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The GH-Method

Applying the Distributional Data Analysis Tool, Glucose Density, with Collected Daily Finger Glucose Data from the Past 10-years Combined with the Continuous Glucose Monitoring Sensor Fasting Plasma Glucose Data from the Past 3-Years of a Patient with Chronic Diseases to Investigate the Close Relationship Between Weight and Glucose Based on GH-Method: Math-Physical Medicine (No. 513)

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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 glucose, weight, blood pressure, and heart conditions by using the collected big data regarding certain biomarkers over the past multiple years. In this article, he only utilizes the collected biomarker data from himself, where the data covers two timespans of 10 years and 3 years for this particular study. Moreover, he can interpret the results and explore additional information since he is most familiar with his own health conditions. The main purpose of writing this series of research articles is to demonstrate the applicability and power of using this specific distributional data weight density (WD) analysis tool. In the past, when he researched certain biomarkers and their relationship with other factors, such as fasting plasma glucose (FPG) and food consumption quantity, he mostly used the average value of those biomarkers, including body weight. However, we know that biomarkers like body weight and glucose would fluctuate along the time scale in the form of a wave which has one key factor for the amplitude of the biomarker, where the other two key factors are frequency and wavelength. Therefore, without focusing on the wave shape of the biomarker and only depending on its mean value, we would lose many vital, interesting, and useful hidden information. These types of mean values, such as HbA1C, or sparsely collected blood lipid data from quarterly testing can only provide partial views of health conditions. However, these biomarkers still have some missing information carrying certain hidden internal turmoil or vital signs, e.g., biomarker variations or its severe stimulations due to all types of external and/or internal stimulators. By applying this basic knowledge of distributional data analysis, he has defined new term known as the general biomarker density or bio-density (BMD) in order to explore additional, different, deeper and useful hidden information in the collected biomarker data and their associated waveforms. The terms WD or glucose density (GD) are defined as the occurrence frequency at a specific body weight or glucose value, for example 5.3% occurrence rate (or probability) at 170 lbs. value in 2021. In this way, he can then calculate and examine each weight or glucose's occurrence rate within a weight range of 164 lbs. to 193 lbs. with a finger-pierced estimated average glucose (eAG) range of 11 mg/dL to 301 mg/dL over the past 10 years, or within a weight range of 165 lbs. to 183 lbs. with a continuous glucose monitoring (CGM) sensor FPG range of 33 mg/dL to 214 mg/dL over the past 3 years. The selected time span of 10 years or 3 years are dependent on the subject of study which is suitable to one specific patient (in this case, himself). By investigating the changes of the peak weight/glucose value with their associated WD%/GD% values from year to year, he can easily observe his weight and glucose situation's moving trend and understand his actual health improvement effort clearly. As a side benefit, he can also reaffirm his previous findings regarding body weight, which is closely related to glucose, particularly FPG. 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

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for doctors to quickly study the health conditions of their patients. Furthermore, the author programmed this algorithm into an iPhone app software. Through the combination of his published papers and medical books along with a widely distributed app for patient's use in the future, he believes that worldwide patients with chronic disease can benefit from his research work. Hopefully, the 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, unorganized, and/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. In summary, the author has chosen to perform his research work using the tools of WD and GD with his collected body weight and glucose data which are measured every day from the past ~10 years (1/1/2012-9/13/2021) for his finger-pierced daily average glucose (finger eAG) and over the past ~3 years (8/8/2018-9/13/2021) for his CGM sensor FPG. In the first case, he has selected a consistent weight range covering 164 lbs. to 193 lbs. with an equal interval of 0.1 lb. with a total of 291 weight points on the x-axis, and with a consistent daily finger eAG range covering 11 to 301 mg/dL with an equal interval of 1 mg/dL with a total of 291 eAG points on the x-axis in order to express the density% diagram and density% amplitude on the y-axis (between 0% and 3%). For the second case, he has selected a consistent weight range covering 164.5 lbs. to 182.6 lbs. with an equal interval of 0.1 lb. with a total of 182 weight points on the x-axis, and with a consistent CGM sensor FPG range covering 33 to 214 mg/dL with an equal interval of 1 mg/dL with a total of 182 weight points on the x-axis in order to express the density% diagram and density% amplitude on the y-axis (between 0% and 3.5%). By using his developed app software program on the iPhone, he can then generate and display these two sets of density data and density curves. Through a closer examination of each diagram in this article, he can describe the following 3 key conclusions: (1) The close inter-relationship between the daily weight and daily glucose can be seen through the correlations between weight and finger eAG within a 10-year period of 69% in time-domain and 61% in density-domain. (2) The close inter-relationship between daily weight and daily CGM sensor FPG can also be seen through the correlations between weight and sensor FPG within a 3-year period of 62% in time-domain and 83% in density-domain. (3) The correlation between two curves in a time-domain has been proven previously by many authors. However, the correlation between two different density% curves (e.g., WD vs. GD) using a density% diagram is somewhat new and questionable. The fact that weight and glucose have an extremely close relationship is undeniable. The conclusion for Case 1 and Case 2 have indicated two different sets of correlation coefficients, where all of the 4 calculated correlations are high (above 60%). From Figure 4, the amplitude of GD% is about 50% higher than the amplitude of WD% which offers additional evidence for this density-domain comparison. Therefore, the author's intuition tells him that this density-domain correlation has its own merit.

