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Research Article

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Approximated Risk Probability of having Atherosclerosis, Cardiovascular Disease, and Stroke during the COVID-19 Period Using the Pre-COVID Period'S Dataset as Baseline of Calculations and Higher-Order Perturbation Equations from Quantum Mechanics Based on GH-Method: Math-Physical Medicine (No. 465)

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Abstract

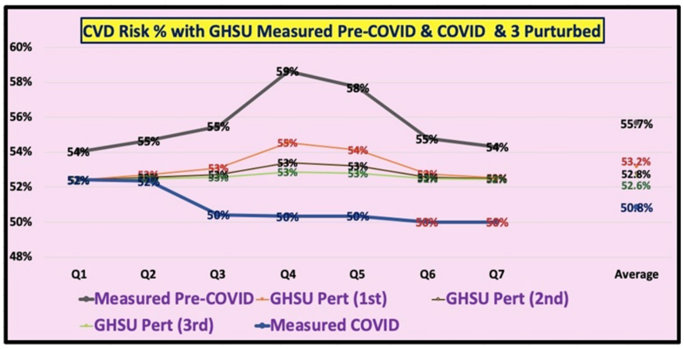
This paper describes the author's assessment on his risk probability percentage of having atherosclerosis, cardiovascular disease (CVD), and stroke. During the 7-quarters of the COVID-19 period from 2/5/2020 to 11/4/2021, he utilized his earlier 7-quarters data from 5/5/2018 to 2/4/2020 or the "pre-COVID period" and higher-order perturbation theory. The purpose of this study is to predict the present and future period's CVD/stroke risks based on the previous period's CVD/stroke risks via an effective approximation method of perturbation theory.

In summary, this approximation method of perturbation equation from quantum mechanics offers high prediction accuracies on the present and future period's (the "COVID period") risks using the past pre-COVID period's dataset and waveform as baseline calculations. The three orders of perturbation equations have provided the following high prediction accuracies in comparison against the COVID period's calculated risks which includes the past 5-quarters of calculated risks and the future 2-quarters speculated risks of the COVID period.

First order perturbation: 95.4%
Second order perturbation: 96.2%
Third order perturbation: 96.6%

The author developed an APP software for his iPhone that is based on the model he created and used since 2018 via an Excel spreadsheet. This APP can assist patients with chronic diseases to help them understand their own perspective of having a CVD or stroke.

COVID-19 is much worse than the original virus SARS that occurred in 2003, in terms of its spreading speed, fatality rate, and emotional impact on the world population. People belonging to the "vulnerable" groups include the elderly with existing chronic diseases and a history of complications along with others suffering psychological disorders, which require additional attention to their health conditions and lifestyle management during the quarantine period. During this harsh and isolated time period, the author achieved better overall health conditions, including lower risk probability of having atherosclerotic conditions, CVD, and stroke. The knowledge and experience he acquired over the past 11 years of medical research and his developed Metabolism Index (MI) model, diabetes prediction tools, and risk models of diabetes complications assist him in many ways. This quarantined lifestyle has forced him to remove all non-essential tasks in his life. As a result, he has turned the COVID-19 crisis into his health advantage! At this stage of his life, there is nothing more important than his health and longevity.



Introduction

This paper describes the author's assessment on his risk probability percentage of having atherosclerosis, cardiovascular disease (CVD), and stroke. During the 7-quarters of the COVID-19 period from 2/5/2020 to 11/4/2021, he utilized his earlier 7-quarters data from 5/5/2018 to 2/4/2020 or the "pre-COVID period" and higher-order perturbation theory. The purpose of this study is to predict the present and future period's CVD/stroke risks based on the previous period's CVD/stroke risks via an effective approximation method of perturbation theory.

Methods

MPM Background

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

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

Patient's Background

The author spent ~30,000 hours over the past 11 years, from 2010 through 2021, to conduct his medical research on metabolic disorders induced chronic diseases and their various complications, specifically focusing on metabolism.

