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Applying the Distributional Data Analysis Tool of Metabolism Index Density (MID%), and Using Daily Metabolism Index (MI) Data from a Chronic Diseases Patient's Past ~6 Years Record to Investigate the Relationship Between his Overall Health Conditions and his Risk Probabilities of having a Stroke or Cardiovascular Disease Based on GH-Method: Math-Physical Medicine (No. 521)

Gerald C Hsu

EclaireMD Foundation, USA

*Corresponding author
Gerald C Hsu, EclaireMD Foundation, USA

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Abstract

Recently, the author conducted a series of medical research projects by applying a distributional data density analysis tool on his weight, glucose, blood pressure (BP), and heart conditions, while using his collected big data regarding certain biomarker's density distribution during certain selected years.

In this article, he investigates his collected metabolism index density (MID%) within a time span of ~6 years (1/1/2016 - 9/13/2021) and its relationship with his risk probability of having a cardiovascular disease (CVD) or stroke within the same time period.

With this data, he can interpret the results and explore additional and in-depth information since he is most familiar with his own health conditions. The findings from his own data is definitely applicable to other patients with chronic diseases. The main purpose of writing this series of research articles is to further demonstrate the applicability and power of the specific distributional data density analysis tool.

When he previously researched certain biomarkers and their relationships with other influential factors, he generally used the average values of those biomarkers. We know that most biomarkers, e.g. glucoses and heart rate (HR), could fluctuate along the time scale in the form of a "wave". Each wave has its own unique amplitude and specific biomedical measuring unit which are associated with this particular biomarker. However, there are two other key factors, frequency and wavelength, needed to be considered as well. Particularly, the frequency component, associated with energy and excessive energy carried by blood cells, would cause damage to the internal organs. Therefore, without focusing on waveform of a biomarker and depending only on its mean value, we would lose many vital, interesting, and useful hidden information. This type of mean value, such as HbA1C, can only provide partial views of our overall diabetic conditions. These biomarkers still have missing information which carry certain hidden internal turmoil or vital signs, e.g. biomarker variation or its severe stimulation due to all types of external and/or internal stimulators. By applying this basic knowledge of distributional data analysis by defining another term known as the "general biomarker density or Bio-density%" (BMD%), he can explore additional, different, in-depth, and useful hidden information from collected biomarker data and their associated waveforms.

The term "biomarker density percentage" (BMD%) is defined as the occurrence frequency at a specific person's biomarker value. With this, he can calculate and examine each biomarker's occurrence rate within a certain biomarker's range over a selected timespan. This certain timespan is dependent on the study which is applied to specific patients (in this article, himself). By investigating the changes of the peak biomarker value with their associated BMD% from year to year, he can easily observe his biomarker's

moving trend and understand his actual health problems or necessary health improvement effort clearly.

The above description provides the reason he keeps searching for applicable tools to analyze the collected big data of any biomarker. If this type of biomarker examination method is accepted by the medical community, it can be an extremely beneficial tool for doctors to quickly study the health conditions of their patients. Furthermore, the author has programmed this algorithm into an iPhone APP software. Through the combination of his published papers and medical books along with a widely distributed APP (a kind of e-Health tool) for patient's use in the future, he believes that worldwide patients with chronic diseases can benefit from his research work. Hopefully, his research papers would not be limited within the scope of a "descriptive style using 26 alphabets" but instead as a "quantitative style using 10 digits". Numbers do not lie as long as we don't use fake data or uncleaned data. Statistics is a tricky tool to use for any research work because it has the obvious characteristics of "garbage in and garbage out (GIGO)". It is also important to know that by using statistics with different selected time-windows for certain studies will result into varying conclusions.

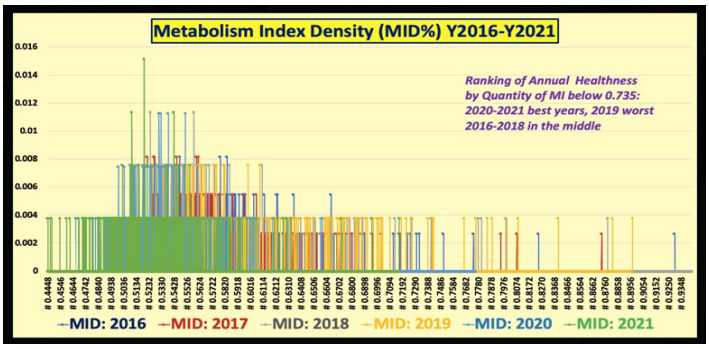
Once he knows his annual health conditions using this metabolism index density (MID%), he can compare them against his calculated annual risk probability of having a CVD or stroke.

