The GH-Method

An Introduction of Medical Research Methodologies of Endocrinology, Chronic Diseases and Their Complications Based on a Type 2 Diabetes Patient's Medical History from 2010 to 2021

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Abbreviations: T2D: type 2 diabetes; PPG: postprandial plasma glucose; FPG: fasting plasma glucose; MPM: math-physical medicine

1. INTRODUCTION

From 2010 to 2021, the author utilized his previously learned knowledge from seven academic disciplines to develop various medical research methodologies, models, and techniques in order to analyze and present results of multiple health issues related to chronic diseases.

This article is organized into 5 parts:

1. Background

2. Stage 1 (2010-2013): Self-study of endocrinology and software development

3. Stage 2 (2014-2017): Metabolism and glucose control of type 2 diabetes

4. Stage 3 (2018-2021): Diabetes induced complications and other chronic diseases

5. Epilogue

2. PART 1 - BACKGROUND

The author spent seventeen years studying seven disciplines across seven colleges. These seven disciplines include: applied mathematics, computer science, mechanical engineering, biomechanics, ocean engineering, structural engineering, and business (finance & marketing).

In addition, he self-studied electronics engineering for twelve years during his professional career in artificial intelligence (AI) based auto-design of various semiconductor chips.

From 1976 to 2002, the author alternated between working as an engineer or starting new ventures as an entrepreneur. During this time, he worked in seven major industries which include: aerospace & defense, naval battle ships and weapon systems, nuclear power, earthquake engineering, computer hardware, computer software, and semiconductors. Most of his professional experiences related to real applications of industrial projects, computer science products (both hardware and software), and artificial intelligence (AI) applications. He also invented a portable computer, a smart printer, a three-dimensional computer-aided design software for architecture and mechanical design, scientific development of software robotics, and medical AI prediction systems. Throughout his early professional career, he conducted research and development tasks daily, but did not publish any academic papers since college.

After selling his successful and publicly traded semiconductor company in mid-2002, he spent seven more years studying abnormal psychology and an additional two years studying behavioral psychology.

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Throughout this nine-year period, he read sixty-eight psychology textbooks and over five hundred clinical reports on psychotherapy along with several published psychology papers. He went on to establish five psychotherapy centers to treat over two hundred traumatized women and children. During 2002-2010, he gained practical knowledge through his day-to-day involvement with the psychotherapy centers.

In 1994, he attempted his 8th venture and later built it into the leading AI-based semiconductor chip design tool company in the world. This new venture catapulted him into the position of highest paid CEO among 15,000 CEOs in Silicon Valley between 1999 to 2002. Through his continuous hard work and dedication over twenty-six years, he accumulated his wealth and success in the high-tech industry.

However, this business fortune did not contribute to his overall wellbeing. On the contrary, it was detrimental to his health. He suffered five cardiac episodes between 1994 and 2006. At that time, he believed the heart attacks were a result of work-related stress only. However, he eventually came to realize it was from a combination of intense stress and neglect of his diabetic condition.

In 2010, his Albumin-to-Creatinine Ratio (ACR) reached 116 (maximum normal range is 30). Also, his weight was at 220 pounds (99.8 kilograms), his Body Mass Index (BMI) was 32.5, his A1C was above 10 percent, and his average glucose was at ~380 mg/dL. He suffered from hypertension, hyperlipidemia (triglycerides at 1161 mg/dL), cardiac episodes, bladder infections, foot ulcers, diabetic fungal infections, and hypothyroidism. Three separate medical doctors advised him that he would most likely need to begin kidney dialysis treatment soon if his condition didn't improve. At the time, he was sixty-three years old and had been taking the maximum dosages of three diabetes medications for the past decade. The three doctors also informed him that he was likely to die within three to five years. This life-threatening message, combined with the threat of painful kidney dialysis treatments, was the final wakeup call.

In August 2010, he moved from Silicon Valley to Las Vegas to escape his daily stress associated with the fast-paced Bay Area high-tech lifestyle. By October 2010, he closed all his remaining business operations and activities and decided to focus on saving his life. He made a vow to himself that he would figure out what went wrong with his health and how to fix it through his own medical study and research.

The three diabetes medications he took for the past decade had not improved his diabetes condition and various related complications. Through his study and research, he found that these medications only dealt with his symptoms and not the root causes of his condition. Therefore, his diabetic symptoms continued to go up and down based on his lack of a consistent healthy lifestyle. Through much trial and error, he was able to slowly taper off his medications over a four-year period. By December 2015, he was able to cease taking all prescribed medications. He has since successfully managed his diabetic condition solely through lifestyle management (diet, exercise, sleep, and stress management). As of October of 2021, his A1C is at 5.8 percent, estimated average glucose (eAG) is 106 mg/dL, weight is 168 pounds (76.2 kilograms), and BMI is 24.8. There are no more presented signs of diabetic complications, except for a diabetic fungal infection.

This is the short version of his story on how he had no choice but to rely on his own efforts to save his life!

In the author's personal view, there is a hierarchy structure of sciences. At the bottom, or foundation, is mathematics. Mathematics presents clear problems and exact answers. Applied mathematics (above mathematics) has three branches consisting of physics, computer science, and statistics. Further up this hierarchy (above physics) is applied physics which has three branches consisting of engineering, biology, and chemistry. Above biology and chemistry are medicine and pharmacology. Finally, psychology sits above medicine and pharmacology. The higher position in this science hierarchy, the more applicable it is at addressing practical problems. However, it also moves further away from the foundation of mathematics. Therefore, it's ability to solve tough problems in the real world can become somewhat limited and difficult.

