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Research Article

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A Comparison of CVD/Stroke Risk Using Metabolism Index and Continuous Glucose Monitor Sensor Collected Glucose Fluctuations over Six and Twelve Periods Based on GH-Method: Math-Physical Medicine (No. 446)

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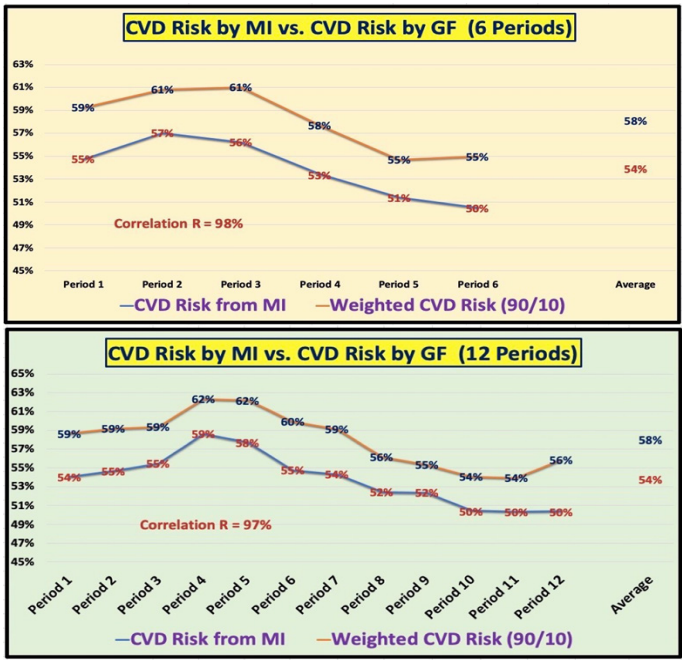
Abstract

In this article, the author investigates the risk differences of having cardiovascular disease (CVD) or stroke over six equal-length periods (~180 days for each period) and twelve equal-length periods (~90 days for each period) using both metabolism index (MI) and glucose fluctuations (GF). Through the introduction of GF influential factor into his developed risk assessment method, physical and engineering modeling, and mathematical equations, he is able to calculate the risk probability of having severe diabetes related complications, especially for macro-vascular (arteries) diseases, such as CVD and stroke.

The author included a few excepts from other research papers regarding the subject of glycemic variability (GV) and the reason he adopts GF instead of using GV in his research work due to GF's non-ambiguity of definition and ease-of-collection of data. Of course, the advantages of using GF to replace GV has become easier due to the wide acceptance of the continuous glucose monitor (CGM) sensor device for diabetes patients.

In summary, by presenting the extra influential factor of GF into his developed risk model of having CVD or stroke based on MI, he can obtain a more accurate picture regarding the CVD risk assessment. In his MI model, all of the input data used are average values over a specific period of time in ten major influential categories (~500 elements). As a matter of fact, in his existing risk model of having CVD/stroke based on MI, glucose values only contribute 10% of the total influences on CVD risk. In this particular study, by including 10% influences contribution from GF and 90% reduction of the other 10 MI factors, it will highlight the impact and importance of the GF factor for CVD risk. As a result, the risk percentages are only "relative" risk numbers and not "absolute" risk numbers. It is more significant to examine the changes of risk percentages over a certain time scale which are the CVD risk number's moving trend and CVD risk curve's pattern. This would be helpful in assessing various hidden relationships between diabetes conditions and CVD risk levels.

The two periods contain extremely high correlation coefficients of 98% for 6-periods and 97% for 12-periods using the MI and CVD risk including GF, where they have the same data moving pattern and curve shape similarity. This fact also demonstrates that although GF is important, the overall metabolism condition is more crucial in terms of determining the CVD risk. In general, the introduction of GF into CVD risk based on MI has increased the CVD risk by an additional 4% from 54% to 58%.



Introduction

In this article, the author investigates the risk differences of having cardiovascular disease (CVD) or stroke over six equal-length periods (~180 days for each period) and twelve equal-length periods (~90 days for each period) using both metabolism index (MI) and glucose fluctuations (GF). Through the introduction of GF influential factor into his developed risk assessment method, physical and engineering modeling, and mathematical equations, he is able to calculate the risk probability of having severe diabetes related complications, especially for macro-vascular (arteries) diseases, such as CVD and stroke.

