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Research Article

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Using Glucose and Its Associated Energy to Study the Risk Probability Percentage of Having a Stroke or Cardiovascular Diseases from 2018 through 2020 (GH-Method: Math-Physical Medicine)

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Introduction

The author uses the GH-Method: math-physical medicine (MPM) approach to investigate his risk probability on metabolic disorders induced cardiovascular disease (CVD) or stroke ("Risk"). This article focuses on a specific period from 2018 through 2020 by using glucoses and their associated energies to compare the existing results utilizing his overall metabolism conditions.

Methods

In 2014, the author applied topology concept, finite-element engineering technique, and nonlinear algebra operations to develop a complex mathematical model of metabolism. This model contains 10 categories, including four output categories (weight, glucose, blood pressure, and lipids), and six input categories (food, water intake, exercise, sleep, stress, and routine life patterns). These 10 categories are comprised of approximately 500 detailed elements. He also defined two new parameters: metabolism index (MI), as the combined score of the above 10 metabolism categories and 500 elements along with the general health status unit (GHSU), as the 90-days moving average value of MI. Since 2012, he has collected about 2 million data of his own biomedical conditions and personal lifestyle details.

Following the mathematical metabolism model, he further developed a diabetic complications model containing some detailed equations to predict his risk probabilities of having a stroke, cardiovascular diseases (CVD), or chronic kidney diseases (CKD). These risk assessment models include a patient's baseline data including age, race, gender, family genetic history, medical history, and bad habits, which has approximately 20% contribution on the total risk.

It also includes the following two major areas with 40% contribution from each area:

1. **Medical conditions** - individual M1 through M4, i.e. obesity, diabetes, hypertension, hyperlipidemia and others. It should be emphasized here that diabetes (i.e. glucose) alone contributes about 20% of the total risk.
2. **Lifestyle details** - individual M5 through M10 which affect medical conditions.

In addition, he also uses his defined two terms, MI and GHSU, as a combined score of M 1 through M 10 and 90-days moving average MI, for his calculation (Figure 1). Of course, all of these 10 metabolism factors (m 1 through m 10) are inter-related.

Metabolism	Mi Score	Data	Details	Data
M1 (weight)	1.0222	172.6 lbs	Waistline/BMI	33.12 in./25.8
M2 (Glucose)	0.9572	115 mg/dL	FPG/PPG	114/115
M3 (BP)	0.9018		SBP/DBP/HR	117/71/60
M4 (Lipid)	0.8519		LDL/HDL/TG	123/49/110
			ACR/TSH	19.0/2.66
M5 (Exercise)	0.6881	15,742 steps	Post-meal	4,038 steps
M6 (Water)	0.7174			
M7 (Sleep)	0.6248		hours/wakeups	6.9/1.3
M8 (Stress)	0.5045			
M9 (Food)	0.6338		Quantity/Quality	0.7629/0.5047
			Meal carbs/sugar	13.2 g
M10 (Routine)	0.7370			
MI	0.5849			
GHSU	0.5876			

Figure 1: Scores of metabolism categories (M1-M10) during 2019

With this mathematical risk assessment model, he can obtain three separate risk probability percentages associated with each of the three calculations mentioned above. As a result, this model would offer a range of the risk probability predictions of having a CVD or stroke based on the patient's metabolic disorder conditions, unhealthy lifestyles, and the combined impact on the body (Figure 2).