Keywords: Weight density; Glucose density; Continuous glucose monitoring; Fasting plasma glucose

Abbreviations: WD: weight density; FPG: fasting plasma glucose; GD: glucose density; eAG: estimated average glucose; CGM: continuous glucose monitoring; Finger eAG: finger-pierced daily average glucose; HbA1C: hemoglobin A1C; MPM: math-physical medicine; PPG: postprandial plasma glucose

1. INTRODUCTION

Recently, the author conducted a series of medical research projects by applying a distributional data density analysis tool on his glucose, weight, blood pressure, and heart conditions by using the collected big data regarding certain biomarkers over the past multiple years. In this article, he only utilizes the collected biomarker data from himself, where the data covers two timespans of 10 years and 3 years for this particular study. Moreover, he can interpret the results and explore additional information since he is most familiar with his own health conditions. The main purpose of writing this series of research articles is to demonstrate the applicability and power of using this specific distributional data weight density (WD) analysis tool.

In the past, when he researched certain biomarkers and their relationship with other factors, such as fasting plasma glucose (FPG) and food consumption quantity, he mostly used the average value of those biomarkers, including body weight. However, we know that biomarkers like body weight and glucose would fluctuate along the time scale in the form of a wave which has one key factor for the amplitude of the biomarker, where the other two key factors are frequency and wavelength. Therefore, without focusing on the wave shape of the biomarker and only depending on its mean value, we would lose many vital, interesting, and useful hidden information. These types of mean values, such as HbA1C, or sparsely collected blood lipid data from quarterly testing can only provide partial views of health conditions. However, these biomarkers still have some missing information carrying certain hidden internal turmoil or vital signs, e.g., biomarker variations or its severe stimulations due to all types of external and/or internal stimulators. By applying this basic knowledge of distributional data analysis, he has defined new term known as the general biomarker density or bio-density (BMD) in order to explore additional, different, deeper and useful hidden information in the collected biomarker data and their associated waveforms.

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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 programmed this algorithm into an iPhone app software. Through the combination of his published papers and medical books along with a widely distributed app for patient's use in the future, he believes that worldwide patients with chronic disease can benefit from his research work. Hopefully, the 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, unorganized, and/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.

2. METHODS

2.1 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 the biochemical medicine (BCM) approach vs. 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: MPM 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".

2.2 The author's case of diabetes and complications

The author has been a severe type 2 diabetes (T2D) patient since 1996. He weighed 220 lbs. (100 kg, BMI 32.5) at that time. By 2010, he still weighed 198 lbs. (BMI 29.2) with average daily glucose of 250 mg/dL (HbA1C of 10%). During that year, his triglycerides reached to 1161 (diabetic retinopathy or DR) and the 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 need for kidney dialysis treatment and future high risk of dying from severe diabetic complications. Other than the cerebrovascular disease (stroke), he has suffered most of the 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 condition: weight, postprandial plasma glucose (PPG), 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 the lab-tested A1C from 10% to ~6.5%. One of his major accomplishments is that he no longer takes any diabetes medication 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 dining 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 condition 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 intervention or insulin injections. These good results are due to his non-traveling, low-stress, and regular daily life routines. His knowledge of chronic diseases, practical lifestyle management experiences and developed various high-tech tools contributed 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 his glucose measurements every 5 minutes for a total of ~288 times each day. He has maintained the same measurement pattern to the present day. In his research work, he uses the CGM sensor glucose at a time-interval of 15

minutes (96 data per day). By the way, the difference of average sensor glucose 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 2/19/20-8/13/21.

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 aim of achieving 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 and FPG prediction models using neuroscience.

2016: PPG and 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 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 his time and effort on medical research work and shared his findings and learnings with other patients worldwide.

2.3 Weight density (WD) and glucose density (GD)

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 time and X ij is the biomarker level at time instant t ij, and T is the overall observation length of weight. For the case in this article, the total T is 291 (e.g., from 164.0 lbs. to 13.0 lbs. with an equal interval of 0.1 lbs. between two weight end-points).

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

$$D(x) = \int_{1}^{T} (Y(t)\,dt)/T \quad \text{with} \quad x1 < Y(t) < x2$$

where x1 and x2 are boundaries of his selected weight range.