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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.

CVD/Stroke Risk Model Based on Metabolism

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 or 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 more than 2 million data of his own biomedical conditions and personal lifestyle details.

Following the mathematical metabolism model, he further developed a series of models regarding diabetic complications which contain some detailed equations to predict his risk probabilities of having a stroke, CVD, chronic kidney diseases (CKD), and pancreatic beta-cells self-recovering assessment. These risk assessment models include a patient's baseline data including age, race, gender, family genetic history, medical history, and bad habits which contribute approximately 20% to the total risk. Furthermore, it also includes the following two major areas each with a 40% contribution:

1. Medical conditions - individual M1 through M4 which include 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 M1 through M10 and 90-days moving average MI, for his calculation. Of course, all of these 10 metabolism factors (m1 through m10) are inter-related. The "break-even line" between heathy state and unhealthy state for both MI and GHSU is 0.735 or 73.5%.

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.

The Author'S Diabetes History

The author was a severe type 2 diabetes patient since 1996. He weighed 220 lb. (100 kg) at that time. By 2010, he still weighed 198 lb. with an average daily glucose of 250 mg/dL (HbA1C at 10%). During that year, his triglycerides reached to 1161 (high risk for CVD and stroke) and albumin-creatinine ratio (ACR) at 116 (high risk for chronic kidney disease). He also suffered from five cardiac episodes within a decade. In 2010, three independent physicians warned him regarding the needs of kidney dialysis treatment and future high risk of dying from his severe diabetic complications.

In 2010, he decided to self-study endocrinology with emphasis on diabetes and food nutrition. During 2015 and 2016, he developed four mathematical prediction models related to diabetes conditions: weight, postprandial plasma glucose (PPG), fasting plasma glucose (FPG), and HbA1C (A1C). Through using his developed mathematical MI model and the other four glucose prediction tools, by the end of 2016, his weight was reduced from 220 lbs. (100 kg) to 176 lbs. (89 kg), waistline from 44 inches (112 cm) to 33 inches (84 cm), average finger-piercing glucose from 250 mg/dL to 120 mg/dL, and A1C from 10% to ~6.5%. One of his major accomplishments is that he no longer takes any diabetes related medications since 12/8/2015.

In 2017, he had achieved excellent results on all fronts, especially his glucose control. However, during the pre-COVID period, including both 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 his diabetes control caused by stress, dinning out frequently, post-meal exercise disruption, jet lag, along with the overall negative metabolic impact from the irregular life patterns; therefore, his glucose control was somewhat affected during the two-year traveling period of 2018-2019.

He started his self-quarantined life on 1/19/2020. By now, 4/10/2021, his weight was further reduced to ~165 lbs. (BMI 24.4) and his A1C was at 6.2% without any medication interventions or insulin injection. In fact, with the special COVID-19 quarantine lifestyle since early 2020, not only has he written 200 new research articles and published a total of 400 medical papers

in various medicine and engineering journals, but he has also achieved his best health conditions for the past 26 years. These achievements are resulted from his non-traveling, low-stress, and regular daily life routines. Of course, his in-depth knowledge on chronic diseases, sufficient practical lifestyle management experiences, and his own developed high-tech tools have also contributed to his excellent health improvements.

On 5/5/2018, he applied a continuous glucose monitoring (CGM) sensor device on his upper arm and checks his glucose measurements every 5 minutes for a total of 288 times each day. He has maintained the same measurement pattern to present day.

During the past 11 years, he has continuously investigated, studied, and analyzed his collected ~2 million data regarding his health status, medical conditions, and lifestyle details. He applies his physics knowledge, engineering models, mathematical tools, and computer programming to conduct his medical research work. His entire medical research work is based on the aims of achieving both "high ***precision***" with "***quantitative*** proof" in the bio-medical findings, not just through linguistic expressions with qualitative words, vague statements, or complex medical terminologies. His personal goal is aimed at saving his own life through research, and then helping family members along with other patients through distributing his knowledge learned and experiences gained from his 11-years medical research work to combat these chronic diseases and complications at the root-cause level.