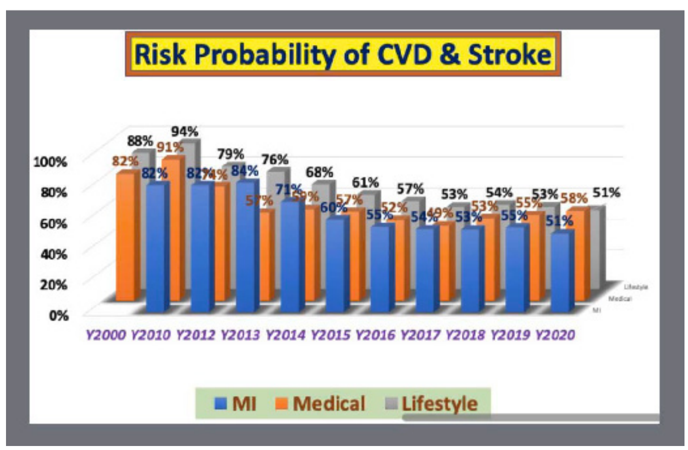

Figure 2: CVD/Stroke Risk Probability % from 2010 through 2020

The author is a 73-year-old male who has a history of three severe chronic diseases for 25 years. He has also experienced five cardiac episodes from 1994 through 2008 and was diagnosed with an acute renal problem in early 2010. In addition, he also suffered from foot ulcer, bladder infection, diabetic retinopathy, and hyperthyroidism. His HbA1C level at 2010 was 10.0% when his average glucose was above 250 mg/dL.

In 2014, he developed the mathematical metabolism model and started his stringent lifestyle management program. As a result, his overall health conditions have been noticeably improving since 2014 when he started to reduce the dosage of his diabetes medications. By the end of 2015, he completely stopped taking his medications. For the entire period of 2016-2020, his HbA1C average value is 6.6% without medication.In 2017, he reached to an extremely healthy state, the lowest MI score and CVD risk probability %. However, in 2018 and 2019, he traveled to 50 international cities and attended 60+ medical conferences which caused a lot of stress and endured irregular life routines; therefore, both of his MI score and CVD risk % were higher than 2017. During this year of 2020, the author has been on self-quarantine since 1/19/2020. His lifestyle has changed dramatically due to the impact on his diet, exercise, sleep, stress, daily routines, and so forth.He worked even harder to maintain his lifestyle management in order to strengthen his immunity to improve his survival probability of the possible COVID-19 infection.This isolated and non-disturbed life routine has actually assisted him in improving his metabolism, glucose control, and more.His recent HbA1C was at 6.3%. Therefore, for the past 5-months, he has achieved the best state of his overall health conditions within the past decade.

This article covers the recent period of 2018 through 2020 by focusing his CVD Risk % and other four diabetes related factors.

Results

The author has written a few medical papers regarding the risk probability of having a CVD/stroke, or chronic kidney diseases (CKD) based on his annual data for the past decade.

Figure 1 indicates his medical conditions (M1 through M4), lifestyle details (M5 through M10), and his MI & GHSU scores for the entire year of 2019. It illustrates a data table containing some "real" data with familiar units instead of using the "normalized" values of Mi where i = 1 through 10. For example, m2 equals to his annual average glucose value divided by 120 mg/dL where 120 is used as the normalization base.

He collected and analyzed a big dataset from 1/1/2012 to 6/10/2020 based on his medical conditions, lifestyle, and MI scores, which provided a foundation for the comprehensive examination of his risk probabilities of having CVD, stroke, renal complication, and diabetic retinopathy progression (i.e. improving or worsening).

Here is his annualized risks probability % based on MI of having a CVD or stroke (Figure 2), the boldface data reflect 2018-2020:

Y2000:85% (weight 220 lbs., BMI 32.5, waistline 44 in.)
Y2010: 82% (weight 198 lbs., waistline 44 inches, BMI 29.2, glucose 280 mg/dL)
Y2012: 82% (glucose 128 mg/dL)
Y2013: 84% (glucose 133 mg/dL)
Y2014: 71% (developed metabolism model, glucose 135 mg/dL)
Y2015: 60% (weight & FPG control, glucose 129 mg/dL)
Y2016: 55% (PPG control & discontinued medication, glucose 119 mg/dL)
Y2017: 54% (BMI 25, glucose 117 mg/dL)
Y2018: 53% (heavy traveling, glucose 116 mg/dL)
Y2019: 55% (heavy traveling, glucose 114mg/dL)
Y2020 : 51% (weight 171.8 lbs., BMI 25.0, waistline 32.5 in., glucose 110.5 mg/dL)

Due to his heavy traveling schedules from 2018 through 2019, his risks were 53% and 55%, respectively; however, for the past 162 days in 2020, his recent stabilized quarantine life has actually reduced his CVD risk down to 51%.

