, hypertension and hyperlipidemia, are also no longer health concerns.

Risk Probability of Heart Attack or Stroke

As the results of metabolic condition control, as shown in Figure 9: Risk Probability of Heart Attack and Stroke Using 4 Models, his risk probability of having a heart attack or stroke has dropped from 74% in 2000 (followed by three cardiac episodes from 2001-2006) to 62% in 2012 and finally decreased to 26.4% in 2017 (compatible with 26.7% by the Framingham Study).

Year	Probability MI	Probability Medical	Probability Lifestyle	Year Averaged
2000		74%	83%	79%
2012	74%	62%	70%	69%
2013	77%	38%	66%	60%
2014	59%	42%	54%	51%
2015	43%	39%	44%	42%
2016	36%	31%	38%	35%
2017	34%	26%	33%	31%
2018	33%	31%	33%	32%
7-Years	52%	34%	34%	40%

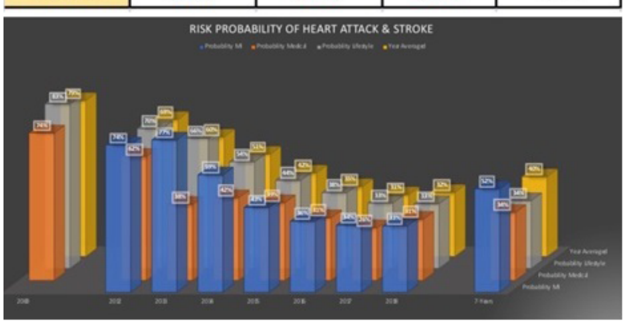

Figure 9: Risk Probability of Having a Heart Attack Using 4 Models.

It should be noted that his weighting factor sensitivity results are within the range of +/- 10% to +/- 18%.

Conclusion

As shown in Figure 10: Flow Diagram of T2D Control, the quantitative results from the developed prediction models including metabolism, Weight, FPG, PPG, A1C, reflect the accuracy and applicability for Type-2 diabetes control via a guided lifestyle management. The utilization of math-physical medicine is also proven quite effective for this investigation. As shown in Figure 8: Health Data Comparison Between 2010 and 2017, the author's health condition has been improved significantly due to his own efforts.

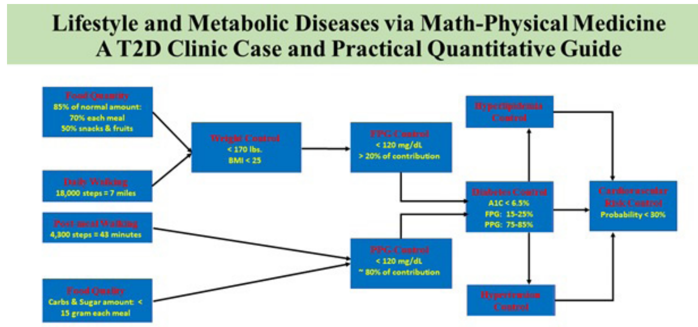

Figure 10: Flow Diagram of T2D Control.

This same big data dynamic simulation approach using math-physical medicine could also provide an early warning to patients with chronic disease of having a heart attack or stroke in the future.

The author has not only saved his own life, but also wants to offer his findings, results, methodologies, and tools to other patients with chronic disease. Hence, they can understand their environment interactions, lifestyle improvements, and disease control with an ultimate goal of improving their well-being. He firmly believes that for chronic diseases, prevention is more important and effective than treatment; therefore, if you can predict your disease condition accurately, then you can control it in a correct and effective manner.

Acknowledgment

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.

Reference and Other Information

The author created math-physical medicine by himself in order to save his life. Although he has read many medical books, journals, articles, and papers, he did not specifically utilize data or methodology from other medical references. All of his knowledge, information, technique, and methodology about mathematics, physics, engineering, and computer science came from his lifelong learning. He has never hired any scientific assistant or associate to help with his research work except for a part-time programmer. He applied his own invention of "Software Robotic" concept and methodology to produce his needed computer software on this project. He did not receive financial assistance or grants from institutions; however, he spent his own money which he earned from a successful high-tech venture in Silicon Valley.