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Using GH-Method: Math-Physical Medicine to Investigate the Risk Probability of Metabolic Disorders Induced Cardiovascular Diseases, Stroke, and Renal Complications

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Introduction
The author uses GH-Method: math-physical medicine (MPM) approach to investigate two clinical cases A and B of risk probability on metabolic disorders induced cardiovascular diseases (CVD) or stroke ("Risk"). He addresses the multiple correlations among three metabolic bio markers, i.e. body weight, glucose, and blood pressure (BP), which are also closely related to both CVD and stroke. He further examines Case A's bladder and renal complications due to diabetes and hypertension.

Methods
In 2014, the author applied topology concept, finite-element engineering technique, and nonlinear algebra operations to develop a mathematical metabolism model which contains four output categories (weight, glucose, BP, other lab-tested data), six input categories (food, water drinking, exercise, sleep, stress, routine life patterns and safety measures), and approximately 500 detailed elements. He further defined a new parameter, metabolism index (MI), as the combined score of the above 10 metabolism categories and 500 elements. Since 2012, he has collected and stored ~1.5 million data of his own body and personal lifestyle. It should be noted that through his developed predicted weight and glucose (FPG, PPG, A1C) models, he has successfully reduced his glucose level from 280 mg/dL (A1C 10%) in 2010 to 116 mg/dL (A1C 6.4%) during his "no medication" period from 2015 through 2019. In addition, his ACR has dropped from 116 in 2010 down to 8 in 2018.

He then developed a set of algorithms which include a patient's baseline data (e.g. age, race, gender, family genetic history, medical history, bad habits, etc.), and conducted the following three calculations:

1. Medical conditions - individual M1 through M4: i.e. obesity, diabetes, hypertension, hyperlipidemia and others
2. Lifestyle details - individual M5 through M10
3. MI scores - a combined score of M1 through M10

With this mathematical risk assessment model, he can obtain three separate risk probability percentages to offer a range of the risk prediction of having CVD or stroke resulting from metabolic disorders, unhealthy lifestyles, and their combined impact on the human body.

Regarding these three prominent influential bio markers, i.e. weight, glucose, and BP, he further applied both calculated correlation coefficients from time-series and observed physical patterns from spatial analysis to conduct three sets of dual-factors analyses ("triangular dual-analysis"). These big data statistical analyses could provide many insights on a patient's case.

It should be noted that he has accentuated the two different situations of CVD/stroke due to rupture or blockage of arteries impacted by glucose, BP, lipid and renal complications caused by damage from micro-vessels or leakage impacted by glucose and BP.

Results
Case A is a 72-year-old male (the author), who has a history of three severe chronic diseases for 25 years. He suffered five cardiac episodes from 1994 through 2008 and was diagnosed with an acute kidney problem in early 2010. His big data from 2012 to 2019 of medical conditions, lifestyle, and MI, provides a foundation for his complete examination of his disease conditions and lifestyle details using his math-physical medicine research approach.

Case B is a 71-year-old female, who has a history of three chronic diseases for 22 years. She suffered one cardiac episode in mid-2018. She only collected her completed medical conditions data since 2013, but similar to the majority of patients, there are no lifestyle details.

Case A's Risk (based on medical, lifestyle, & MI in Figure 1) was in the range of 82%-94% during 2010 (his weight was >200 lbs., BMI >30), and gradually decreased to his historic lowest level, 49%-54% during 2017 (his weight was <170 lbs., BMI <25). However, due to his heavy traveling schedules of attending >50 medical conferences, his Risk has slightly risen to 53%-54% in 2018 and 55%-56% in 2019 (through 9/8/2019). Further examination of Risk results revealed that between 2017 and 2019 his medical conditions increased by 7% (from 49% to 56%), while

Risk on Lifestyle and MI increased by only 2% (from 53% to 55%, and from 54% to 56%, respectively). It is obvious that hectic traveling schedules indeed brought negative impacts on glucose, BP, and lipid significantly even though he tried diligently to keep the same lifestyle during traveling.