In the beginning, from 2010 to 2013, he self-studied internal medicine and food nutrition. He specifically focused on six chronic diseases i.e., obesity, diabetes, hypertension, hyperlipidemia, CVD & stroke, and chronic kidney disease (CKD) which he has suffered since 1995. In 2014, he allotted the entire year to develop a complex mathematical metabolism model which includes 4 body output categories (weight, glucose, blood pressure, and lipids) and 6 body input categories (food, water, exercise, sleep, stress, and daily life routine regularity). There are around 500 detailed elements included in these 10 basic categories. By the end of 2014, he has finally developed a mathematical metabolism index (MI) model embedded in a specially designed application software "eclaireMD" on iPhone for his daily use in order to improve and maintain his overall health conditions.

During the metabolism model development process, he has defined two new variables MI and general health status unit (GHSU), where GHSU is the 90-days moving average value of MI that is similar to the relationship between HbA1C (A1C) and 90-days moving average glucoses. The analysis results of this dynamic and complex model can be expressed through 2 health variables, MI and GHSU, in order to describe a person's health status and also identify shortcomings in any specific health area at any moment in time.

In the following two-year period, 2015 and 2016, he dedicated his time to research four prediction models related to his diabetes measurements i.e., weight, postprandial plasma glucose (PPG), fasting plasma glucose (FPG), and A1C.

As a result, from using his own developed metabolism model and 4 prediction tools, his weight reduced from 220 lbs. (100 kg, BMI 32.5) to 168 lbs. (77 kg, BMI 24.8), waistline from 44 inches (112 cm) to 33 inches (84 cm), average finger glucose from 280 mg/dL to 101 mg/dL, and HbA1C from 10% to 6.2%. One of his remarkable accomplishments is that he no longer takes any diabetes medications beginning on 12/8/2015.

In 2017, he achieved better performance scores on lifestyle management, multiple medical conditions through selected biomarkers, and lower MI values due to his simple and enjoyable medical research work and its associated simple lifestyle which have no travel, no presentations, and decreased social interactions.

During 2018 and 2019, he traveled to 50+ international cities to attend 65+ medical conferences and made ~120 oral presentations. This hectic schedule inflicted damage to both of his diabetes control and his overall metabolism score, through eating out frequently along with exercise disruption, and irregular life routines through travel and increased work schedule.

The author eluded the 2003 SARS threat in China and Taiwan. In early January of 2020, when the strange "Wuhan pneumonia" rumors suddenly appeared on Eastern Asian news networks, he immediately recognized the danger associated with this newly found virus. The spread of this disease depends mainly on the physical contact among people. Therefore, he initiated his "self-quarantine" in the United States on 1/19/2020, about two months earlier than the majority of Europeans and Americans who became aware of its potential damage and severity. As of today, 6/11/2020, he has been self-quarantined for almost 6 quarters or 17 months. This COVID-19 quarantine life pattern with home cooked meals and persistent walking exercise of 7 miles or 11 kms each day have made his conditions of diabetes control (from his glucose and A1C results) and overall metabolism (from his GHSU and MI results) reach to the "best-performed" situation over the past 25 years.

Data Collection

Since 1/1/2012, the author measured his glucose values using the finger-piercing method: once for FPG and three times for PPG each day. On 5/5/2018, he applied the Libre Freestyle continuous glucose monitoring (CGM) sensor device on his upper arm and checked glucose measurements every 15 minutes, a total of ~96 times each day. After the first bite of meal, he measured his PPG level every 15 minutes for a total of 3-hours (180 minutes). He collected nearly 2 million data with carefully selected math-physical analysis tools, such as the GH-Method: math-physical medicine, to help discover many hidden information about his body and internal organs. This also provided many useful tips to improve his health maintenance. As he mentioned in his previously published medical papers, glucose is the primary criminal, blood pressure and lipids are the accomplices, while body weight is the fundamental factor. Combining all of these related biomedical risk factors together, they will eventually damage almost all internal organs through the blood circulatory system and their connected nervous, lymphatic, and *immune system*s. These are the root cause of many complications, such as atherosclerosis, CVD, stroke, chronic kidney disease (CKD), diabetic retinopathy, neuropathy, foot ulcer, bladder infection, constipation, and more.

In addition to data collection of his medical conditions, he accumulated the *lifestyle* detailed data regarding exercise, water intake, sleep, stress, food & meals, and daily life routines. The starting dates for these 6 *lifestyle* categories range between 1/1/2012 and 6/1/2015.