It should be noted that the author uses a CGM sensor device which adopts the "flash glucose monitoring (FGM)" method. The following is an excerpt from daTribe Learn (diatribe.org):

"Flash Glucose Monitoring

What It Does: Flash Glucose Monitoring (FGM) is the newest method of glucose testing that is seen as a hybrid between meters and CGMs. The Abbott FreeStyle Libre is currently the only flash glucose monitoring product available, and it is currently only approved in Europe. In Flash Glucose Monitoring, patients have a sensor inserted on their upper arm and a separate touchscreen reader device. When the reader device is swiped close to the sensor, the sensor transmits both an instantaneous glucose level and eight-hour trend graph to the reader. This allows people to get individual blood sugar readings (like BGM) and trend information (like CGM). However, unlike CGM, FGM does not have hypo- or hyperglycemia alarms and will only provide a trend graph if it has been swiped in the past eight hours.

The FreeStyle Libre system does not require fingerstick calibration, so users can dose insulin based on its readings (except for when hypoglycemic, when glucose levels are rapidly changing, or when symptoms don't match the system's readings)."

Other GV Research Work

There are many available articles regarding the subject of glycemic variability (GV), however, the author decides to include the following combined excerpt from two particular published articles (References 4, 5, and 6). These three references have cited a total of 114 published papers. In this way, readers do not have to search for key information from a long list of their cited reference articles. References 4 focuses on comparison of many published GV articles. Reference 5 focuses on algorithm, method and firmware design of a web-based APP software for calculating GV values.

Here is the combined excerpt:

"Several pathophysiological mechanisms were reported, unifying the two primary mechanisms: excessive protein glycation end products and activation of oxidative stress, which causes vascular complications. Intermittent high blood glucose exposure, rather than constant exposure to high blood glucose, has been shown to have deleterious effects in experimental studies. In in-vitro experimental settings and in animal studies, glycemic fluctuations display a more deleterious effect on the parameters of CV risk, such as endothelial dysfunction. There is a significant association between GV and the increased incidence of hypoglycemia. Hypoglycemic events may trigger inflammation by inducing the release of inflammatory cytokines. Hypoglycemia also induces increased platelet and neutrophil activation. The sympathoadrenal response during hypoglycemia increases adrenaline secretion and may induce arrhythmias and increase the cardiac workload. Underlying endothelial dysfunction leading to decreased vasodilation may contribute to CV risk. Published studies have demonstrated that ***GV, particularly when associated with severe hypoglycemia, could be harmful not only to people with diabetes but also to non-diabetic patients in critical care settings****. Overall, the pathophysiological evidence appears to be highly suggestive of* ***GV being an important key determinant of vascular damage****. Growing evidence indicates that significant GV, particularly when accompanied by hypoglycemia, can have a harmful effect not only on the onset and progression of diabetes complications but also in clinical conditions other than diabetes treated in intensive care units (ICUs).* ***In addition to HbA1c, GV may have a predictive value for the development of T1DM complications. In insulin-treated T2DM, the relevance of GV varies according to the heterogeneity of the disease, the presence of residual insulin secretion and insulin resistance. HbA1c is a poor predictor of hypoglycemic episodes because it only considers 8% of the likelihood of severe hypoglycemia; on the contrary, GV can account for an estimated 40% to 50% of future hypoglycemic episodes. HbA1c is a poor predictor of hypoglycemic risk, whereas GV is a strong predictor of hypoglycemic episodes. GV was an independent predictor of chronic diabetic complications, in addition to HbA1c. We should note that PPG and GV are not identical, even if they are closely related.*** *The attention dedicated to GV is derived from the above evidence concerning its effects on oxidative stress and, from the latter, on chronic diabetes complications. Control of GV has been the focus of a number of interventional studies aimed at reducing this fluctuation.* ***Diet and weight reduction are the first therapeutic instrument that can be used for reducing GV.***

Despite the various formulas offered, simple and standard clinical tools for defining GV have yet to evolve and different indexes of GV should be used, depending on the metabolic profile of the studied population. Moreover, the absence of a uniformly accepted standard of how to estimate postprandial hyperglycemia and GV adds another challenge to this debate.