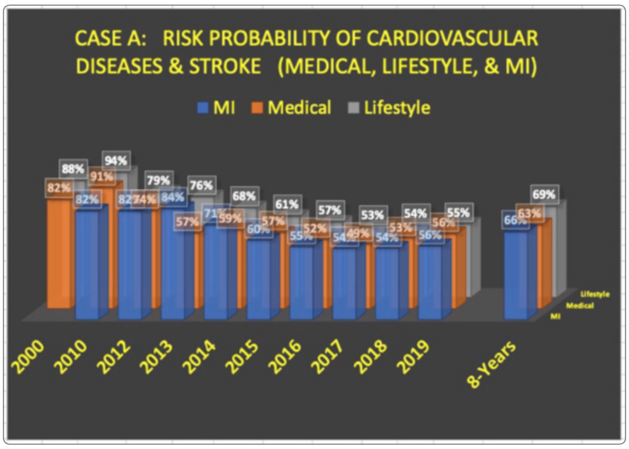


Figure 1: Case A's Risk probability of having CVD or stroke (2010-2019)

From the period of 3/1/2014 - 9/8/2019, his three sets of "high" correlation coefficients are shown below (Figure 2):

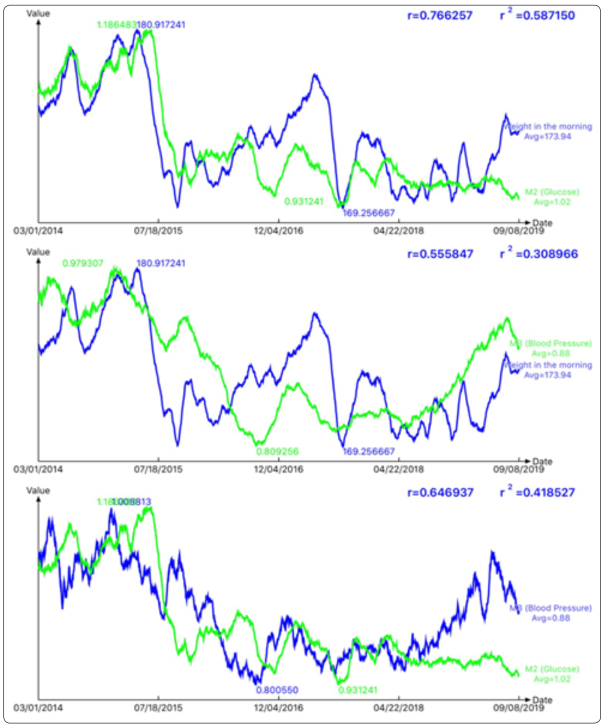


Figure 2: Case A's triangular correlations among weight, glucose, and BP (Time-Series)

77% between weight and glucose
56% between weight and BP
65% between glucose and BP
In his spatial analysis diagrams (Figure 3), three clustered data shapes between "parameter A" and "parameter B" are similar to skewed long footballs or cucumbers. This means that when parameter A's value is changing (either increase or decrease), parameter B's value also changes accordingly.

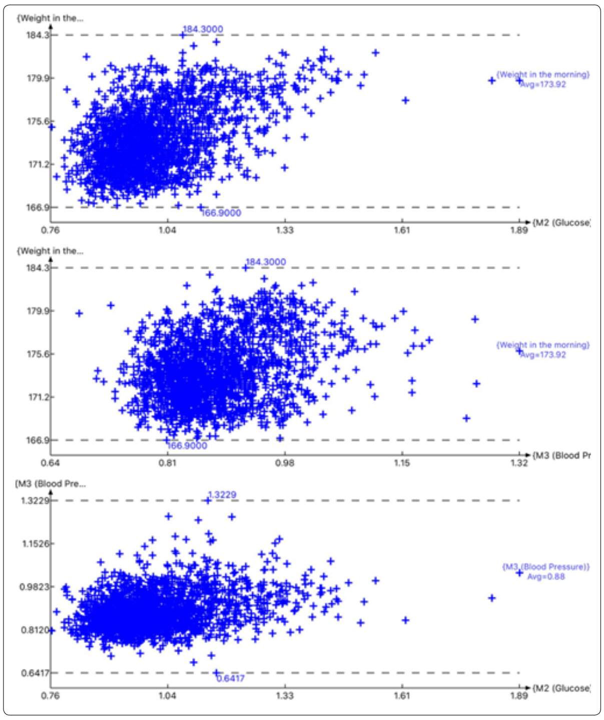


Figure 3: Case A's triangular patterns among weight, glucose, and BP (Spatial Analysis)