In summary, ***the author conducts this research work using the tools of MID% with his collected daily metabolism index (MI) data over a period of ~6 years (1/1/2016 - 9/13/2021). He then compares his annual health conditions based on the MID% against his calculated annual risk probability of having a CVD or stroke within the same time period.***

Each of the 6-year calculated MI values has its own unique MI range (maximum MI and minimum MI) and his defined MI's "normal conditions", i.e. ***MI values below 73.5% is healthy and above 73.5% is unhealthy.*** This makes a combined study and its data presentation quite difficult. In order to combine these 6 separate MIR% charts into one single diagram, he must redefine a common "general-scale" of ***the MI data range from 0.4448 (44.48%) to 0.9348 (93.48%) with an equal interval of 0.0001 (0.01%). With this new numbering system, he can then re-align these 6 different "normal conditions or target values" of MID% into one single diagram with consistent x-axis of MI values for a direct comparison. The total number of MI data on x-axis of this MID% diagram is 4901.***

Now, he is able to plot all of the 6 MID% curves into one combined diagram with their relative positions which carry certain biomedical meanings, especially the overall health status. Through a closer examination of this diagram, he provides the following three conclusive statements:

1. Time-domain curves of MI provides useful information, including its fluctuations over a 6-year time span. However, many hidden information cannot be discovered easily.
2. Although the combined MID% diagram in the density-domain looks complicated initially, the annual colored MID% curves can indicate the moving-trend of the MID%, including its covered range and its peak shifting from the higher MI values in earlier years (right-side of the diagram) toward the lower MI values in recent years (left-side of the diagram).
3. By merging the two bar charts of annual health condition via MID% and calculated CVD/Stroke risk probability, their reversed correlation (i.e. heathy years of 2020-2021 having lower CVD risks, and vice versa) are very obvious. This observed conclusion is logical since his CVD risk calculations are mainly based on his calculated MI values; however, this article has also demonstrated that even the MID% still carry the same characteristics as the MI value itself.



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Once he knows his annual health conditions using this metabolism index density (MID%), he can compare them against his calculated annual risk probability of having a CVD or stroke.

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 his ~500 published medical papers.

The first paper, No. 386 describes his MPM methodology in a general conceptual format. The second paper, No. 387 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 depicts a general flow diagram containing ~10 key MPM research methods and different tools.

In particular, his paper No. 453 illustrates his GH-Method: math-physical medicine in great details, "Using Topology concept of mathematics and Finite Element method of engineering to develop a mathematical model of Metabolism in medicine in order to control various chronic diseases and their complications via overall health conditions improvement".

The Author'S Case of Diabetes and Complications

The author has been a severe T2D patient since 1996. He weighed 220 lb. (100 kg, BMI 32.5) at that time. By 2010, he still weighed 198 lb. (BMI 29.2) with an average daily glucose of 250 mg/dL (HbA1C of 10%). During that year, his triglycerides reached to 1161 (diabetic retinopathy or DR) and albumin-creatinine ratio (ACR) at 116 (chronic kidney disease or CKD). He also suffered from five cardiac episodes within a decade. In 2010, three independent physicians warned him regarding his needs of kidney dialysis treatment and future high risk of dying from severe diabetic complications. Other than cerebrovascular disease (stroke), he has suffered most known diabetic complications, including both macro-vascular and micro-vascular complications.