Another personal view from the author is that there is an abundance of intelligent and capable predecessors (i.e. innovators, scholars, scientists) who have already discovered or invented so many amazing and useful facts, concepts, theories, equations, and models. The author feels there is no need to reinvent the wheel and instead should apply existing theories, equations, models, and inventions (using mathematics and physics as bases) in order to save research time and effort, and develop new breakthroughs in the process. Under this logic, the author's developed GH-Method: math-physical medicine is not an invention, it is merely another application using the most fundamental branches of mathematics and physics to apply them within medical research.

3. PART 2 - STAGE 1 (2010-2013): SELF-STUDY and SOFTWARE DEVELOPMENT

From the fortune the author made through his high-tech venture successes, it became a habit for him to "buy" rather than to "make" something he needed. From 2010-2011, he used his own funds to hire eighty-two medical doctors in China and six part-time doctors in the US to assist him on his medical research project. By November 2011, he realized he had not achieved his goal of learning more about diabetes and its complications. He spent most of his time and effort managing other people's work instead of expanding his own knowledge sphere.

By the end of 2011, he decided to start over and do everything himself, without the aid of hired medical researchers. The main purpose of his research was to further expand his knowledge base in order to save his own life. During the past twelve years of dedicated medical research work, he finally figured out how to turn himself from an engineer and a businessman into a medical research scientist.

However, his "do-it-yourself" approach had one major drawback. It took him much longer and with much more effort to read all the medical papers and textbooks in order to figure out the hidden inter-connectivity between different internal organs and diseases.

Initially, he decided to focus on studying endocrinological diseases and food nutrition. At first, he couldn't fully understand the medical terminology in the textbooks and papers he read. He only understood parts of introductions and conclusions and didn't understand the sections on methods and results. Sometimes he would reread papers ten or more times in order to truly understand their methods and conclusions. Through his stubborn and tenacious approach to conquering all challenges, he was finally able to comprehend the readings. Thus far, he has skimmed or read through 50-80 medical textbooks and ~2,000 published medical papers.

The central pathway of his self-study and research is from lifestyle through metabolism to chronic diseases and then into their induced complications, such as heart, brain, kidney, eyes, nerves, etc. Recently, he also expanded his self-learning scope from metabolism through immunity to infectious diseases, as well as into areas such as cancers and dementia (which are metabolic disorder related diseases). His focus has always been on prevention and control of diseases, not medical interventions or treatments, because he does not have a medical license.

From 2002 to 2010, he developed a "software robot" product. One of his previous dreams was to develop an AI-based software architecture which can automatically generate the needed software codes using Java language based on user defined and described system requirements via a common interface language of English. By 2009, he completed the design and code development of this software robot's prototype which was ready for commercialization. However, in 2010, he became very sick and had to give up on this product. When he started his self-learning of internal medicine in 2011, he decided to develop a dedicated medical research software tool utilizing his ready-made software robot as its architecture base. Since 2011, the development and enhancement of his medical software tool, "eclaireMD Chronic", has been ongoing and will continue into the foreseeable future. He continues to add and strengthen the software while collecting his own and a few other patients' real-life data of medical conditions and lifestyle details for analyses. Thus far, he has collected ~3 million data regarding his own health conditions and lifestyle details along with an additional ~6 million cleaned and reorganized food nutrition data transferred from the United States Department of Agriculture (USDA).

The “big data analytics” approach is extremely practical and useful for his medical research project. Almost ~90% of existing medical papers he has read uses the statistics approach. Unfortunately, statistics has its fair share of shortcomings and is sometimes mathematically debatable (depending on certain situations and constraints). The author has also used some statistics tools, such as regression models and probabilities, to conduct some of his medical research projects. A well-organized and cleaned database can indeed provide many different and useful views of a problem from different angles. For example, a person can depict a fruit cake using equations, formulas, or languages to describe the starchy outer shell with white creamy surface color, various fruits inside, and chocolate as the topping. However, the big data analytics approach is like using a knife to cut this fruit cake in any desirable angle. Each different cutting angle can reveal different views of this same fruit cake; therefore, they can offer additional information about the inside views of this cake. If we compare this cake analogy to a human body, we can see its power and applicability on dealing with human health and medical issues.

Artificial intelligence is just another add-on tool to collect all stored knowledge and previous experiences to provide an accurate prediction of the future. This AI approach is extremely useful for the tasks of a simulation or prediction.

Since 2010, the author has spent between 30,000 to 40,000 hours during the past ~12 years to study and research nutrition, lifestyles, diseases, and health. In total, including his previous nine years of psychology study, he has already spent ~21 years on the general subject of “health and happiness.” This twenty-one year investment has no relation to his younger self’s desire of chasing power, fame, and money. Now, he strives for the two fundamental elements of any person’s life - health and happiness.

4. PART 3 - STAGE 2 (2014-2017): METABOLISM and GLUCOSE

4.1 GH-method: math-physical medicine

Since the author has never studied biology or chemistry, he cannot apply his knowledge and tools to these two disciplines to study medicine in a traditional way. He must rely on his learned theories and concepts from mathematics, physics, modeling techniques, and engineering to observe different biophysical phenomena (a result of biological structure and its internal chemical interactions) before collecting, organizing, and analyzing collected data in order to derive accurate analysis results or useful predictions. After data analysis, he will then establish some accurate mathematical models and derive adequate equations in order to predict their future behaviors, outcomes or outputs correctly. During this data process and data analysis, knowledge of computer science applications, including both big data analytics and artificial intelligence, are heavily utilized. That was the process he previously used to design space shuttle, naval battle ships, nuclear power plants, computer devices, software robots, and semiconductor design tools. In December 2017, he attended the International Diabetes Federation annual conference in Abu Dhabi and made his first presentation on his unique medical research approach, which he would later name the GH-Method: math-physical medicine (MPM).