Through his research for the past 5-years, he has already detected that glucose is the principal criminal that is "murderer" and blood pressure with lipids are the accessory criminals that are "accomplices" in terms of induced complications from chronic diseases, specifically CVD, stroke, renal problems, and diabetic retinopathy. Numerous research results from medical journal publications and medical conference presentations have shown that diabetes contributes about 40% to 67% to most of these metabolic disorder complications.

It should also be noted that the risk probability percentages are expressed on a "relative" scale and not on an "absolute" scale.

	Risk %	Sensor Energy	Finger Energy	PPG enegy	M2	M2**2	Finger Glu	Finger Glu**2
2018	0.53	14697	13812	62.7	0.9703	0.9415	116	13540
2019	0.55	17643	12066	59.4	0.9537	0.9095	114	13083
2020	0.51	11107	6061	50.3	0.9189	0.8444	110	12159

	Risk %	Sensor Energy	Finger Energy	PPG enegy	M2	M2**2	Finger Glu	Finger Glu**2
2018	100%	100%	100%	100%	100%	100%	100%	100%
2019	104%	120%	87%	95%	98%	97%	98%	97%
2020	96%	76%	44%	80%	95%	90%	95%	90%

Figure 3: Table of CVD risk probability % and four other normalized scores, using 2018 data as the base, (Sensor Energy, Finger Energy, PPG Energy, Finger Glucose, and Finger Glucose Square)

A table in Figure 3 shows six normalized scores using the 2018 data as the normalization base (CVD/Stroke risk probability, Sensor Energy, Finger Energy, PPG Energy, Finger Glucose, and Finger Glucose Square).

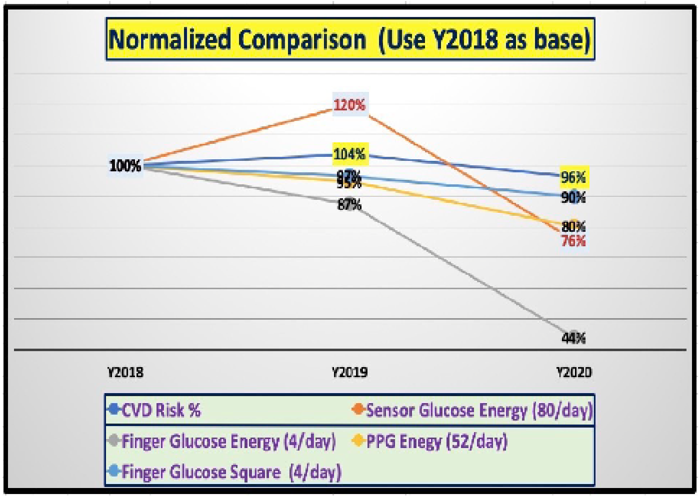

Figure 4: Normalized comparison among 5 sets of percentage data using data of Year 2018 as the normalization base

In Figure 4, a line chart from 2018 to 2020 illustrates the comparison between CVD or Stroke risk probability percentage and the following four normalized data: In Figure 4, a line chart from 2018 to 2020 illustrates the comparison between CVD or Stroke risk probability percentage and the following four normalized data:

1. Energy associated with his sensor glucoses (96 data per day).
2. Energy associated with his finger glucoses (4 data per day).
3. Energy associated with his sensor PPG (39 data per day).
4. Finger glucose square which is proportional to Energy associated with his finger glucoses, i.e. item 2.

The 2018 data provides the base of normalization reflecting the behavior pattern of data, either moving upward or downward. Figure 5 and Figure 6 are discussing these two different patterns of data behavior.

