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Applying Distributional Data Analysis Tool of Weight Density to Investigate Weight Changes from Obesity to Normal Condition Over the Past 10 Years of a Chronic Disease Patient Based on GH-Method: Math-Physical Medicine (No. 512)

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Abstract

Recently, the author conducted a series of medical research projects by applying a distributional data density analysis tool of weight density (WD) on his glucose, weight, blood pressure, and heart conditions by using his collected big data regarding certain biomarkers over the past multiple years. In this article, he only utilizes the collected biomarker data on himself, but the timespan of the data covers 10 years for his case. Moreover, he can interpret the results and findings better since he is most familiar with his own health conditions. The major purpose of writing this series of research articles is to demonstrate the applicability and power of using this specific distributional data density 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, including body weight, would fluctuate along the time scale which has one major difference associated with the "amplitude of biomarker". Therefore, without focusing on the biomarker's wave shape 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, or sparsely collected blood lipid data, like quarterly blood lipid lab-data, can only provide some partial views of our health condition. However, these biomarkers still have missing information carrying certain hidden internal turmoil, e.g., biomarker variations or its severe stimulations due to all types of external and/or internal stimulators. Therefore, by applying the basic knowledge of distributional data analysis, he has defined another term known as the 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. WD is defined as the occurrence frequency at a specific body weight value, for example 5.3% occurrence rate (or probability) at 170 lbs. value during 2021. In this way, he can then calculate and examine each weight's occurrence rate within a weight range of 164 lbs. to 193 lbs. over the past 10 years that is suitable to a specific patient (in this case, himself). By observing the changes of the peak weight value with its associated WD% from year to year, he can easily examine his obesity and overweight situation's moving trend and understand his actual weight improvement effort clearly. The above description provides the reason he keeps on searching for more 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 could be an extremely beneficial tool for doctors to quickly study the health conditions of their patients. Furthermore, the author has also 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 chronic diseases patients 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, unorganized, and/or uncleaned data. Statistics is a tricky tool to use for research 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 WD tool with his collected body weight data that are measured early morning over the past ~10 years from 1/1/2012 to 9/13/2021. Furthermore, he has

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selected a consistent weight range covering 164 lbs. to 193 lbs. with an equal interval of 0.1 lbs. with a total of 291 weight points on the x-axis of the 10 WD% diagram and the WD% amplitude on the y-axis (between 0% and 8.2%). By using his developed app software program on the iPhone, he can generate these 11 sets (10 annual plus 1 combined) of WD% data and WD% curves, then combine them into one diagram with the same scales of both x-axis (291 data points) and y-axis (0.0% to 8.2%). Through a closer examination of each diagram in this article, he can describe the following 3 key observations: (1) In the combined WD% diagram with 10 different colored annal WD% curves, we can clearly observe that the blue-colored earlier year of 2012 with a higher weight "lump" is moving towards the red-colored recent year of 2021 with a lower weight "lump". This moving trend by color has demonstrated his weight improvement. (2) His peak body weight associated with the highest WD% of each year is moving from the heaviest of 189 lbs. in 2012 towards the lightest of 170 lbs. in 2021. With his constant height of 5'9.5" over these 10 years, he has improved his weight condition with a BMI of 28 in 2012 through 8 years of continuous condition of being overweight, and then finally reach to a normal BMI of 25 in 2021. (3) Using a time-domain analysis of his morning weight vs. daily consumed quantity of food and meal, he has identified a high correlation of 65% between his weight and his food consumption. Of course, there are many influential factors of body weight, but undeniably the key factor is the food intake quantity. Although the time period for this analysis is only a shorter period of 5.5 years because his food data collection started on 4/1/2015, it is still a rather long timespan. The conclusion is that his weight dropped 8% from 180 lbs. to 166 lbs. when his food quantity was reduced by half, from 102% to 49% (100% is defined as his normal food intake amount at ~10 years ago).

Keywords: Weight density; Glucose; Body weight; Biomarkers; Chronic diseases

Abbreviations: WD: weight density; CGM: continuous glucose monitoring; HbA1C: hemoglobin A1C; MPM: math-physical medicine; FPG: fasting plasma glucose; PPG: postprandial plasma glucose

1. INTRODUCTION

Recently, the author conducted a series of medical research projects by applying a distributional data density analysis tool of weight density (WD) on his glucose, weight, blood pressure, and heart conditions by using his collected big data regarding certain biomarkers over the past multiple years. In this article, he only utilizes the collected biomarker data on himself, but the timespan of the data covers 10 years for his case. Moreover, he can interpret the results and findings better since he is most familiar with his own health conditions. The major purpose of writing this series of research articles is to demonstrate the applicability and power of using this specific distributional data density 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, including body weight, would fluctuate along the time scale which has one major difference associated with the "amplitude of biomarker". Therefore, without focusing on the biomarker's wave shape 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, or sparsely collected blood lipid data, like quarterly blood lipid lab-data, can only provide some partial views of our health condition. However, these biomarkers still have missing information carrying certain hidden internal turmoil, e.g., biomarker variations or its severe stimulations due to all types of external and/or internal stimulators. Therefore, by applying the basic knowledge of distributional data analysis, he has defined another term known as the 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.