4.2 Metabolism index model

The author spent the entire year of 2014 to develop his metabolism model. Metabolism is dealing with energy inputs and outputs of the body. At first, he was inspired by the topology concept of mathematics. He observed that the human body with its various internal organs are very similar to the mathematical concept of a topological subject because its fundamental characteristics are retained and unchanged even under various types and degrees of deformation. If there is no partial rupture of an organ or a total break-down of certain biomedical systems inside a body (poor lifestyle practices and bad habits may damage or deform the organs and the total system of a body), then the basic characteristics of a body and its organs remain the same. Even if the subjects' or body's biomarker values are altered and is still within its allowed limitations, the human body's life and organ functions are savable because the body's original characteristics and functions are preserved.

Secondly, he applied the finite element method of engineering that he studied at MIT in 1973 to build up his metabolism model. He subdivided human health and energy into ten different but interrelated categories and a total of nearly five hundred detailed elements. These ten categories are four basic medical conditions (weight, glucose, blood pressure, and blood lipid) and six lifestyle details (food and meals, water consumption, exercise, sleep, stress, and daily routines). Each category contains a different number of elements. For example, stress has over forty elements, sleep has over ten elements, and daily life routines and habits have over fifty elements. The category of food and meals is the most complex category, which contains several hundred elements. This metabolism is not a "big data" problem but rather a "big relationship" problem. This is because the total possible relationships among those ten categories is a large number. In theory, there are ~3.629 million possible relationships (=10!), like having 3.629 million rubber bands encircling ten nails on a piece of a wooden board. At first, we nail in those ten category nails at thirty-six degrees each, centered around the origin of the circle. When we start to change the location of these nails by either moving toward the inside or toward the outside of the circle which is similar to moving the glucose value outward (higher glucose) or inward (lower glucose), it creates stress (expansion or contraction) inside of these rubber bands. He further defines the total metabolism as the summation of all those stresses inside of those 3.629 million rubber bands. Of course, this is a difficult problem to be solved if we want to identify an exact answer. Therefore, he came up with an approximation model using geometric algebra operations to calculate his desired Metabolism Index (MI) value. The final equation derived for calculating this approximated MI value has been written on paper, totalling fourteen pages.

4.3 Glucose and HbA1C predictions

From 2015 to 2018, he developed the following 4 math-physical models (using prediction equations, not relying solely on statistical tools):

(1) Weight prediction model (2015)

(2) Postprandial Plasma Glucose (PPG) prediction models (2015)

(3) Fasting Plasma Glucose (FPG) prediction model (2016)

(4) HbA1C prediction models (2016)

The above four prediction models achieved a linear accuracy between 95 percent to 99.9 percent. In addition, he was able to figure out the major influential factors and their contribution margins for these four biomarkers. For example, FPG has five contributing factors and PPG has nineteen contributing factors.

4.4 Optical physics, big data & AI

The most complicated category of the MI model is food and diet which possesses the biggest portion of his collected data. Furthermore, the link between PPG and carbohydrate and sugar (carbs/sugar) intake amounts is the toughest to deduce. He has tried the PPG prediction method using a popular concept in the nutrition field, glycemic index (GI) and glycemic load (GL), but the derived results based on GI were unsatisfactory. GL involves quantity of food which is troublesome to collect on a daily basis. In 2015, he thought that the different ingredients, especially carbs/sugar amounts, were the reflection of the different internal molecular structure of plants or meats, and that different molecular structures would result in different optical waves (further turning into a different color of food material). The amplitude, frequency, and wavelength of those optical waves (color of food material) could indicate the type of ingredient and the portion amount. Therefore, by applying optical physics principles and optical wave theory, he explored their internal linkages through software programming. A standard iPhone camera can take a meal's photo with 20 megapixels in one picture, or 20 million optical pixels. Each light pixel is represented by a unique combination of 8 alpha-numerical digits. Each meal's photo using an iPhone camera would capture 160 million digits, which could be utilized to calculate the intake amount of carbs/sugar within each meal. By utilizing his developed PPG prediction model, he could obtain the predicted PPG value instantly. The iPhone's computer processing unit (CPU) is fully capable of processing these 160 million digits within a few seconds. Using this optical physics approach, along with big data analytics and developed AI algorithms, it yielded an extremely high prediction accuracy of greater than 99.5 percent on his Predicted PPG values. This calculated prediction accuracy is based on a total of 7,568 food photos (7,128 daily meals with 440 snacks/fruits) during the past six and a half years.

4.5 Input versus output (root cause vs. symptom)

When the author was an engineering student, his professor told the students that they should always try to locate or identify the inter-connection or inter-relationship between the input (root causes of disease or external forces on a structure) and output (symptom of disease or structural deformation). In early 2015, the author struggled for almost one year trying to identify the real reason behind his elevated FPG. At first, he analyzed his FPG data (metabolism output or symptom of disease) against lifestyle inputs, such as food, exercise, sleep, and stress, but could not find any connections. On March 17, 2016, he woke up at 3AM from a dream and realized that he must not be constrained by his previous learning from engineering schools, and instead should think out-of-the-box about this elevated FPG problem. He then started to compare his FPG against his other biomarkers (metabolism outputs). He analyzed the relationship between FPG against PPG, blood pressure, and lipid without any success. By 7:00 in the morning, he finally found that his body weight and his FPG (both belong to the outputs of a body) had an extremely high correlation coefficient of over 90 percent. It turns out that his elevated FPG of 17 mg/dL was caused by his elevated weight of six pounds from March 2014 to March 2015. He had over-eaten fatty nuts and seeds (both food quantity and food quality, lifestyle input elements m9a and m9b), therefore his body weight gradually increased from 175 to 181 pounds, which then further elevated his FPG (medical conditions output m2) by 17 mg/dL from 118 md/dL to 135 mg/dL. This medical example explains that we can examine one symptom against another symptom in order to identify some hidden connections.