In 2010, he decided to launch his self-study on endocrinology, diabetes, and food nutrition in order to save his own life. During 2015 and 2016, he developed four prediction models related to diabetes conditions: weight, PPG, fasting plasma glucose (FPG), and A1C. As a result, from using his developed mathematical metabolism index (MI) model in 2014 and the four prediction tools, by end of 2016, his weight was reduced from 220 lbs. (100 kg, BMI 32.5) to 176 lbs. (89 kg, BMI 26.0), waistline from 44 inches (112 cm, nonalcoholic fatty liver disease /NAFLD) to 33 inches (84 cm), average finger glucose reading from 250 mg/dL to 120 mg/dL, and lab-tested A1C from 10% to ~6.5%. One of his major accomplishments is that ***he no longer takes any diabetes medications since 12/8/2015.***

In 2017, he has achieved excellent results on all fronts, especially his glucose control. However, during the pre-COVID period of 2018 and 2019, he traveled to approximately 50+ international cities to attend 65+ medical conferences and made ~120 oral presentations. This hectic schedule inflicted damage to his diabetes control, through dinning out frequently, post-meal exercise disruption, jet lag, and along with the overall metabolism impact due to his irregular life patterns through a busy travel schedule; therefore, his glucose control and overall metabolism state were somewhat affected during this two-year heavier traveling period.

During 2020 with a COVID-19 quarantined lifestyle, not only has he published ~400 medical papers in 100+ journals, but he has also reached his best health conditions for the past 26 years. By the beginning of 2021, his weight was further reduced to 165 lbs. (BMI 24.4) along with a 6.1% A1C value (daily average glucose at 105 mg/dL), without having any medication interventions or insulin injections. These good results are due to his non-traveling, low-stress, and regular daily life routines. Due to his knowledge of chronic diseases, practical lifestyle management experiences, and developed various high-tech tools contribute to his excellent health status since 1/19/2020, which is the start date of being self-quarantined.

On 5/5/2018, he applied a CGM sensor device on his upper arm and checks glucose measurements every 5 minutes for a total of ~288 times each day. He has maintained the same measurement pattern to present day. In his research work, he uses the CGM sensor glucose at time-interval of 15 minutes (96 data per day). By the way, the difference of average sensor glucoses between 5-minute intervals and 15-minute intervals is only 0.4% ***(average glucose of 114.81 mg/dL for 5-minutes and average glucose of 114.35 mg/dL for 15-minutes with a correlation of 93% between these two sensor glucose curves)*** during the period from 2/19/20- to 8/13/21.

Therefore, over the past 11 years, he could study and analyze the collected 2+ million data regarding his health status, medical conditions, and lifestyle details. He applies his knowledge, models, and tools from mathematics, physics, engineering, and computer science to conduct his medical research work. His medical research work is based on the aims of achieving both "high precision" with "quantitative proof" in the medical findings.

The following timetable provides a rough sketch of the emphasis of his medical research during each stage:

- 2000-2013: Self-study diabetes and food nutrition, developing a data collection and analysis software.
- 2014: Develop a mathematical model of metabolism, using engineering modeling and advanced mathematics.
- 2015: Weight & FPG prediction models, using neuroscience.
- 2016: PPG & HbA1C prediction models, using optical physics, artificial intelligence (AI), and neuroscience.
- 2017: Complications due to macro-vascular research such as cardiovascular disease (CVD), coronary heart disease (CHD) and stroke, using pattern analysis and segmentation analysis.
- 2018: Complications due to micro-vascular research such as chronic kidney disease (CKD), bladder, foot, and eye issues such as diabetic retinopathy (DR).
- 2019: CGM big data analysis, using wave theory, energy theory, frequency domain analysis, quantum mechanics, and AI.
- 2020: Cancer, dementia, longevity, geriatrics, DR, hypothyroidism, diabetic foot, diabetic fungal infection, linkage between metabolism and immunity, and learning about certain infectious diseases such as COVID-19.
- 2021: Applications of linear elastic glucose theory (LEGT) and perturbation theory from quantum mechanics on medical research subjects, such as chronic diseases and their complications, cancer, and dementia. Using metabolism and immunity.it's as the base, he expands his research into cancers, semantic, and COVID-19.

To date, he has collected more than two million data regarding his medical conditions and lifestyle details. In addition, he has written 498 medical papers and published 400+ articles in 100+ various medical journals, including 6 special editions with selected 20-25 papers for each edition. Moreover, he has given ~120 presentations at ~65 international medical conferences. He has continuously dedicated time and effort on medical research work and shared his findings and learnings with other patients worldwide.