The majority of these studies have used time-averaged glucose values measured as glycosylated hemoglobin (HbA1c), an indicator of the degree of glycemic control, which is why HbA1c has become the reference parameter for therapies aimed at reducing the risk of complications from diabetes. ***Chronic hyperglycemia is almost universally assessed by HbA1c which has been shown to correlate closely with mean glucose levels over time, as determined by continuous glucose monitoring (CGM).*** *However, the relative contribution of postprandial glycemic*

excursions and fasting to overall hyperglycemia has been the subject of considerable debate. Monnier et al. suggested that the relative contributions of fasting and postprandial glucose differ according to the level of overall glycemic control. ***Fasting glucose concentrations present the most important contribution to hemoglobin glycosylation, whereas at lower levels of HbA1c, the relative contribution of postprandial hyperglycemia becomes predominant.*** *Collectively, GV is likely to be incompletely expressed by HbA1c, particularly in patients with good metabolic control.*

GV is a physiological phenomenon that assumes an even more important dimension in the presence of diabetes because it not only contributes to increasing the mean blood glucose values but it also favors the development of chronic diabetes complications. ***It appears that GV is poised to become a future target parameter for optimum glycemic control over and above standard glycemic parameters, such as blood glucose and HbA1c. Avoiding both hyperglycemia and hypoglycemia by careful use of SMBG and the availability of new agents to correct hyperglycemia without inducing hypoglycemia is expected to reduce the burden of premature mortality and disabling CV events associated with diabetes mellitus. However, defining GV remains a challenge primarily due to the difficulty of measuring it and the lack of consensus regarding the most optimal approach for patient management.***

The risk of developing diabetes-related complications is related not only to long-term glycemic variability, but may also be related to short-term glucose variability from peaks to nadirs. *Oscillating glucose concentration may exert more deleterious effects than sustained chronic hyperglycemia on endothelial function and oxidative stress, two key players in the development and progression of cardiovascular diseases in diabetes. Percentages of hyperglycemia (levels between 126 and 180 mg/dl) and hypoglycemia (levels below 70.2 mg/dl) episodes should be used in the GV related research.* ***Mean amplitude of glycemic excursions (MAGE), together with mean and SD, is the most popular parameter for assessing glycemic variability and is calculated based on the arithmetic mean of differences between consecutive peaks and nadirs of differences greater than one SD of mean glycemia. It is designed to assess major glucose swings and exclude minor ones.***

The features discouraging use of glycemic variability as a parameter in clinical practice and trials are the difficulty of interpreting numerous parameters describing this phenomenon and a limited number of computational opportunities allowing rapid calculation of glycemic variability parameters in CGM data.

The UK Prospective Diabetes Study (UKPDS) showed that after an initial improvement, glycemic control continues to deteriorate despite the use of oral agents to enhance insulin secretion and to reduce insulin resistance. This deterioration can be attributed to the progressive decline of β-cell function. Even in subjects with well-controlled type 2 diabetes, 70% of the variability of A1C can be explained by abnormalities in postprandial glucose. Chronic sustained hyperglycemia has been shown to exert deleterious effects on the β-cells and the vascular endothelium. Monnier et al. and Brownlee and Hirsch have recently emphasized that another ***component of dysglycemia, i.e., glycemic variability, is even more important than chronic sustained hyperglycemia in generating oxidative stress and contributing to the development of secondary diabetes complications.*** *In vivo studies have convincingly demonstrated that hyperglycemic spikes induce increased production of free radicals and various mediators of inflammation, leading to dysfunction of both the vascular endothelium (3) and the pancreatic β-cell."*

Glycemic variability: adverse clinical outcomes and how to improve it?