In conclusion, for Case A, his weight, glucose, and BP are closely related to each other in terms of their biological patterns, physical behaviors, or moving trends.

A special glucose segmentation analysis was conducted using Sensor glucose data's high glucose components (Figure 11 & 12). It increases Case A's risk probability of having a CVD or stroke by 0% to +2% due to the excessive leftover energy associated with high glucose components (Figure 13).

Case B's Risk (based on medical conditions only in Figure 4) fluctuated between 52% and 57% during the period of 2013 through 2019. When she had a cardiac episode in the mid-2018, her Risk level was at 56% (why at 56%, not higher?). It should be noted that, before her episode of having chest pain, she gained ~9 lbs. over 3.5 years at a rate of ~3 lbs. per year (Figure 7). For a patient with severe chronic disease, this weight gain caused a higher risk of having CVD or stroke.

During the period of 3/1/2014 - 9/8/2019, her three sets of correlation coefficients are as follows (Figure 5)
- 33% between weight and glucose (no correlation)
- 47% between weight and BP (no correlation)
+ 58% positive correlation between glucose and BP (it should be noted that both of her glucose and BP are under various medications control)

In her spatial analysis diagrams (Figure 6), three clustered data shapes of "parameter A" and "parameter B" are similar to varying sizes of "horizontal" rectangular boxes. This means that whenever parameter A's value changes (either increase or decrease), parameter B's value stays at a pseudo-constant level. These physical patterns are due to the use of different medications to control her glucose and BP conditions.

In conclusion, for Case B, her glucose and BP have no obvious correlation with her weight. This phenomena are resulted from her various medications (Figure 8). From this study of clinical Case B, the role of medication on her body has a double-edged effect. It shows that medication has an effective control on the symptom of the disease; however, the chemical compounds of medications have also covered up the opportunity to observe the physical phenomena of natural biological behaviors and vital disease characteristics. One of the logical explanations for Case B's cardiac episode occurring at 56% Risk level is probably due to the effectiveness of the medication control on the chronic disease symptoms. This is the reason that the author selected these two distinctive cases to conduct his research and draw comparisons of both similar and different physical phenomena.

In terms of nephrology and urology, Case A's risk probability of having renal complications due to metabolic disorders has dropped from 69% in 2000, through 57% in 2012, and finally down to 33% in 2019. His nocturnal urinations has dropped from three times per night in 2014 down to 1.5 times per night in 2019. These significant improvements are due to his successful control of his glucose and blood pressure.

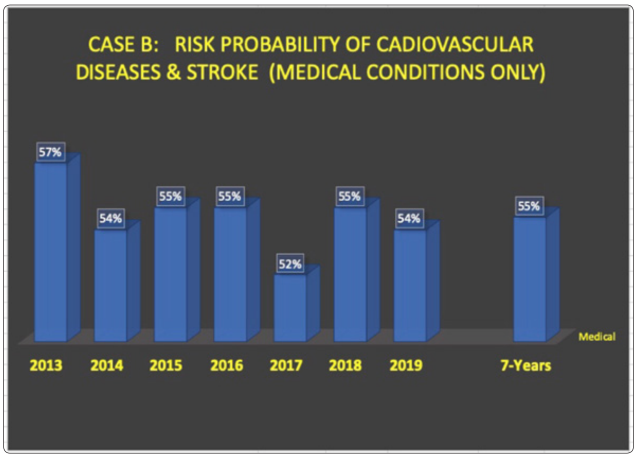


Figure 4: Case B's Risk probability of having CVD or stroke (2013-2019)