In total, over the past ~10 years, he has collected ~2 million data on his body & organs, including medical diseases, health conditions, and various *lifestyle* details.

Lifestyle, Metabolism, Immunity, Diseases, and Death

As indicated in one of his published papers, "Linkage among *metabolism*, *immune system*, and various diseases using GH-Method: math-physical medicine", the most effective protection against COVID-19 is our *immune system*. The *immune system* is closely related to overall *metabolism*. We can safely say that *metabolism* and immunity are two sides of the same coin; when combined together, they contribute ~90% of the total annual death cases in US. In order to strengthen our overall *metabolism*, we must manage our daily lifestyle to build a strong and firm foundation of *metabolism* and immunity to protect our health and prolong life.

In short, lifestyle is similar to the product quality and production capacity of an arsenal based on the overall educational, technological, and industrial power of a nation, whereas *metabolism* is similar to the effectiveness and destruction power of the ***weapons*** available to soldiers which are produced by an arsenal. ***Immunity*** is similar to the overall military strength of the ***armed forces*** (assembly of strong soldiers with powerful weapons), while diseases (chronic diseases and complications, dementia, cancer, and infectious diseases) are similar to an ***enemy's invasion force***. Lastly, the outcome of ***death*** is similar to the study of ***casualty of war***, which is the study of probability and rate of casualty, including injury and death.

Risk Model of CVD or Stroke

The framework of his mathematical risk probability model of having atherosclerotic conditions, CVD, and stroke consists of four parts with brief descriptions:

(A) Genetics (~10-15% influences) includes age, race, and health/medical history of family members.

(B) Personal background (~10-15% influences) includes personal bad habits (cigarette smoking, alcohol intake, and illicit drug use), obesity (weight and waistline due to overeating and bad life habits), and personal medical history. Weight problems and bad habits are difficult to change over a short period of time. They are types of "semi-permanent" issues, while genetics are "permanent" issues that are difficult to change or be controlled by patients.

(C) Medical condition (~35-40% influences) includes artery blockage (glucose and lipids) or artery rupture (glucose and blood pressure) resulting from hyperlipidemia, hypertension, diabetes and other metabolic disorders.

(D) Lifestyle management details (~35-40% influences) include proper exercise, water intake, sleep (hours, wake up time, and sleep quality), stress (more than 40 different kind of stressors, including more than 20 different psychological conditions), food and meals (quantity such as portion size for weight control, carbs/sugar intake amount for glucose control, along with food quality for nutritional balance and proper diet), and regularity of daily life routines for geriatrics and longevity concerns.

Based on the above-mentioned four parts and collected big data, he established certain assumptions and different weighting factors, existing conditions, practice guidelines, and mathematical models from 11 years of reading many biomedical books and more than 1,000 medical journal papers, along with his own findings from his medical research work, to calculate 7 different risk probability percentages for the following 7 categories, A, B, C, D, A+B+C, A+B+D, and A+B+C+D.

He developed a specific module in his eclaireMD APP software to automatically assess and calculate the numerical process of risk probability of having a CVD or stroke for patients with chronic diseases. The input data used in this article are the results from the customized software.

Higher-order Interpolation Perturbation Theory

The author applies the higher-order interpolation perturbation method to obtain his three "perturbed PPG" waveforms based on one perturbation factor of his calculated GHSU value (90-days average of MI) that is also the "Slope in Perturbation Equation". He uses the calculated CVD risks in Pre-COVID period as his reference baseline.

The following polynomial function is used as a generic perturbation equation:

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

Where A is the perturbed CVD risk, Ai is the calculated risk for certain time segment, and ***x is the "perturbation factor"*** *based on different GHSU values.*

For this particular study, he chooses his ***Ai where i=1 to 3.*** Therefore, the perturbation theory equation from above can be simplified to the following form:

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

Or, the third-order interpolation perturbation equation can then be expressed in the following general format:

A i = A1 + (A2-A1) *(slope 1) +
(A2-A1) *(slope 2) + (A2-A1) *(slope*3)

More specifically, the following formats of the three perturbation *equations are utilized in the calculations for this study:*

A of first order
= A1+(A2-A1)*(slope 1)

A of second order
= A1+(A2-A1) *(slope 2)

A of third order
= A1+(A2-A1) *(slop 3)

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)

It should be noted that the first parameter of A1 must be modified by an "initial conversion factor" to match his starting CVD risk level of the targeted period that is the COVID period.