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

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

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

He then developed his app software program using the above-described algorithm.

3. Results

Figure 1 shows his weight and finger eAG over ~10 years (from 1/1/2012 to 9/13/2021) which has a correlation of 69% in the time-domain diagram.

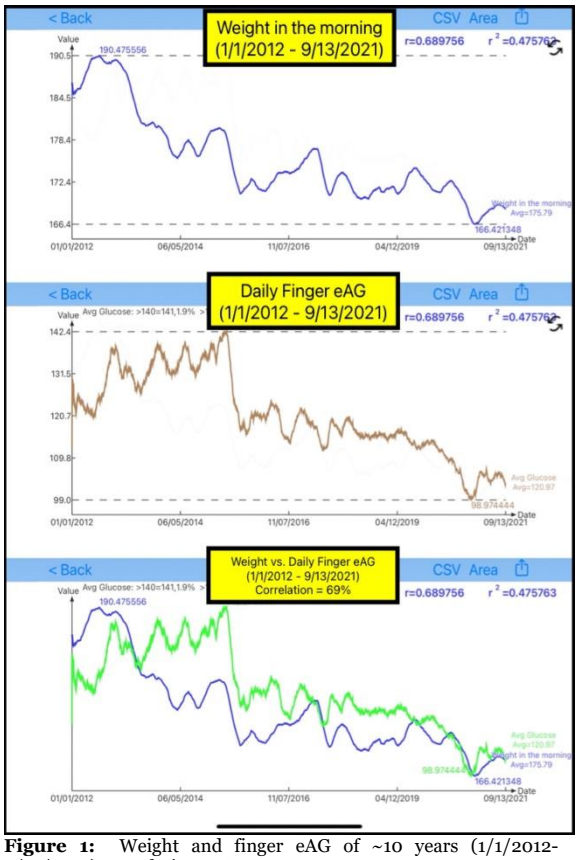

Figure 1: Weight and finger eAG of ~10 years (1/1/2012-9/13/2021), correlation 69%.

Figure 2 displays the time-domain and the density-domain of weight vs. finger eAG (from 1/1/2012 to 9/13/2021) which has a correlation of 61% in the density-domain diagram.

Figure 3 illustrates the time-domain and density-domain of weight vs. CGM sensor FPG (from 8/8/2018 to 9/13/2021) which has a correlation of 62% in the time-domain diagram and another correlation of 83% in the density-diagram.

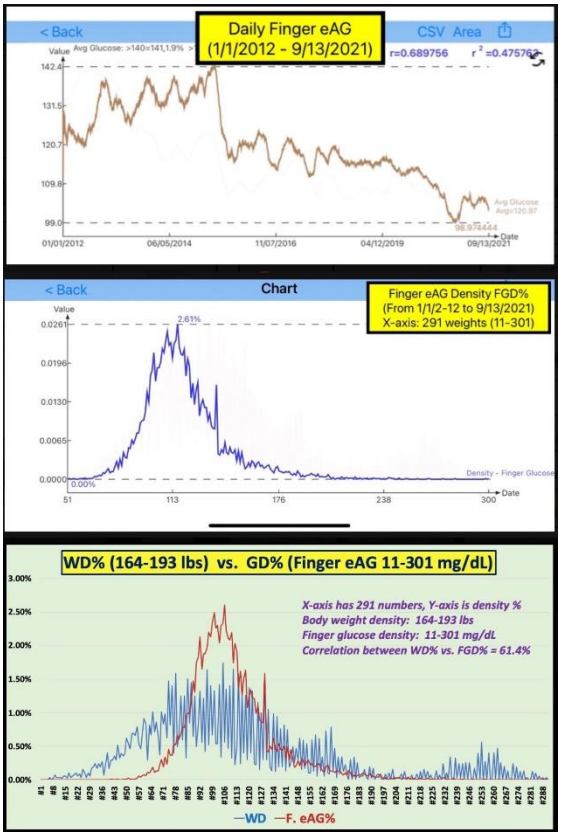

Figure 2: Time-domain and density-domain of weight vs. finger eAG (1/1/2012-9/13/2021).