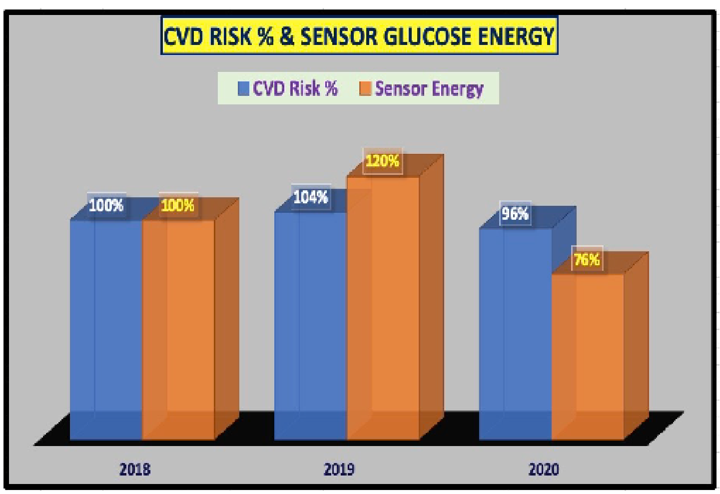

Figure 5: Normalized comparison between CVD risk probability % and energy associated with sensor glucoses

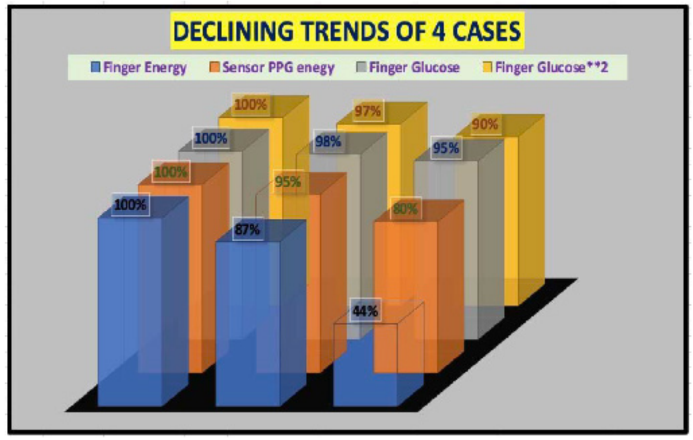

Figure 6: Normalized comparison between 4 glucose related calculations

From the bar chart in Figure 5, it is evident that the pattern of data change is most similar between CVD risk % and Sensor Glucose Energy (energy associated with his sensor glucoses). They concurrently trended up in 2019 and then down in 2020. This pattern is due to the CVD risk % utilizing the most completed coverage and largest data size from both medical conditions and lifestyle details. Furthermore, energy associated with sensor glucose utilized a group of more completed glucose values within a day (96 data from midnight to midnight at 15-minute interval).

However, the bar chart in Figure 6 shows all parameters and pattern of data changes of finger pierced glucose, energy associated with finger glucose (four data per day, missing glucose waveform information), and sensor PPG (39 data per day, missing non-meal related time span). The consistent downward moving trend is extremely noticeable where the year 2019 is lower than 2018 and 2020 is lower than 2019. The main reason for this phenomenon is due to the limited size of finger glucose data and the fact that glucose only contributes 20% of CVD risk assessment based on the author's assumption.

Conclusion

This article describes the impact of glucose, particularly the energy associated with it, on the risk probability percentage of having a CVD or stroke.Based on this study, the author formed two conclusive statements.

First, the more available input data provided by glucose, the better quality or accuracy of his predicted CVD or Stroke risk probability would be.

Second, by understanding the energy associated with glucose is more important than only having knowledge about glucose itself.However, as a rule of thumb, by utilizing the value of "glucose square" will provide enough information to estimate the energy associated with glucose. The author believes that more research work must be done to genuinely understand glucose, instead of spending most of the resources to study the effects of diabetes medications.

References

1. Hsu, Gerald C. (2020). "Using mathematical model of metabolism to estimate the risk probability of having a cardiovascular diseases or stroke during 2010-2019(GH-Method: math-physical medicine)." Archives of Infect Diseases & Therapy 4: 28-30.
2. Hsu, Gerald C. (2020). "Estimated relative energy level of four different Finger PPG ranges using wave theory and frequency domain analysis(GH-Method: math-physical medicine)."
3. Hsu, Gerald C. (2020). "Relationship between metabolism and risk of cardiovascular disease and stroke, risk of chronic kidney disease, and probability of pancreatic beta cells self-recovery using GH-Method: Math-Physical Medicine."
4. Hsu, Gerald C. (2020). "Relationship between metabolism and probability risks of havingcardiovascular diseases or renal complications using GH-Method: Math-Physical Medicine."