The perturbation factor of ***Slope*** is an arbitrarily selected parameter that controls the size of the perturbation. The author has chosen a function of GHSU, as his perturbation factor or slope, which is further defined as follows:

In this particular study, the author selects the GHSU value (90-days moving average MI) as his "perturbation factor". The high-bound GHSU is 0.6216 (62.16%) and the low-bound GHSU is 0.4969 (49.69%). The midpoint value between the high-bound and low-bound is 0.5593 (55.93%). Therefore, he adopts his selected value of GHSU at 0.555 (55.5%).

Furthermore, he uses 7-quarters from 5/5/2018 to 2/4/2020 as his pre-COVID period, where the CVD risk data serve as the baseline of calculations for his predicted CVD risk values of the COVID period from 2/5/2019 to 11/4/2021. It should be noted that there are two future quarters (~5 months) data from 6/11/2021 to 11/4/2021 that belong to the future timeframe. Therefore, in order to make a result comparison, *the author utilizes his experience-based guesstimating 50% of the CVD risk value for the last two future quarters.*

The equations for 3 slopes are:
Slope 1
= (Selected GHSU - Low-bound GHSU) / (High-bound GHSU - Low-bound GHSU)

Slope 2
= (Slope 1 * Slope 1)
or (Slope**2)

Slope 3
= (Slope 1 * Slope 1 * Slope 1)
or (Slope**3)

Therefore, in this particular study, the three slope values are calculated as follows:

Slope 1 from Carbs = 0.47
Slope 2 from Carbs = 0.22
Slope 3 from Carbs = 0.10

Results

Figure 1 has two parts. The upper diagram shows the relationships among Lifestyle, *Metabolism*, Immunity, Diseases, and Death. The lower diagram shows his annual risks of having a CVD/Stroke based on metabolism index or GHSU.

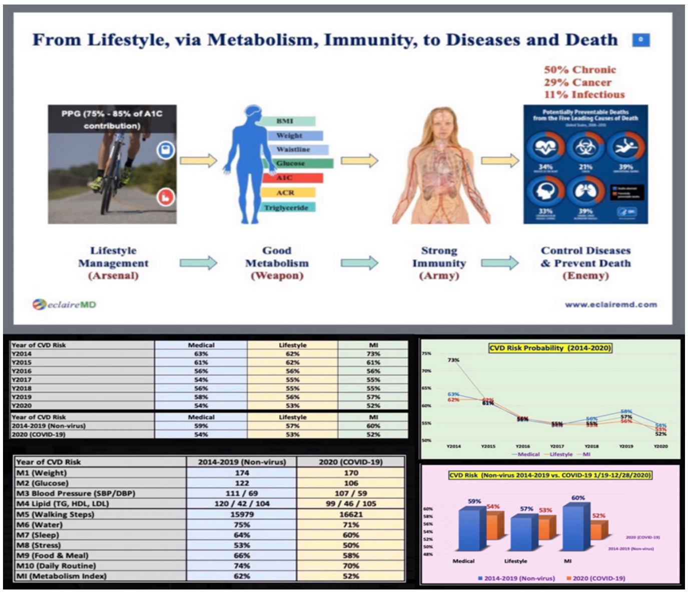


Figure 1: Relationships among Lifestyle, Metabolism, Immunity, Diseases, and Death (upper diagram) with annual CVD/Stroke risks based on metabolism index

Figures 2 displays a summarized data table for the 14 quarters from 5/5/2018 to 11/4/2021 by using GHSU (MI) risk (A+B+C+D). It contains input data of calculated CVD risks of the pre-COVID period (7 quarters) and COVID period (7 quarters) with initial condition (i.e., conversion percentage of 97%) and 3 perturbation factors (0.47, 0.22, and 0.10).

