

Analysis of the relationship between weight and sensor average FPG using 3 methods, time-domain analysis, spatial-domain analysis, and linear regression analysis, over a 3.5-year period from a type 2 diabetes patient based on GH-Method: math-physical medicine (No. 542)

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Abstract

In the author's previous research reports, he mainly applied physics theories, engineering models, mathematical equations, computer big data analytics and artificial intelligence (AI) techniques, as well as some statistical approaches. The majority of medical research scientists' published papers he has read thus far are primarily based on statistics tools. As a result, in this article, he selected some basic statistical tools, such as correlation, variance, p -values, and regression analysis to study the predicted fasting plasma glucose (FPG) using his measured weight in early morning as input.

The first approach of data analysis, starting in 2015, the author utilized a time-domain analysis tool for his glucose research work. This time-domain model has x -axis for displaying the time units, such as days or years, and y -axis for exhibiting certain biomarker's amplitude, such as glucose or body weight. He then transforms the time-domain data into the frequency-domain via fast Fourier Transform operation in order to estimate the energy associated with hypoglycemic (high blood sugar) which damages our internal organs to various degrees. Sometimes, he also calculates the correlation coefficient (R) between two biomarker datasets.

In early 2018, inspired by Dr. John Snow's famous Broad Street cholera spread on a 2D spatial map of London, UK, the author developed the second approach, a spatial-domain model, to investigate and explore some hidden relationships existing between any selected two biomarkers. In this article, he studies his body weight versus FPG values over the past 3.5-years. The graphic diagram of this spatial analysis can demonstrate physical connections between two biomarkers easily and clearly. He further created two additional user-defined (either horizontal or skewed) rectangular boxes inside each spatial diagram to display the visible "data coverage percentage" within the boxed areas of the total dataset. Actually, the graphic-box presentation is similar to the mathematical concept for the "variance or R Square" of regression analysis in statistics. These two skewed rectangular boxes are determined by the maximum values and minimum values of two biomarkers, weight and FPG. However, these two rectangular boxes are simpler to use and clearer in visual graphic presentation which are different from depending on the comprehension of the numerical meanings in statistical terms, for example $R > 0.5$, p -value > 0.05 , for a statistically significant connection.

The third approach applies the standard regression analysis tools from statistics, whether linear, nonlinear, single, multiple, exponential, or others. In this study, he will not repeat the detailed introduction of regression analysis in his Method section because it is available in any statistics textbook.

This article displays three analysis results of his body weight versus the average sensor FPG values over a period of 3.5-years from 5/8/2018 to 11/5/2021 by utilizing these three approaches.

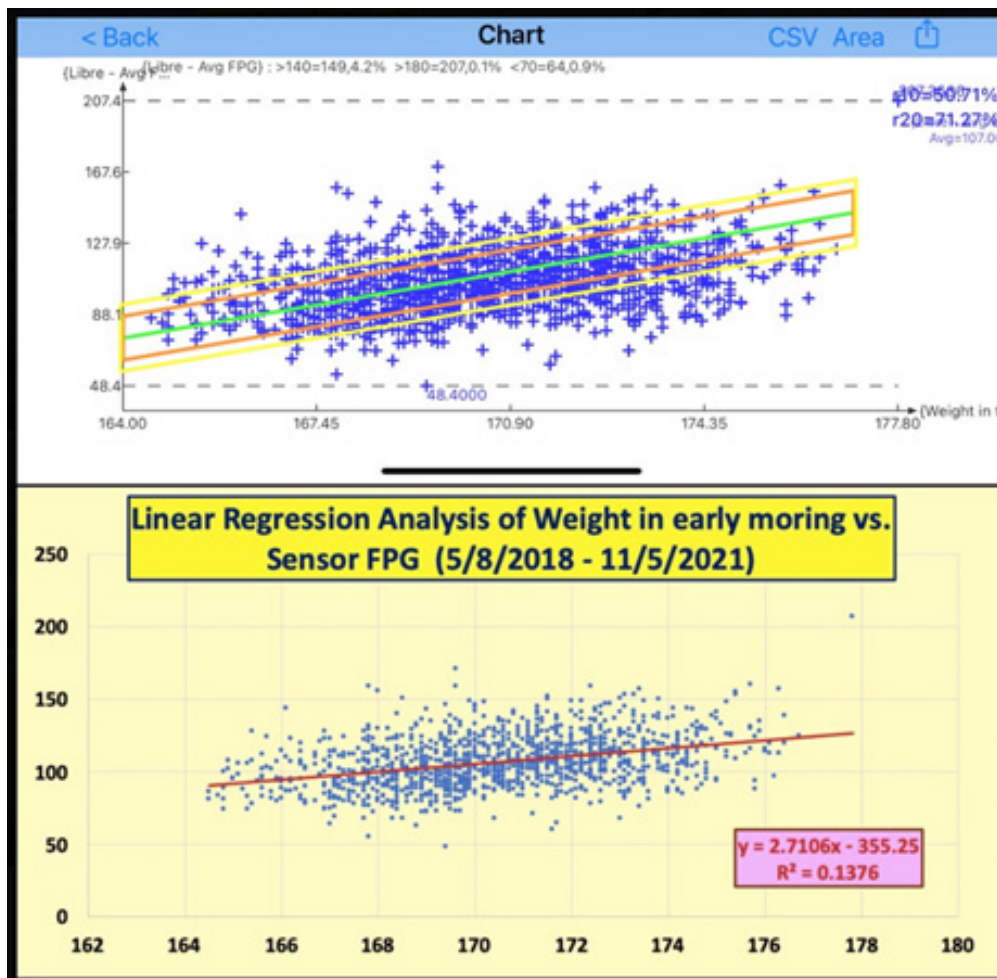
Since 5/8/2018, the author has been utilizing a continuous glucose monitoring (CGM) sensor device on his upper arm that collected and recorded the complete glucose data continuously at 15-minute time intervals on his iPhone. He accumulated 96 glucoses per day over the past ~3.5 years. During his sleep hours, from 00:00