In 2021, he read an article on cancer which had some difficulties identifying the direct linkage of symptoms between diabetes and cancers. However, the author started to compare their root causes and identified that around 60 to 70 percent of root causes for both diabetes and cancers are identical. After all, cancers are just another type of metabolic disorder and chronic disease. But cancers have rather unique "environmental" root causes, such as poison, pollution, radiation, and hormone treatments, while diabetes do not have those environmental causes.

5. PART 4 - STAGE 3 (2018-2021): DIABETES INDUCED COMPLICATIONS and OTHER CHRONIC DISEASES

5.1 Data presentation of segmentation and contribution analyses

Every biomarker's data range can be segmented using "from-to" time ranges or "high, medium, low" amplitude ranges, such as the ADA diabetes guidelines of time-below-range (TBR) <70 mg/dL, time-in-range (TIR) 70-180 mg/dL, and time-above-range (TAR) >180 mg/dL. After segmenting a dataset into different ranges, we can then calculate each segment's contribution percentage of certain biomarkers, such as glucose.

For presentation of certain analysis results, we can combine two contributing factors with one resulting biomarker performance into one graphic diagram, such as plotting carbs/sugar and exercise with glucose together in one graphic diagram. The author developed a three-dimensional (3D) diagram, but with a presentation model of "2.5-dimension" diagram, to demonstrate this type of multiple relationships. For example, the x-axis is the carbs/sugar intake amount from 0 to 50 grams, the y-axis is the post-meal walking steps from 0 to 5000 steps, and the third dimension (glucose) on the z-axis is shown as a skewed radio wave starting from the origin at the lower-left corner (the lowest glucose) and moving toward the upper-right corner (the highest glucose) on the x-y twodimensional (2D) plane. That is why he calls it a two-and-half dimension diagram which represents 3D information together. He uses this presentation model for many of his diabetes and psychology papers given that one input usually involves at least two critical inputs.

5.2 Candlestick model vs. density model

The author was the CEO of a publicly traded semiconductor company from 1995 to 2002. Not only is he a finance specialist and businessman, but he is also familiar with various mathematical financial models used for stock trading. In nature, both stock price and glucose values are waveforms which fluctuate continuously due to different driving forces. In early 2019, he borrowed the concept of the candlestick model (aka K-line model) used on Wall Street and reprogrammed it into a presentation model for glucose fluctuations in his diabetes papers. For example, using a continuous glucose monitoring (CGM) sensor device, he can collect 96 glucose values per day every fifteen minutes and 288 glucose values per day every five minutes. He then selects five key glucose values per day: opening glucose, maximum high glucose, minimum low glucose, average glucose, and closing glucose. The 4 glucose values, without the minimum low glucose value, constitute an "OHAC model" with a triangular shape, for an approximate PPG diagram within a three-hour time frame after the first bite of a meal.

However, this Candlestick model and OHAC model only deals with a few key data points per day. Therefore, he has further developed a more completed "Density Model" which includes all the collected data within a selected time frame, not daily averaged data. The selected time frame can be any period but having a longer time span is recommended. Not only is the Density Model useful for glucose analysis, but it can also be used for analyzing food, exercise, blood pressure, heart rate, and other disease biomarkers. This model covers a complete spectrum of his collected data, where its graphic representation of final results is quite similar to a normal distribution or Gaussian distribution curve. Therefore, the concepts of mean and standard deviation can also be applied. Incidentally, the density model can be linked with other tools, such as segmentation analysis or contribution analysis.

5.3 From wave theory to energy theory via fast Fourier transform

All biomarkers can be represented by different waveforms as long as they have sufficient data. All waves have three basic characteristics: amplitude, frequency, and wavelength. In a general practice, many biomarker performances are expressed in a time domain initially with the horizontal x-axis as the time scale with the vertical y-axis as the biomarker wave's amplitude scale. We can then use Fast Fourier Transform (FFT) to convert the time domain data or curve into a frequency domain data or curve. In the frequency domain diagram, the horizontal x-axis becomes the frequency scale while the vertical y-axis becomes the original time-domain wave's associated energy scale. Once the glucose wave in the time domain is transformed into the frequency domain, we can then have a clear idea of how much the associated energy of glucose is corresponding to a certain glucose occurrence frequency. After we have the associated energy information, it will be simpler for us to determine how much damage occurs on the internal organs by the associated glucose energies. For example, hypoglycemia (<70 mg/dL) or hyperglycemia (>180 mg/dL) usually occur in the lower frequency range because these two serious conditions should not appear too often unless the patient has severe diabetes. For severe diabetic patients, their lower-frequency numbers would be higher than non-severe diabetic patients. This is how the frequency-domain analysis links with segmentation and contribution analyses along with utilizing time domain to frequency domain transform technique. Therefore, by using frequency domain analyses, we can estimate the risk probability of developing certain induced complications from chronic diseases, such as heart attacks, stroke, kidney failure, diabetic retinopathy, neuropathy, etc.