6/10/21					
(5/5/18-6/10/21)	Measured	GHSU	GHSU	GHSU	Measured
CVD from GHSU(MI)	Pre-COVID	Pert (1st)	Pert (2nd)	Pert (3rd)	COVID
Q1	54%	52%	52%	52%	52%
Q2	55%	53%	53%	52%	52%
Q3	55%	53%	53%	53%	50%
Q4	59%	55%	53%	53%	50%
Q5	58%	54%	53%	53%	50%
Q6	55%	53%	53%	52%	50%
Q7	54%	53%	52%	52%	50%
Average	55.7%	53.2%	52.8%	52.6%	50.8%
CVD from GHSU(MI)	Pre-COVID	Pert (1st)	Pert (2nd)	Pert (3rd)	COVID
Accuracy (vs. COVID)	90.5%	95.4%	96.2%	96.6%	100.0%
R (vs. COVID)		100%	100%	100%	
GHSU (90-days MI)	High-MI	Selected	Low-MI	Convert %	
GHSU (90 days MI)	0.6216	0.555	0.4969	0.97	
Perturbation		1st order	2nd order	3rd order	
(Select-Lo)/(Hi-Lo)		0.47	0.22	0.10	

Figure 2: Input data of calculated CVD risks of both pre-COVID period (7 quarters) and COVID period (7 quarters) with initial condition (i.e., conversion %) and 3 perturbation factors

Figure 3 contains the final result diagrams. The upper diagram illustrates two risk curves of the two reference periods: pre-COVID with higher risk data (black color curve) and COVID with lower risk data (dark blue color curve). All of the three perturbed risk curves, including the first order curve in orange has 95.4% accuracy, the second order curve in dark brown has 96.2% accuracy, the third order curve in green has 96.6% accuracy, are located between the upper bound of the pre-COVID curve and the lower bound of the COVID curve. ***This quiet, calm, routine quarantined lifestyle during the COVID period has actually helped him achieve a better score with lower CVD/ Stroke risk of 50.8%.***

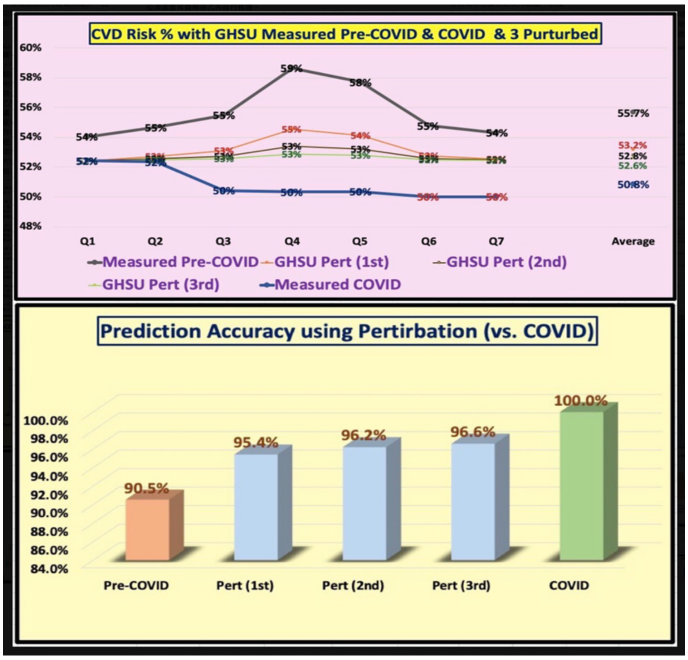


Figure 3: CVD/Stroke risks of predicted COVID period using pre-COVID period's data and perturbation equations to achieve high prediction accuracies

This figure has also demonstrated the power of perturbation theory applications of using a previous data record with a carefully selected "perturbation factor" to predict a present, future, or combined dataset with high accuracy. As a matter of fact, the higher order of perturbation equation yields a higher prediction accuracy.

Conclusions

In summary, this approximation method of perturbation equation from quantum mechanics offers high prediction accuracies on the present and future period's (the "COVID period") risks using the past pre-COVID period's dataset and waveform as baseline calculations. The three orders of perturbation equations have provided the following high prediction accuracies in comparison against the COVID period's calculated risks which includes the past 5-quarters of calculated risks and the future 2-quarters speculated risks of the COVID period.

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