Metabolism Index (MI) Model

In 2014, the author applied mathematical topology concept, engineering finite-element method technique, and nonlinear algebra operations to develop a complex mathematical model of MI.

This MI model contains 10 specific categories, including 4 output categories of medical conditions (body weight, glucose, blood pressure, and lipids), and 6 input categories of lifestyle details (food quantity and quality, drinking water intake, physical exercise, sleep, stress, and daily life routines). These 10 categories are comprised of approximately 500 detailed elements. He has also defined two new resulting parameters: MI, as the combined score of the above 10 metabolism categories and 500 elements using his developed algorithm, along with the general health status unit (GHSU), as the 90-days moving average value of MI.

A physical analogy of this complex mathematical metabolism model is similar to "using multiple nails that are encircled by many rubber bands". For example, at first, we hammer 10 nails into a piece of flat wood with an initial shape of a circle with a center in the middle of the circle, then take 3,628,800 (=10!) rubber bands to encircle the nails, starting with 2 and 2+ nails and finally enclosing all of these 10 nails. These ~3.6 million rubber bands (i.e., small number of data elements of 10 but generate a very big number of possible relationships) indicate the possible inter-relationships existing among these 10 nails (i.e., 10 original metabolism categories). Some rubber bands encircle 2 nails or 3 nails and so on, until the last rubber band encircles all of these 10 nails together (no rubber band to encircle a single nail is allowed). Now, if we move any one of the nails outward (i.e., moving away from the center of the nail circle), then this moving action would create some internal tension inside the encircled rubber band. Moving one nail "outward" means one of these ten metabolism categories is becoming "unhealthy" which would cause some internal stress to our body. Of course, we can also move some or all of these 10 nails outward or inward at different time instant or at the same time, but with different moving scale for each nail. If we can measure and calculate the summation of all of these internal tensions which are created inside of these affected rubber bands, then this summarized tension force is equivalent to the total metabolism value of human health. The higher tension means the higher metabolism value which creates an unhealthy situation. The author uses the above-described physical scenario of moving nails and their encircled rubber bands to explain his developed mathematical metabolism model of human health. Of course, at the end, the author must find a simpler way to develop a set of equations which can produce an approximate solution with sufficient accuracy of this total MI value.

Metabolism Index Density (MID%)

For the case of one particular patient i, the collected biomarker data can be expressed by pairs of data in the format of (t ij, X ij), j = 1 … T, where the t ij represent recording times and X ij is the biomarker level at time instant t ij, and T is the overall observation length of the selected biomarker. ***For the case in this article, the total T is 4,901 (e.g. from MI of 44.48% to 93.48% with an equal interval of 0.01% between two MI end-points). It should be pointed out that this dataset has a big size of data volume due to its ultra-small intervals of 0.0001, however, most of MID% values are zero.***

Therefore, he can describe the above mathematical problem into a more simplified equation for one patient only. The metabolism index density ***% (MID%) for*** one patient can be defined in terms of ***a continuous format*** as follows:

$$GD(x) = \int_{1}^{T} (Y(t)\,dt) / T$$

with x1 < Y(t) < x2
where x1 and x2 are ∫ boundaries of his selected MI range.

The metabolism index density % (MID%) equation for one patient, such as himself, can also be defined in terms of a discrete format as follows:

$$GD(x) = \left(\sum_{j=1}^{T} Y(tj)\right) / T$$

with x1 < Y(t) < x2
where x1 and x2 are boundaries of his selected MI range.

He then develops his APP software program using the above-described algorithm.

Research Method of CVD Risks

In this paper, the author described how to apply his engineering science background, including mathematics, physics, and computer science to conduct his medical research on the subject of "risk probability of having a stroke or CVD/CHD". He has reviewed his ~6-years of data from 1/1/2016 through 9/21/2021, where he has focused on both of his chronic disease's medical conditions and his lifestyle details. After the initial data collection, he then applied the same mathematical risk model which he developed 4 years ago based on the GH-Method: math-physical medicine approach.

As a part of his medical research, he applied the acquired mechanical and structural engineering knowledge to develop several biomedical scenarios to research these chronic diseases (obesity, diabetes, hypertension, hyperlipidemia) and their induced various complications. These complications include CVD, CHD, stroke, CKD, DR, pancreatic beta cells impairment, and even cancer or dementia, which have severe impacts on human health. In the worst case scenario, deaths caused by diseases are often triggered by a single disease or a combination of various diseases.