WD is defined as the occurrence frequency at a specific body weight value, for example 5.3% occurrence rate (or probability) at 170 lbs. value during 2021. In this way, he can then calculate and examine each weight's occurrence rate within a weight range of 164 lbs. to 193 lbs. over the past 10 years that is suitable to a specific patient (in this case, himself). By observing the changes of the peak weight value with its associated WD% from year to year, he can easily examine his obesity and overweight situation's moving trend and understand his actual weight improvement effort clearly.

The above description provides the reason he keeps on searching for more 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 could be an extremely beneficial tool for doctors to quickly study the health conditions of their patients. Furthermore, the author has also 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 chronic disease patients 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, unorganized, and/or uncleaned data. Statistics is a tricky tool to use for research 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), 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 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 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 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)

For the case of one particular patient i, the collected weight data can be expressed by pairs of data in the format of (t ij, X ij), j = 1 … T, where the t ij represents recording time and X ij is the weight 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 (from 164.0 lbs. to 13.0 lbs. with an equal interval of 0.1 lbs. between two weight endpoints).

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

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

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

The WD equation for one patient, such as himself, can also be defined in terms of a discrete format as follows:

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

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

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

3. Results

Figure 1 shows the stored raw data and process using his iPhone app. It demonstrates the results of his WD% for each year over the past decade. It should be pointed out that the x-axis range is different for each year due to the built-in data auto-selection algorithm of his software.

From Figure 1, we can observe clearly that the blue-colored earlier year of 2012 with a higher weight "lump" is moving towards the red-colored recent year of 2021 with a lower weight "lump". This moving trend by color has demonstrated his weight improvement.

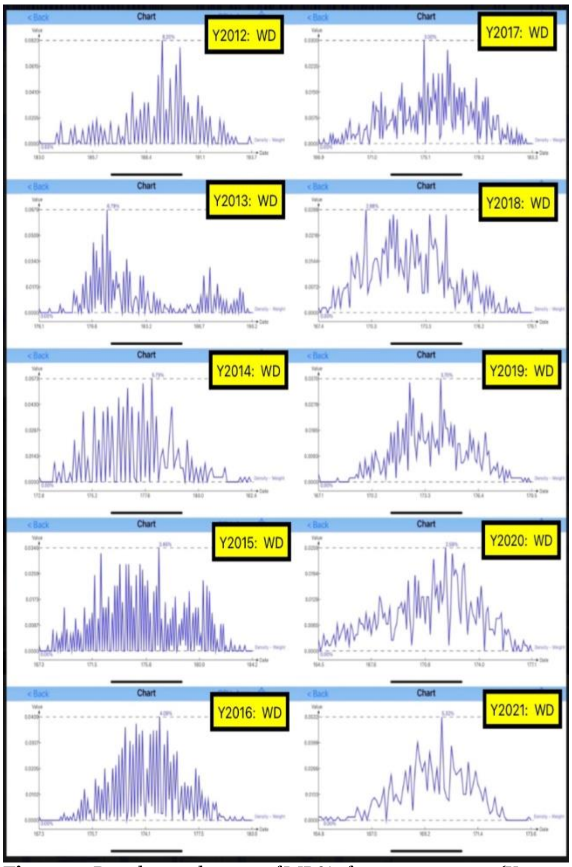

Figure 1: Raw data and curves of WD% of 10 separate years (Y2012 through Y2021).

The top diagram in Figure 2 depicts the combined 10 WD% curves for each year of the 10 years WD%.

The middle diagram in Figure 2 reflects the peak WD% of each year. It is clear that the WD% changes from year to year.

The lower diagram in Figure 2 reveals the weight value (lbs.) associated with the highest WD% of each year. The peak body weight is moving from the heaviest of 189 lbs. in 2012 towards the lightest of 170 lbs. in 2021.

Figure 3 illustrates the correlation between his body weight in early morning and daily average food intake amount. By using a period of 5.5 years from 4/1/2015 to 9/13/2021, these two curves have shown a high correlation of 65%. His weight dropped 8% from 180 lbs. to 166 lbs. when his food quantity reduced by half, from 102% to 49% (100% is defined as his normal food intake amount at ~10 years ago).

Figure 2: A combined 10-year WD%, peak WD%, and their associated weight values.

Figure 3: Correlation between body weight and food intake amount (4/1/2015-9/13/2021).

4. Conclusion

In summary, the author has chosen to perform his research work using the WD tool with his collected body weight data that are measured early morning over the past ~10 years from 1/1/2012 to 9/13/2021. Furthermore, he has selected a consistent weight range covering 164 lbs. to 193 lbs. with an equal interval of 0.1 lbs. with a total of 291 weight points on the x-axis of the 10 WD% diagram and the WD% amplitude on the y-axis (between 0% and 8.2%).

By using his developed app software program on the iPhone, he can generate these 11 sets (10 annual plus 1 combined) of WD% data and WD% curves, then combine them into one diagram with the same scales of both x-axis (291 data points) and y-axis (0.0% to 8.2%).

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

(1) In the combined WD% diagram with 10 different colored annal WD% curves, we can clearly observe that the blue-colored earlier year of 2012 with a higher weight "lump" is moving towards the red-colored recent year of 2021 with a lower weight "lump". This moving trend by color has demonstrated his weight improvement.

(2) His peak body weight associated with the highest WD% of each year is moving from the heaviest of 189 lbs. in 2012 towards the lightest of 170 lbs. in 2021. With his constant height of 5'9.5" over these 10 years, he has improved his weight condition with a BMI of 28 in 2012 through 8 years of continuous condition of being overweight, and then finally reach to a normal BMI of 25 in 2021.

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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.

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