Recently, the author read an article published on Cardiovascular Diabetologist on July, 4, 2020 (Reference 15) and made an excerpt from this article at below:

"Glycemic variability (GV), defined as an integral component of glucose homoeostasis, is emerging as an important metric to consider when assessing glycemic control in clinical practice. ***Although it remains yet no consensus, accumulating evidence has suggested that GV,*** *representing either short-term (with-day and between-day variability) or long-term GV,* ***was associated with an increased risk of diabetic macro-vascular and microvascular complications, hypoglycemia, mortality rates and other adverse clinical outcomes.***

Glycemic variability (GV), referring to oscillations in blood glucose levels, is usually defined by the measurement of fluctuations of glucose *or other related parameters of glucose homoeostasis over a given interval of time (i.e., within a day, between days or longer term).* ***Although HbA1c was traditionally considered as the gold standard for assessing glycemic control, GV is a more meaningful measure of glycemic control than HbA1c in clinical practice, and is without doubt now being recognized.*** *Despite its clinical significance, there is no consensus on the optimum method for characterizing GV.*

GV and Diabetic Macrovascular and Microvascular Complications

Given that the limitations of HbA1c measurements, growing evidence demonstrated that GV was a significant and clinically meaningful glycemic metric and had drawn attention for its effects on adverse clinical outcomes, including diabetic macro-vascular and microvascular complications, hypoglycemia and mortality *(Table 2). There is considerable evidence to support the negative role of GV in the development of diabetic macro-vascular and microvascular complications.*

GV and Hypoglycemia

Hypoglycemia is the major impediment to therapy in diabetes. While HbA1c remains widely used as a measure of mean glycemia, it may not be the best marker for predicting hypoglycemia. The consolidated evidence to date supported the importance of GV with respect to predicted risk of hypoglycemia. Zinman et al. concluded that ***higher day-to-day FPG variability was associated with increased risks of severe hypoglycemia and all-cause mortality.***

GV and Mortality

A number of studies verified that GV was not only associated with the risk of diabetes-related complications and hypoglycemia, but also simultaneously related to the high incidence of mortality. Interestingly, several studies proposed an independent association of GV with mortality. ***Clinical data indicated that FPG variability might be an important predictor of mortality, particularly for those with their glycemic status uncontrolled. Besides, in hospitalized patients, increased GV was associated with a higher rate of mortality.*** *Recently, in the Action to*

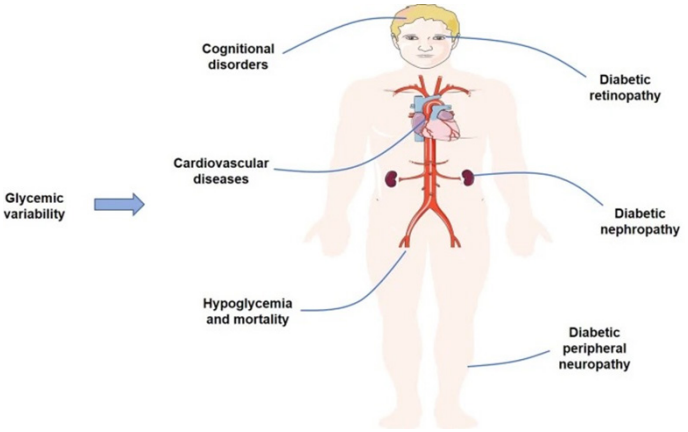
Control Cardiovascular Risk in Diabetes (ACCORD) trial, ***researchers found that HbA1c variability was a strong predictor of all-cause mortality, and this observation was more remarkable in older people with diabetes.***

In addition to the above adverse clinical outcomes, ***GV was also reported to be associated with depressive symptoms, cognitive disorder and even cancer****. In the Israel Diabetes and Cognitive Decline (IDCD) study, GV measured as the SD of HbA1c increased the risk of depressive symptoms. A Taiwan diabetes study explored the relationship between GV and the incidence of Alzheimer disease (AD) in patients with type 2 diabetes mellitus, finding that* ***GV had a worse impact on AD and might be significant predictors for AD****. More importantly, recent study demonstrated that HbA1c variability was a potential risk factor for later tumorigenesis in patients with diabetes, which might be mediated by oxidative stress or hormone variability.*

Conclusion and Future Perspective

We have attempted to summarize the relationships between two categories of GV and the risk for diabetic macrovascular and microvascular complications, hypoglycemia, mortality and other adverse clinical outcomes (Fig. 2). We also generalized the potential beneficial measures including drugs combined with CGM, dietary interventions and exercise training, to improve GV. These findings highlight the important role of GV in the patients with diabetes and provide the essential help for clinicians to manage the blood glucose.