5.4 Linear elastic glucose theory

The author studied mechanical engineering undergraduate courses at the University of Iowa. In the course of strength of materials taught by Professor James Andrews, he learned the basic stress-strain relationship via Young's modulus. He then applied this basic engineering concept to his developed PPG prediction model that involves FPG serving as the baseline of PPG in his ongoing medical research work. By introducing and including 3 GH-Modulus, he can then build a simple, easy, yet accurate predicted PPG model. He defined GH.f Modulus using FPG as the calculated baseline for PPG, GH.p Modulus for converting carbs/sugar intake amount into energy influx to raise the PPG value, and GH.w modulus for converting exercise amount into energy burnout to reduce the PPG value. The three GH-Modulus are dependent on the patient's overall health condition and individual diabetes severity within different timeframes. This situation is similar to Young's modules being dependent on different materials, such as diamond, steel, copper, concrete, etc. The following equation is his developed linear elastic glucose theory (LEGT) model:

Predicted PPG
= FPG*GH.f + carbs/sugar*GH.p + walking k-steps*GH.w

This developed LEGT model has been proven that it can achieve >95% of PPG prediction accuracy.

Regretfully, he did not keep personal data of medical conditions and lifestyle details prior to 2012 when his HbA1C was above 10%, eAG was around 380 mg/dL, BMI over 30, along with suffering from 5 cardiac episodes, kidney problems, and more. In conjunction with the missing data, he is not a licensed medical doctor and does not have access to other patients' records. Moreover, there are very few patients who have strong will power, stubborn persistence, adequate knowledge and experience on data collection, organization, cleaning, along with preparation to be capable for useful data processing and analysis. Otherwise, the author can apply a "nonlinear plastic" model which he learned from Professor Norman Jones at MIT to develop a "nonlinear plastic glucose theory" (NPGT) which can be extremely beneficial for saving patients with severe diabetic conditions. Nevertheless, the LEGT should be sufficient to provide a useful tool for the purpose of prevention and control for most type 2 diabetes (T2D) conditions. This situation is similar to the engineering elasticity theory, which is suitable for most engineering situations, while plasticity theory is valuable for certain special, extreme, or severe circumstances, such as structural impact, structural fracture, or structural failure. In the medical field, the plasticity situation is similar to the damaged pancreatic beta cells.

5.5 Glycemic variability (GV) and statistics

Using a mean value of glucoses, such as average glucose or HbA1C value, it can reveal certain useful information about the diabetes conditions. However, it definitely misses the description of glucose excursion, i.e., glucose fluctuations (GF) which provides significant data. There are various ways to present GF or excursion detailing the glucose impact on different internal organs. This glucose excursion or glycemic variability (GV) deals with glucose wave theory from a distinct approach, specifically belonging to the scope of "Statistics". The ADA published "TxR" guidelines of time-in-range (TIR%) with 70-180 mg/dL for normal glucose range, time-above-range (TAR%) with >180 mg/dL for hyperglycemia, and time-below-range (TBR%) with <70 mg/dL for hypoglycemia (insulin shock) are located somewhere between the average glucose and glucose excursion picture. As a result, the ADA's TxR model can be considered as a "pseudo" analysis tool. There are also other GV statistical methods available such as standard deviation (SD), coefficient of variation (CV), adjusted M-value, mean amplitude of glycemic excursions (MEGA), continuous overall net glycemic action (CONGA), mean of daily differences (MODD), etc. In some of the author's papers, he applied simpler and easier "GF" model which is the daily maximum glucose minus daily minimum glucose. Using this simpler GF term which covers a "wider" range than SD and combined with the mean value of glucose, such as HbA1C; it can offer additional information than the present diabetes clinical practice of relying on HbA1C only. Furthermore, GF provides a quick and rough picture of a patient's overall health along with the risk in developing various complications from diabetes. In addition, the author has also applied certain statistics regression models (such as linear, nonlinear, single variables, multiple variables) to develop regression predicted biomarker values.

5.6 Continuous glucose monitoring (GCM) sensor device collected data

The author has utilized the Libre lifestyle CGM sensor device on his upper arm since May 5, 2018 and has changed it every fourteen days. Furthermore, he installed a Bluetooth device on top of the CGM device in order to automatically transmit sensor glucose data to his developed app software EclaireMD Chronic. These glucose values are organized in two datasets. The first dataset contains 96 glucoses per day every fifteen minutes and the second dataset contains 288 glucoses per day every five minutes. As of October 24, 2021, he has already collected a total of 348,288 sensor glucose data which include 87,072 from 15-minutes and 261,216 from five-minutes. This data collection process utilizes both computer hardware and software.

By using the five-minute sensor glucose (average 113.78 mg/dL) and fifteen-minute sensor glucose (average 113.23 mg/dL) during a period from February 18, 2021 to October 25, 2021, it has a small difference of 0.55 mg/dL or 0.49%; therefore, a denser data collection done at every 5 minutes does not provide more accurate results. As a result, the author continued with the fifteen-minute sensor glucose model for his research work, since it is a sensible and reliable time duration for measuring blood glucose changes. Luckily, a glucose wave has significant changes every ten to fifteen minutes, unlike seismic waves changing every second.

With such a big database available, the research techniques mentioned above, such as candlestick K-line, GV, and glucose excursion, can assist him with his efforts in his medical research work using CGM sensor device collected glucoses.