The engineering analogy of deaths caused by disease and human expected lifespan can be explained simply by using an example of a new machine or a new bridge. If we develop a monitoring system to continuously measure, record, and analyze the external forces, material strength and damages of material of a machine or a bridge, as well as the relationship between force/stress (causes of disease such as lifestyle details) and deformation/strain (symptoms of disease such as medical conditions), we can then have a clear idea how severe the damages are and how long this machine or bridge will last which is their useful life or expected lifespan. Above statements are related to the medical subjects of geriatrics and longevity.

The author self-studied chronic diseases, metabolism, and food nutrition for 4-years from 2010 to 2013. He started his medical research work by building a mathematical metabolism model in 2014. He named his research methodology as the "GH-method: math-physical medicine (MPM approach)". Over the past 11 years of his MPM research, he has learned that the most important factor is knowing how to apply physics principles and engineering modeling techniques to various biomedical problems. This is different from inserting your biomedical data into some existing mathematical equations extended from physical theories and engineering models. The reason for doing this is that the original mathematical equations associated with the inventors' theories or models usually come along with their original boundary conditions. This may or may not be perfectly fit into your biomedical situations directly; therefore, you must understand the scope and applicability of these physical theories and engineering models first, and then find a suitable way to apply them. In other words, by learning other people's wisdom first and then find a way to apply their wisdom to your own biomedical problem is the most practical way to solve these biomedical problems.

The author's simple numerical calculation of CVD risk probability is based on his knowledge and applications of physics law/concept and engineering modeling technique, big data analytics, and his developed mathematical metabolism model. It has depicted a possible way to extend lowering the risk probability of having CVD risks via an effective metabolic condition improvement and lifestyle maintenance program. This practical method has already been applied and proven effectively in the author's own case of control of his diabetes and its complications without taking medications over the past 6 years.

The author hopes that this method can also be easily applied to other patients who face the risks of having strokes or CVD/CHD. Although he has already collected 2+ million data of his own health data using a customized computer software, the methodology and risk prediction tool are equally applicable and useful for other patients. For example, if patients are able to collect sufficient data regarding their routine check-ups on chronic disease conditions from a hospital or laboratory, then they can directly plug the input data of M1 through M4 into the risk prediction model. They can also utilize the same approach to deal with their own actually collected or best guesstimated lifestyle data of M5 through M10 in order to conduct the computational risk probability analysis.

Results

Figure 1 shows the time-domain analysis of his MI values and GHSU values (90-days moving average value of MI) during the past ~6-years period from 1/1/2016 to 9/21/2021. This time-domain diagram reflects his maximum MI at 101.47%, his minimum MI at 44.48%, and his average MI at 56.33%.

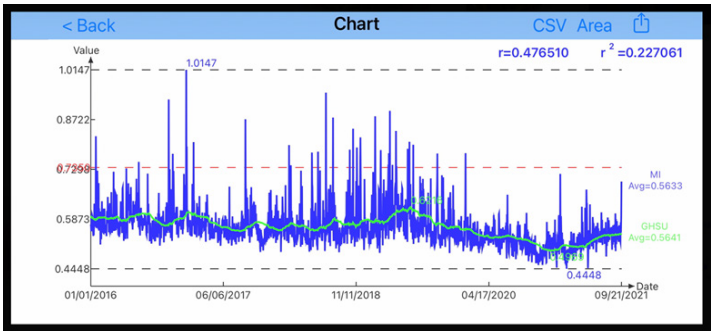

Figure 1: Time-domain analysis results of his MI & GHSU curves within a period of ~6 years (1/1/2016 - 9/21/2021)

Figure 2 illustrates the comparison of density-domain's 6 annual MID% using consistent MI range between 0.4448 and 0.9348. By using a visual check of the curve's color, we can see that, from the left side of lower MI values moving toward the right side of higher MI values, the green curve (2021) and blue curve (2020) are the best years, while the other years (2016-2019) are worse than the 2020-2021 period. We can observe the similar trend by observing the color change on the horizontal X-axis at the level of zero of MID%.