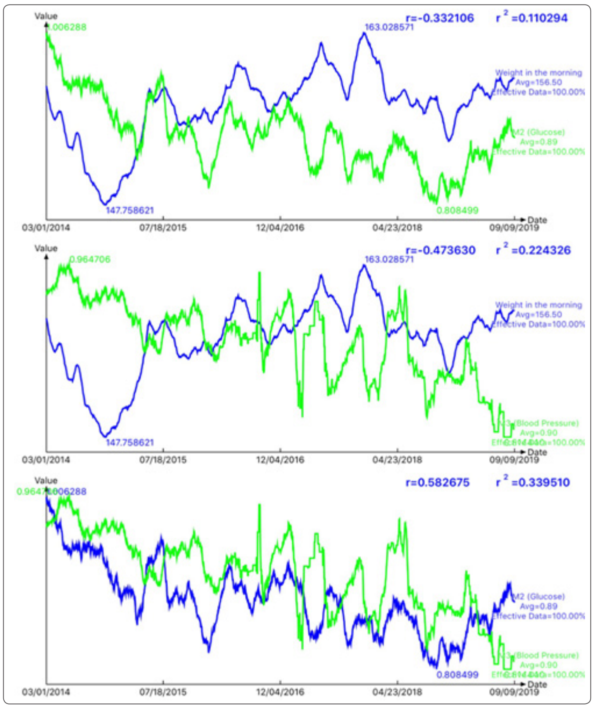


Figure 5: Case B's triangular correlations among weight, glucose, BP (Time-Series)

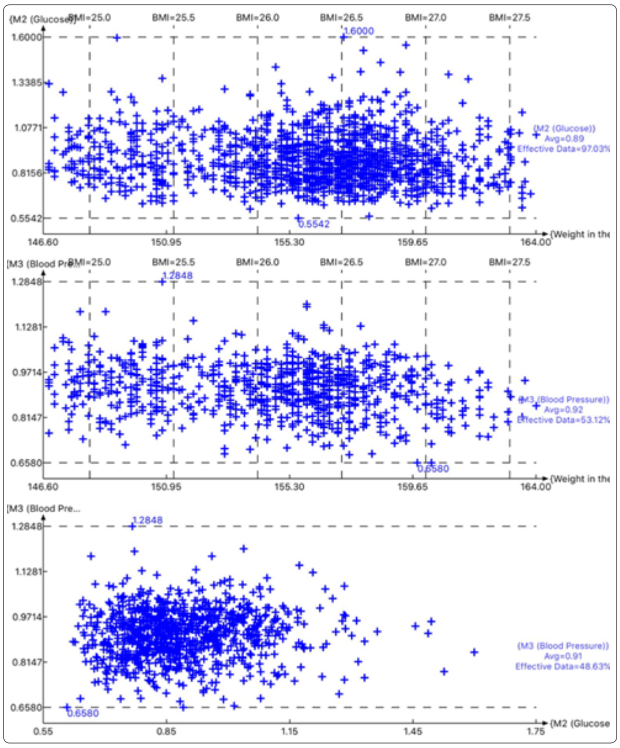


Figure 6: Case B's triangular patterns among weight, glucose, and BP (Spatial Analysis)

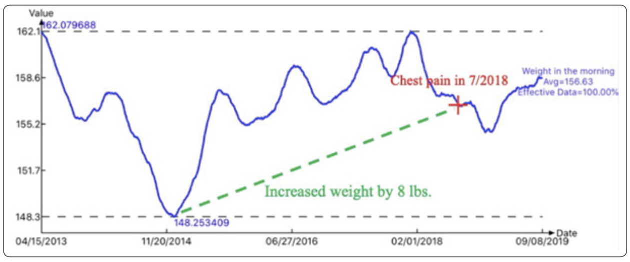


Figure 7: Case B's weight changes (2013-2019) and cardiac episode (mid-2018)