5.7 Big data analytics

Since January 2012, the author has collected his glucose via the traditional finger-prick method four times a day, once in the early morning when he wakes up, and two hours after the first bite of every meal. After applying the CGM sensor device on May 8, 2018, for the purpose of data consistency with the doctor's recommended testing for diabetes patients, he has used the CGM data at 120-minutes moment after first bite of meal as his finger PPG value in his Chronic software. Over the past three and a half years (907 days) of CGM usage period, he still continues with the finger pricking method as the calibration data for his CGM sensor data. This is due to the CGM data being usually higher in the first two to three days of installation and then becoming lower for the last two to three days. Therefore, only the Libre CGM sensor data collected from the middle range of eight to ten days for the fourteen-day lifespan is more reliable. However, the two extreme ends of the first two to three days and the last two to three days, he always uses the finger-pricking glucose data to serve as a calibration tool. Furthermore, he has modified his software to accept the calibrated data only as the stored glucose values. In summary, thus far, his collected finger glucoses have reached 14,328 data over the past ten years (3,582 days) and 348,288 over the last three and a half years (907 days). The raw data includes 362,616 with additional 18,140 processed data of average (mean), maximum, minimum, open, close, SD, glucose fluctuation (GF=max-min), FG/eAG, PPG/eAG, FPG/PPG, CV, MAGE, CONGA, MODD, finger A1C, sensor A1C from 15-minutes, sensor A1C from 5-minutes, combined sensor A1C, A1C with GF, and the ADA's A1C. In the category of glucose alone, there are 380,756 data stored in his database. With other glucose related items, the total glucose data size has around 500,000 data points.

The category of Food Nutrition related data is another big data set. Since May 1, 2015, he kept a record of his food information which comprises of 7,528 meal photos (on his iPhone), carbohydrates amount, sugar amount, post-meal walking steps, corresponding PPG, twelve food material categories, 238 consumed food materials, 6,719 eaten food items, 238 different food glycemic index, AI predicted PPG (using optical physics), Natural Intelligence or NI predicted PPG (using his eyes and brain to estimate PPG), 7,528 food portion % (food quantity), bowel movement amount (for weight prediction and gastrointestinal health). In addition, he has a rough estimate of his food related data size which has reached to over 500,000 data points.

Finally, the Metabolism Index (MI) contains all ten categories and nearly 500 elements to summarize his health condition and be used for risk assessment of developing into various complications affecting the heart, brain, kidney, eyes, foot, skin, and nervous system. These direct input data for around 500 elements for 3,582 days contain 1,791,000 data points.

There are other miscellaneous data with a total size between 200,000 to 300,000 data points.

By combining his glucose, diet, metabolism and miscellaneous data sets together, his collected and stored total data size has reached around 3 million data on his iPhone, which is backed up on his cloud storage. This database does not take account of the purchased, cleaned, and transferred of over six million publicly-available food nutritional data from the USDA for his optical physics and AI application of PPG prediction.

5.8 Various HbA1C formulas

Using certain linear regression analysis methods and his collected HbA1C data from 43 "near-quarterly" lab-tested results (mainly from one single lab to avoid data integrity issues), he has developed several predicted HbA1C formulas as shown below:

(1) Finger A1C
= finger eAG /16.7

(2) Sensor A1C
= sensor eAG /18.7

(3) Combined A1C
= 0.4*finger A1C + 0.6*sensor A1C

(4) A1C with glucose fluctuation
= (0.3*sensor eAG + 0.7*sensor GF) / 16.25

(5) ADA defined A1C
= (finger eAG or sensor eAG +46.7) / 28.7

Without using the ADA defined formula, his average predicted HbA1C result utilizing the four predicted A1C formulas would match almost perfectly with the average forty-two lab-tested HbA1C result along with high correlation coefficients (67% - 70%) between his predicted A1C curve and lab-tested A1C curve. The lower correlation is due to insufficient lab-tested A1C data.

It should be mentioned that based on glucose density distribution and segmentation & contribution analyses, his finger PPG occupies 75 percent of A1C and finger FPG occupies 25 percent of A1C. On the other hand, the CGM sensor PPG occupies 38 percent of A1C, sensor FPG occupies 29 percent of A1C, sensor between-meals and pre-bed glucoses occupy 33 percent of A1C.

Excerpt from the "Metabolical" book written by Lustig, Robert H. MD, HarperWave, Harper Collins Publisher, New York, 2021 and some of his related research work:

"The following 8 intra-cellular or sub-cellular pathological processes (or pathways) are the basic causes of chronic diseases which are not mutually exclusive. Each interacts with the others, and so they tend to cluster together.

These 8 processes are:

(1) Glycation

The carbohydrates (fructose, i.e., sugar, or glucose) and an amino acid (e.g., proteins) are related for glycation. (The author: Sugar has connection).

(2) Oxidative stress

If there are more oxygen redials than antioxidants, it causes cellular dysfunction and cell death. The color of real food is an indication that these plants contain antioxidants we can't make on our own. (The author: Consuming real food helps oxidative stress).

(3) Mitochondrial dysfunction

Chronic disease is mitochondrial. The single best stimulus to make more and fresh mitochondrial is "exercise." Your mitochondrial can't overturn a bad diet. (The author: Both diet and exercise are important).

(4) Insulin resistance

Insulin lowers the blood glucose. Its main job is to store energy for a rainy day. Two organs need insulin to function, liver and adipose tissues. (The author: Even the brain needs insulin). Insulin resistance is the central problem in metabolic syndrome. Processed food is by far the biggest player. (The author: Eating real food, not processed food makes a huge difference on insulin resistance).

(5) Cell membrane integrity & fluidity

Cell membranes are composed of a lipid belayer. There are 7 different types of fats in your diet, and all can impact your cell membranes in different ways. Saturated fatty acids could reduce the cells'overall fluidity. Unsaturated fats are better than saturated fats. (The author: Excessive fat from food is bad for health).