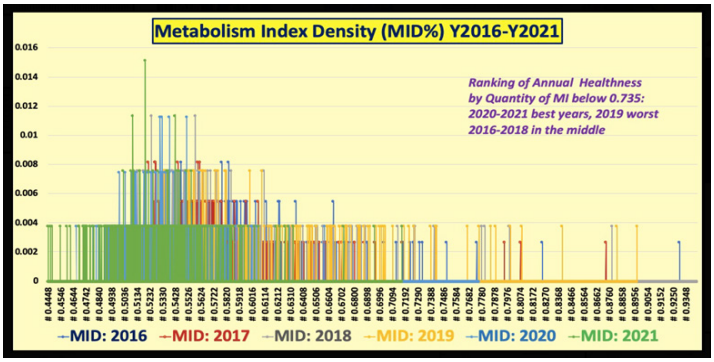

Figure 2: Density-domain analysis results using 6 years MID% values within a period of ~6 years (1/1/201 - 9/21/2021)

A more detailed analysis of the total MID% associated with the case of MI < 0.735 indicates that 2019 actually is the worst year (i.e. the lowest summation of MID% from MI less than 73.5%) due to his busy traveling lifestyle to attend many international medical conferences.

Figure 3 displays the combined so bar charts of the annual health status (top) versus annual CVD risks (bottom). His annual health status is calculated by the following equation:

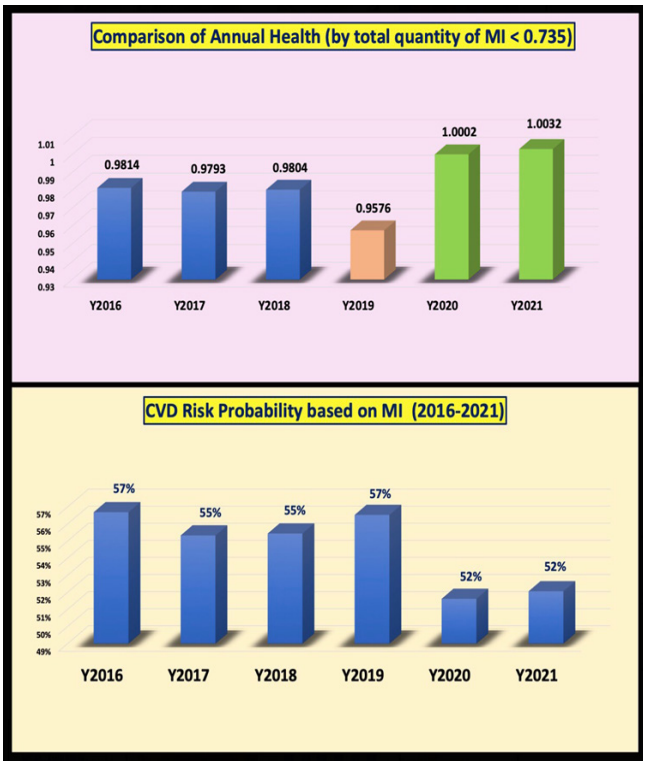

Figure 3: Comparison of health status versus CVD/Stroke risk during a period of ~6 years (1/1/2016 - 9/21/2021)

Health status

= Summation of MID% (between minimum MI at 0.4448 and break-even MI at 0.7350)

When the annual health status reflects a higher value, this indicates being healthier due to the calculated value is the summation of healthy MI values which is less than 73.5%. On the contrary, when the CVD/Stroke risk shows a lower value, then his CVD risk is lower (i.e. better). Therefore, when comparing these two sets of bars, the top diagram and the bottom diagram have a "reciprocal" contrast.

Conclusions

*In summary, the author conducts this research work using the tools of **MID%** with his collected **daily metabolism index (MI) data over a period of ~6 years (1/1/2016 - 9/13/2021)**. He then compares his annual health conditions based on the MID% against his calculated annual risk probability of having a CVD or stroke within the same time period.*

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References

For editing purposes, majority of the references in this paper, which are self-references, have been removed for this article. Only references from other authors' published sources remain. The bibliography of the author's original self-references can be viewed at www.eclairemd.com.

Readers may use this article as long as the work is properly cited, and their use is educational and not for profit, and the author's original work is not altered.

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