Figure 2: The effects of glycemic variability on the adverse clinical outcomes.



GV has been identified to be closely associated with the risk of adverse clinical outcomes and provides a better predictor of such complications. However, it still lacking a clear universal definition and different indices have been proposed to evaluate it. With the availability of CGM in clinical practice, the assessment of GV became not only possible but also required. *Also, CGM was frequently superior to continuous subcutaneous insulin infusion and could guide individuals' therapeutic changes to reduce GV, hypoglycemia and CVD.* ***A recent study reported that "flash glucose monitoring", a new approach to glucose monitoring, has a long sensor lifetime of 14 days and emerged as a practical solution to the glucose monitoring.*** *Meanwhile, a real-world data from Spain indicated that flash glucose monitoring allowed frequent glucose checks and reduced GV, as well as hypoglycemia. Consequently, in order to provide a more comprehensive assessment of GV, the new approach of glucose monitoring is advocated to adopt in clinical practice.* ***Future developments in new technologies, such as CGM systems and flash glucose monitoring, and indices for better deciphering and defining GV should contribute to improve understanding of the clinical relevance of GV in the management of diabetes.*** *Although GV had drawn attention for its effects on diabetic macrovascular and microvascular complications, hypoglycemia and mortality, several studies have shown conflicting results. Caprnda et al. failed to show the association between diabetic complication and GV in patients with type 2 diabetes. Furthermore, in the Diabetes Control and Complications Trial, within-day GV, as determined from quarterly glucose profiles, did not play an explicit role in the development of microvascular complications. However, we found that these results employed* ***the 7-point glucose profiles, which might be insufficient to characterize GV correctly when compared with CGM.*** *Thus, these negative results may not necessarily disprove the importance of GV in the development of diabetic complications. Additionally, the mechanisms linking GV and related complications risk remained unclear.* ***Recent studies corroborated that GV was correlated with oxidative stress or erythrocyte membrane stability, emphasizing its participation in the pathogenesis of related complications.*** *Further prospective research to explore the explicit mechanisms linking GV and related complications is warranted. Finally, setting clear definitions and taking* ***potential beneficial measures for addressing GV is essential. Further research in these domains will contribute to blood glucose control and management."***

Glucose Fluctuations (GF)

The concept and practice of glycemic variability (GV) have existed since the clinical usage of CGM devices to monitor severe diabetes patients and insulin treatments ***in hospitals.*** *Many medical papers have been published on GV; however, there is no universally accepted formula or equation for generally accepted applications.*

Defining GV remains a challenge primarily due to the difficulty of data collection with its associated data cleaning, processing, comprehension and interpretation of the results by physicians and patients along with no consensus regarding the optimal approach for its clinical management. For example, the GV derivation involves the usage of standard deviation (SD) from statistics. Although SD is widely used, it has limitations because the assumption of measured glucose data as being normally distributed (similar to a Gaussian distribution) is typically not the case for bio-waves and medical data. Besides, many research articles use glucose data collected within a few days from hospitalized patients rather than use glucose data collected over a long period, such as years, from outpatients. The reason is that until recently, after 2016-2017, the continuously glucose monitoring (CGM) sensor devices became available to diabetes ***out-patients*** to collect their own glucose data at home, instead of in the hospitals or clinic centers. However, the tasks of glucose data transfer from CGM device to a computer and then the necessary follow-on tasks of data processing, data management, and data analysis still remain a challenge, particularly for out-patients. Due to the lack of professional training and academic knowledge in this domain, most patients and clinical physicians have encountered difficulties with these tasks. Data without careful cleaning and proper preparation would create a situation of "garbage inputs" result into "garbage outputs" which fits the common expression in computer science industry of "garbage in and garbage out".