(6) Inflammation

Foreign invaders (e.g., viruses and bacteria) can damage cells directly. We need an inflammatory response, unfortunately there are 4 downsides. There are connections between metabolism and inflammation. (The author: Metabolism and immunity are two sides of the same coin and immunity defends inflammation). Chronic diseases have four inter-connected problems, nutrition, metabolism, inflammation, immunity. Screw up one and you screw up the other three. (The author: Nutrition helps metabolism and immunity).

(7) Epigenetics, not genetic

The metabolic syndrome studies say only 15% is genetic, the rest is environmental. (The author: The term of environmental includes lifestyles). But environment can change gene as well through a phenomenon called epigenetics. Altered nutrition, such as processed food, appears to be a primary driver of altered epigenetics. (The author: Avoid consuming any processed food).

(8) Cell autophage

Clearing biological waste products is a process known as autophage, and it plays a key role in healthy aging, especially in the brain. All organs do better with autophage, which is an essential process that maintain healthy cells by removing damaged proteins and malfunctioning organelles, especially mitochondria. (The author: Mitochondria is an organelle containing enzymes responsible for producing energy). Old mitochondria make a lot of oxygen radicals. Autophage is under various nutritional controls. Intermittent fasting lowers insulin and raises ketones, both of which promote autophage. (The author: He has been conducting intermittent fasting since November 8, 2020).

All of these 8 pathologies are directly related to food and nutrition. In order to maintain excellent health and avoid metabolic disorder syndrome, we must consume real food with good nutrition. Processed food must be avoided since it causes the most damage to the body and our metabolism system.

The key to fending off chronic diseases is to keep the eight intra-cellular pathological pathways running correctly.

Drugs and nutraceuticals don't work for metabolic syndrome. All of the eight pathologies are driven by and are responsive to specific components of real food, because real food gets where it needs to inside the cell. Processed food poisons the eight pathways instead.

Food is related to all of the eight pathologies. However, exercise is only related to 5 pathologies, i.e., mitochondrial dysfunction, insulin resistance, inflammation, epigenetics, and cell autophage. Exercise has no relationships with glycation, oidative stress, cell membrane integrity & fluidity.

The author has conducted various Segmentation and Correlation analyses of glucoses which is one of the key methods of diabetes research. For example, FPG is highly related to body weight and body weight is controlled by food portion (quantity) mainly with exercise, sleep, stress as secondary contributors. In addition, he has also identified that FPG in the early morning is also highly correlated to body temperature in the early morning. PPG's nineteen contribution factors are largely due to diet (~60 percent) and exercise as the secondary factor (~40 percent) if he ignores other third-tier factors. Therefore, the ratio of food (60 percent) versus exercise (40 percent) is 1.5 (=60/40) while food contributes into 8 intra-cellular or sub-cellular pathological processes (or pathways) and exercise contributes only 5 pathways with a ratio of food versus exercise of 1.6 (=8/5).

These research results have linked his results using GH-Method: math-physical medicine approach almost exactly with the Dr. Robert H. Ludwig's book-mentioned biomedical pathological approach.

5.9 Quantum mechanics & perturbation theory

In 2020, the author compared the human body (inner space) to the universe (outer space). All of the different but interconnected internal organs and diseases are similar to the planets existing in outer space which are mutually influenced (for example, the ocean tide waves on earth are influenced by moon). Therefore, he started to apply certain quantum mechanics concepts and equations to his internal organ study, especially to diabetic-related diseases. At first, he transformed his glucose data from time domain into frequency domain via Fast Fourier Transform (FFT). Second, he modified Albert Einstein's famous theory of relativity equation of E=m*(c**2) into his desired glucose energy equation of E=n*(a**2). Einstein's m is mass and c is the speed of light. The author's glucose energy equation's n is the frequency number and a is the glucose amplitude of Y-axis value in the time domain. As energy is proportional to the square of a wave's amplitude; therefore, the glucose associated energy is directly proportional to the square of glucose amplitude times its corresponding frequency number. After calculating the glucose energy using the equation of E=n*(a**2), we can then estimate the glucose induced damages to the internal organs.

The perturbation theory is another application from quantum mechanics which has already been proven to be one of the best approximation techniques. The author applies the first-order, second-order, and third-order interpolation perturbation equations in order to obtain his "perturbed PPG." This is another form of predicted PPG using one measured sample PPG waveforms and one selected perturbation factor, such as carbs/sugar intake amount, which is the "Slope." The "measured PPG" waveform is used as his reference or baseline waveform.

The following polynomial function is the perturbation equation:

A = f(x)
= A0 + (A1*x) + (A2*x**2)+(A3*x**3) + ... + (An*x**n)

Where A is the perturbed glucose, A i is the measured glucose, and x is the perturbation factor based on a chosen carbs/sugar intake amount.

The first-order interpolation perturbation equation can also be expressed in the following simplified format for risk probability studies:

A i = A1 + (A2-A1)*(slope 1)

Where:
A1 = original risk A at time 1
A2 = advanced risk A at time 2
(A2-A1) = (Risk A at Time 2 - Risk A at Time 1)

The perturbation factor or Slope is an arbitrarily selected parameter that controls the size of the perturbation. The author has chosen a "slope" for his perturbed glucose as follows:

Slope
= (Selected value - Low-bound value) / (High-bound value - Low-bound value)

By applying the perturbation theory from quantum mechanics, for certain biomarkers, he was able to reach ~95 percent accuracy using the first-order equation, ~97 percent accuracy using the second-order equation, and ~99 percent accuracy using the third-order equation. The perturbed glucoses can be used as another predicted glucoses with extremely high accuracy.