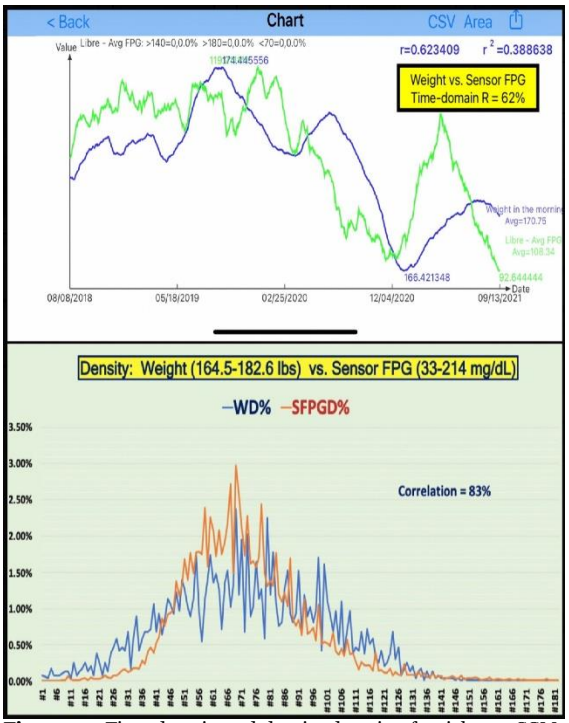

Figure 3: Time-domain and density-domain of weight vs. CGM sensor FPG (8/8/2018-9/13/2021).

Figure 4 reveals the comparison of 2 density-domain charts together. The top diagram is for weight vs. finger eAG over ~10 years which has a correlation of 61% in the density-diagram. The bottom diagram is for weight

vs. CGM sensor FPG over ~3 years which has a correlation of 83% in the density-diagram.

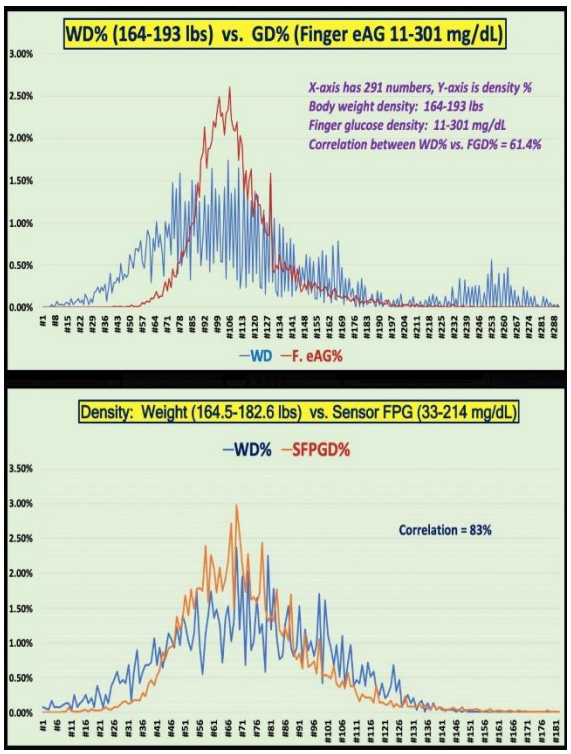

Figure 4: Comparison of 2 density-domain charts: weight vs. finger eAG over ~10 years (top) and weight vs. CGM sensor FPG over ~3 years (bottom).

4. Conclusion

In summary, the author has chosen to perform his research work using the tools of WD and GD with his collected body weight and glucose data which are measured every day from the past ~10 years (1/1/2012-9/13/2021) for his finger-pierced daily average glucose (finger eAG) and over the past ~3 years (8/8/2018-9/13/2021) for his CGM sensor FPG.

In the first case, he has selected a consistent weight range covering 164 lbs. to 193 lbs. with an equal interval of 0.1 lb. with a total of 291 weight points on the x-axis, and with a consistent daily finger eAG range covering 11 to 301 mg/dL with an equal interval of 1 mg/dL with a total of 291 eAG points on the x-axis in order to express the density% diagram and density% amplitude on the y-axis (between 0% and 3%).

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By using his developed app software program on the iPhone, he can then generate and display these two sets of density data and density curves.

Through a closer examination of each diagram in this article, he can describe the following 3 key conclusions:

(1) The close inter-relationship between the daily weight and daily glucose can be seen through the correlations between weight and finger eAG within a 10-year period of 69% in time-domain and 61% in density-domain.

(2) The close inter-relationship between daily weight and daily CGM sensor FPG can also be seen through the correlations between weight and sensor FPG within a 3-year period of 62% in time-domain and 83% in density-domain.

(3) The correlation between two curves in a time-domain has been proven previously by many authors. However, the correlation between two different density% curves (e.g., WD vs. GD) using a density% diagram is somewhat new and questionable. The fact that weight and glucose have an extremely close relationship is undeniable. The conclusion for Case 1 and Case 2 have indicated two different sets of correlation coefficients, where all of the 4 calculated correlations are high (above 60%). From Figure 4, the amplitude of GD% is about 50% higher than the amplitude of WD% which offers additional evidence for this density-domain comparison. Therefore, the author's intuition tells him that this density-domain correlation has its own merit.

5. 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.

1) Matabuena M, Petersen A, Vidal JC, et al. Glucodensities: A new representation of glucose profiles using distributional data analysis. Stat Methods Med Res. 30(6);1445–1464:2021.

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