Based on the above-mentioned theoretical and technical viewpoints, the author decided to conduct his study on "just" apply-

ing the ***basic concept*** of glycemic variability (i.e., glucose fluctuation between peak and nadir), and without touching certain created terms or derived formulas by some research doctors described in some of their publications. However, the author further combined the primary characteristics of ***wave theory*** e.g., frequency, amplitude, and wavelength along with the concept of ***energy theory*** to include the estimated energy associated with the glucose fluctuations.

He decided to abandon the usage of this term of "glycemic variability or GV" and directly utilize the term of "glucose fluctuations (GF)" in his research work where GF equals to the value of maximum glucose minus minimum glucose. Not only does the simpler definition and form of GF provide a straightforward interpretation and easier comprehension to be applied by both physicians and patients, but it also fully represents the meaning of glycemic variability. The word "variability" can involve and signify many various things to different people.

GV or GF can indeed be applied to many clinical cases of greater mortality for those in intensive care unit or at-home, ***increased rate and risk of diabetes complications****, and postprandial beta-cell dysfunction (insulin health).*

Results

Collected Input Data

The author has collected 288 glucose data per day (every 5 minutes) and extracted 96 Glucose data per day (every 15 minutes) from the CGM sensor device and then entered them into his computer software since 5/5/2018. During the past 1,093 days (from 5/5/2018 to 5/2/2021), he has collected 314,784 glucose data from his 5-minute model and utilized 104,928 glucose data from his 15-minute model for this specific analysis project.

For this study, he divides the big dataset into two time periods: six periods with ~180 days each and twelve periods with~90 days each.

Next, he calculates his GF, maximum glucose minus minimum glucose of each day, and his CVD risk based on MI.

He names this simply as the "weighted CVD risk model," which contains 90% from MI and 10% from GF. He then compares this weighted CVD risk against his original CVD risk using MI only.

Graphic Diagrams of Results

Figure 1 shows the input data table and graphic results (line charts) of daily GF against CVD risk using MI along with the weighted CVD risk against CVD risk using MI for 6 periods.

Although the correlation coefficient is 58% between GF and CVD using MI is moderately high, the difference between their data moving patterns and curve shapes can still be seen easily in the middle diagram of Figure 1. The CVD risk using MI is reduces period after period while GF has fluctuations. From the biomedical viewpoint, the GF values are determined by diabetes conditions and lifestyle details, in particular diet and exercise; however, the GF curve still possesses its own unique characteristics and behaviors.

In the lower diagram of Figure 1, the extremely high correlation coefficient is 98% between CVD including GF and CVD using MI indicates that the two risk predictions are similar to each other. The major contribution of GF is that it increases the average CVD risk by 4%.

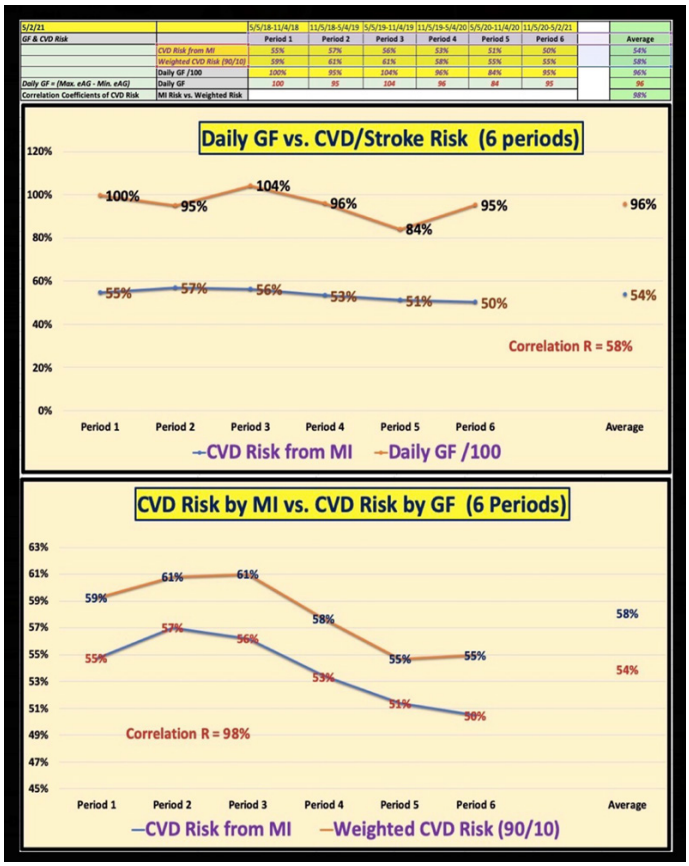


Figure 1: Data table and graphic results of CVD/Stroke risk using MI and including GF of 6 periods