5.10 Metabolic disorder induced complications and longevity

(1) Risk probability of having complications

Since his metabolism model contains four basic biomarkers and six major lifestyles; therefore, it can serve as the foundation of his risk model for many chronic disease complications with certain selected and emphasized factors based on previous medical research findings. For example, the CVD/CHD (heart) and stroke are mainly resulted from macro-vessel (artery) complications. As a result, he added an amplified contribution factor by blood pressure for the artery rupture scenario and blood lipids for artery blockage situation. The neuropathy, retinopathy, and chronic kidney problems contain amplified contribution factor by blood pressure for micro-vessels leakage scenario. Furthermore, triglycerides provide an amplified contribution factor for diabetic retinopathy. Albumin creatinine ratio (ACR), protein in urine, contributes to chronic kidney disease (CKD), but ACR also has a strong relationship with blood pressure, thyroid stimulating hormone (TSH), and triglycerides (blood lipids).

(2) Longevity

In December 2019, he developed a mathematical equation using MI values as the base to estimate a patient's expected life span by comparing the calculated health age against biological age. This health age formula is expressed as follows:

Effective Health Age
= Real Biological Age * (1+((MI-0.735)/0.735)/AF)

Where AF (amplification factor) = 2

He has written a few papers regarding longevity and published them in several geriatric journals.

5.11 Neuro-science study on glucose and self-repair of pancreatic beta cells

The glucose production is controlled by our brain. Once we wake up and light enters our retina or when food arrives in our stomach, this process turns into a neuro-message to be sent to the brain. After receiving these transmitting messages, the brain then makes a decision and provides feedback. It informs the liver to produce or release glucose and for the pancreas to produce or release insulin to regulate glucose. These observed phenomena explain why the 10+ mg/dL glucose increase between the moment we wake up and the first bite of breakfast, with increasing PPG amount between the first-bite moment of meal and 15-20 minutes after the first bite.

The author has conducted an experiment of eating over four-hundred specific meals over the past two years. The increased PPG at 60-minutes after the first bite are 30-40 mg/dL for solid egg meals and ~10 mg/dL for liquid egg meals. These 20-30 mg/dL PPG difference between two different food preparation methods can be interpreted using a neuro-scientific viewpoint. At the first-bite of meals, the stomach sends two messages immediately to the brain that include the food arrival and the specific physical state of the food entry. Therefore, liquid foods can trick our brain to treat them as if we were drinking water. This neuro-scientific interpretation can explain these observed PPG differences. Based on his various research projects, he has tried to apply both eating liquid foods (~200 experiments) and maintaining intermittent fasting practice (~300 experiments) to control his glucose excursion. This practice has contributed to his lower average glucose during 2020-2021.

By analyzing and observing detailed glucose behaviors over the past seven years, including FPG improvements without food and exercise, PPG improvement with reduced amounts of carbs/sugar and increased post-meal walking steps, the author has drawn a bold conclusion regarding his pancreatic health. His pancreatic beta cells have been self-repaired at an annual rate of 2.8 percent to 4.5 percent; therefore, over the past seven years, his insulin conditions, including either insulin secretion or insulin resistance or both, have been improved approximately 20 percent to 30 percent (assuming an annual improvement rate of ~3 to 4 percent).

5.12 Other diabetic complications or metabolic disorder-induced diseases

Utilizing his developed GH-Method: math-physical medicine approach, he has studied many diseases, including neuropathy (e.g. foot ulcers), retinopathy, immunity, diabetic constipation, diabetic fungal infection, cancers prevention, dementia (Alzheimer's disease) prevention, and even psychological issues (diabetes patient's behavior, border-line personality disorder, patients' behavior during the COVID-19 quarantine period, MD suicides, etc.).

6. PART 5 - EPILOGUE

Since the author's presentation at the International Diabetes Federation (IDF) annual conference in 2017, along with being recognized by several diabetes research organizations and medical research scientists, he has continued writing medical papers and working on several book publications. To date, he has written 564 medical papers and published over 500 papers in various journals, including 20 percent of them in journals of physics, science, and engineering (his original learned disciplines). His published papers and conference presentations include over 100 non-endocrinology conferences or journals, such as Cancer, Dementia, Alzheimer's, Central Nervous System, Neurology, Infectious Diseases, Oncology, Pharmacology, Toxicology, Pediatrician, Antibiotics, Vaccine, Biomedicine, Stem Cell, System Biology, Liver and Pancreatic diseases, Nephrology and Urology. Over one hundred non-endocrinology conferences and journals have expressed interested his presentations and/or reading his papers regarding his research method, the GH-Method: math-physical medicine research methodology.

His mission is to help diabetics worldwide through the existing medical community or by directly outreach. The author has found that publications appear to be a more effective way than conferences to reach a broader spectrum of medical professionals and patients. Since late 2020, he has also began publishing his books which consist of his medical papers. Through Amazon's highly effective publishing and distribution channels, his books can reach both medical professionals and patients worldwide. The core reason of doing so is to prevent diabetics from suffering from complications similar to himself, therefore, the author felt compelled to spread his lifestyle management message of preventive medicine and his 12-years medical research results to whomever wishes to save their own lives or their patients' lives.

The author believes that everyone deserves to have the basic human rights of health, happiness, and freedom. That is why he has spent twenty-one years continuously conducting his study and research on both psychology and internal medicine. The author considers this as his mission in the next chapter of his life, and ultimately, his life's calling.