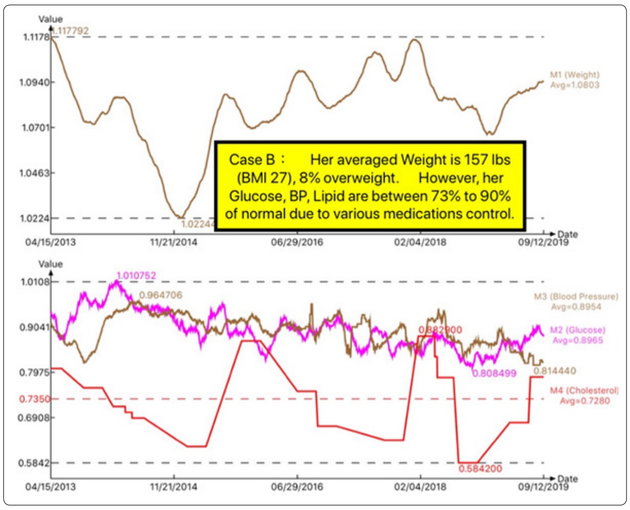


Figure 8: Case B's weight (M1), glucose (M2), BP (M3), and lipid (M4) (4/15/2013 - 9/8/2019)

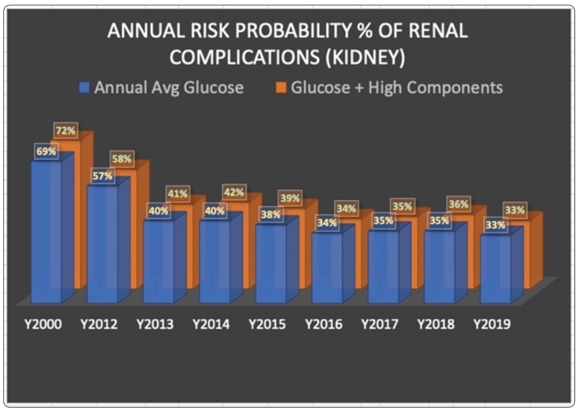


Figure 9: Risk probability % of Case A's renal complications

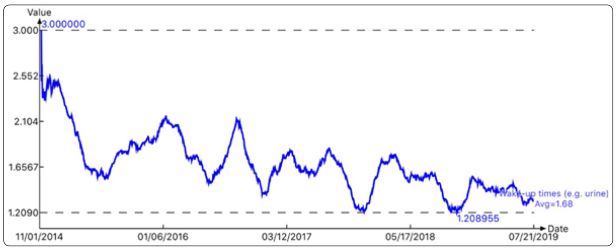
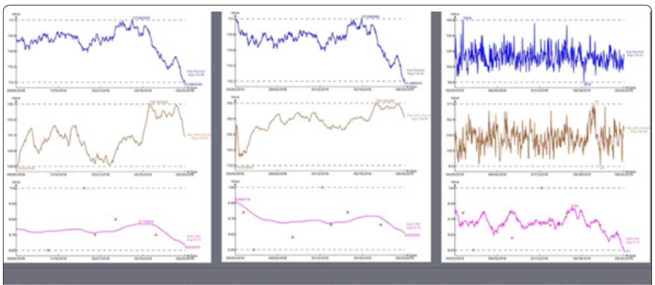
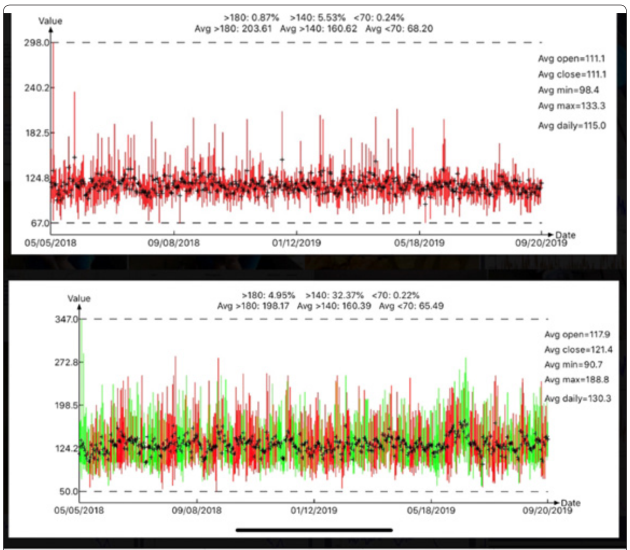