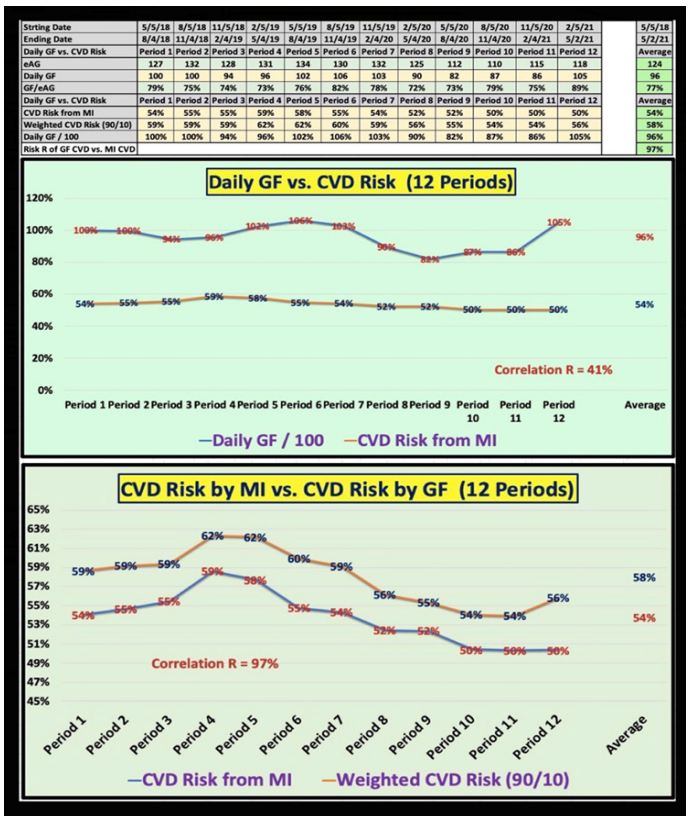


Figure 2: Data table and graphic results of CVD/Stroke risk using MI and including GF of 12 periods

Figure 2 illustrates the input data table and graphic results (line charts) of daily GF against CVD risk using MI and weighted CVD risk against CVD risk using MI for 12 periods.

Figure 2 is an "enlarged and more detailed" version of Figure 1. It displays similar observations and conclusions, except with twice the amount of details.

Conclusions

In summary, by presenting the extra influential factor of GF into his developed risk model of having CVD or stroke based on metabolism index (MI), he would obtain a slightly more accurate picture regarding the CVD risk assessment. In his MI model, all of input data used are then averaged values over a specific period of time of ten major influential categories (~500 elements). As a matter of fact, in his existing risk model of having CVD/stroke based on MI, glucoses only contribute 10% of the total influences on CVD risk. In this particular study, by including 10% influences contribution from GF and reducing the other 10 MI factors down to 90%, it would highlight the importance and impact of GF factor on CVD risk. Therefore, those risk percentages are only the "relative" risk numbers, and they are not the "absolute" risk numbers. It is more important to examine the changes of risk percentages over certain time scale i.e., CVD risk number's moving trend and CVD risk curve's pattern. This would be helpful on assessing some hidden relationships between diabetes conditions and CVD risk levels.

For both 6-periods and 12-periods, the two extremely high correlation coefficients (98% for 6-periods and 97% for 12-periods) have revealed that both of CVD risk using MI and CVD risk including GF have the same data moving pattern and curve shape similarity. This fact has also demonstrated that although GF is important, but the overall metabolism condition is garbage more important in terms of deciding the CVD risk. Overall speaking, the introduction of GF into CVD risk based on MI has increased the CVD risk by an extra 4%, from 54% to 58% [1-15].

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