Figure 10: Case A's urology impact: Night urination decreased from 3 times to 1.5 times (11/2/2014 - 7/21/2019)



(5/5/2018-9/20/2019)	Daily Data	90-days (from 5/5/2018)	90-days (from 8/5/2018)	Average of 3
Finger Daily Glucose (mg/dL)	115.01	115.42	115.36	115.26
Sensor Daily Glucose (mg/dL)	130.30	129.62	130.88	130.27
eclaireMD Daily A1C (%)	6.72%	6.74%	6.73%	6.73%
7 Lab-tested A1C (%)	6.73%	6.73%	6.73%	6.73%

Figure 11: Case A's Daily Glucose and HbA1C (Finger vs. Sensor: 5/5/2018 - 9/20/2019)



(5/5/2018-9/20/2019)	> 180 mg/dL	> 140 mg/dL	< 70 mg/dL
Finger Daily Glucose (mg/dL)	204	161	68
Finger Daily Glucose Portion (%)	0.9%	5.5%	0.2%
Sensor Daily Glucose (mg/dL)	198	160	65
Sensor Daily Glucose Portion (%)	5.0%	32.4%	0.2%

Figure 12: Case A's Candlestick Charts and Segmentation Analysis of high glucoses (Finger vs. Sensor: 5/5/2018 - 9/20/2019)

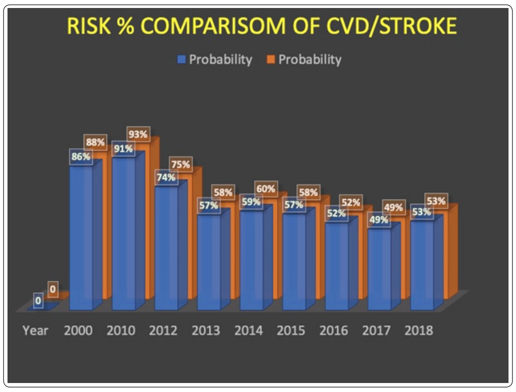


Figure 13: Case A's CVD/Stroke risk variance with high glucose components

Conclusion

This article describes the impact of medical conditions on metabolic disorders, lifestyle details, and MI, and the risk probability of having a CVD, stroke, bladder, and renal complications. Furthermore, through both time-series and spatial analysis of the triangular dual-analysis among weight, glucose, and blood pressure, the roles of both "overweight" and "medications" are observed and discussed quite clearly based on various results. It has demonstrated the importance of weight on risk probability of having a CVD or stroke and the effectiveness of medication on controlling chronic diseases.

It should be noted that the "daily lipid" data are not easily obtained by a patient, except through lab-tested results from a clinic or hospital. Therefore, this study lacks big data analytics on lipids. However, the author believes that the lipid's relationship with weight, glucose, and BP should be quite similar to the findings listed here.

These case studies confirmed the author's hypothesis that glucose is the "crime offender" while both BP and lipid are "accomplices" of CVD, stroke, and renal complications [1- 4].

References

1. Hsu Gerald C (2018) Using Math-Physical Medicine to Control T2D via Metabolism Monitoring and Glucose Predictions. Journal of Endocrinology and Diabetes1:1-6.
2. Hsu Gerald C (2018) Using Signal Processing Techniques to Predict PPG for T2D. International Journal of Diabetes & Metabolic Disorders 3: 1-3.
3. Hsu Gerald C (2018) Using Math-Physical Medicine and Artificial Intelligence Technology to Manage Lifestyle and Control Metabolic Conditions of T2D. International Journal of Diabetes & Its Complications 2: 1-7.
4. Hsu Gerald C (2018) Using Math-Physical Medicine to Analyze Metabolism and Improve Health Conditions. Video presented at the meeting of the 3rd International Conference on Endocrinology and Metabolic Syndrome 2018, Amsterdam, Netherlands.