midnight to 07:00 am, he collects a total of 28 FPG data. He uses the mean value from these 28 collected FPG data for his comparison study. He also measured his body weight twice daily, once in early morning and before going to bed at night. He chooses his body weight in the early morning for this comparison study.

In summary, these three approaches have their individual pros and cons. From a mathematical viewpoint, the second approach of spatial analysis is the same as the linear regression analysis, using mean, least square mean, standard deviation, correlation coefficient, variance, etc. However, the spatial analysis model offers advantages to application flexibility, clear graphic presentation, and associated result interpretation.

There are three specific conclusions worth mentioning:

1. In time-domain, he can easily examine the correlation coefficients, R , by viewing and comparing both weight waveform and FPG waveform, especially a high 71% of R for the two 90-days moving average curves. This means that his FPG values are following the ups-and-downs of his weight values in early morning. It also indicates that overweight or obesity can directly impact the health of pancreatic beta cells by causing insulin resistance.
2. In spatial-domain, the blue-colored data cloud of weight versus FPG and the green-colored central trend-line are skewed at an ~ 37 -degree angle (slope = $1/2.7106$). In addition, his **selected orange box occupies $\sim 51\%$** of the total dataset area, while the **selected yellow box occupies $\sim 71\%$** of the total dataset area. The 51% and 71% are **similar to the definition of “variance or R square”**; therefore, this spatial diagram is almost the same as the linear regression analysis diagram.
3. For type 2 diabetes (T2D) patients who are also over-weight or obese, they should focus on “weight reduction” first and then control their postprandial plasma glucose (PPG) level through the reduction of carbs/sugar intake amounts and increasing their post-meal exercise level. For T2D and “skinny” patients, they already have insulin resistance conditions and therefore must focus on control of their diet and exercise in order to reduce their PPG level.



Introduction

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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 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 type 2 diabetes (T2D) patient since 1996 and 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 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, 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 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 and 2021 with a strict COVID-19 quarantined lifestyle, not only has he written and 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 the knowledge of chronic diseases, practical lifestyle management experiences, and his developed various high-tech tools, they contributed to his excellent health status since 1/19/2020, which is the start date of being self-quarantine.

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). Incidentally, 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 ~3 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, utilizing optical physics, 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, dementia, and COVID-19. In addition, he has also developed a few useful analysis methods and tools for his medical research work.

To date, he has collected nearly 3 million data regarding his medical conditions and lifestyle details. In addition, he has written 536 medical papers and published 500+ articles in 100+ various medical journals, including 7 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 to share his findings and knowledge with patients worldwide.

Results

Figure 1 illustrates two time-domain analysis diagrams combined together which covers the time period from 5/8/2018 to 11/5/2021. The top diagram displays the daily weight and average sensor FPG with $R = 37\%$ and $R\ square = 14\%$. The bottom diagram reveals the **90-days** moving average weight and average sensor FPG with $R = 71\%$ and $R\ square = 51\%$.

Figure 2 presents three diagrams combined which covers the same time period from 5/8/2018 to 11/5/2021.

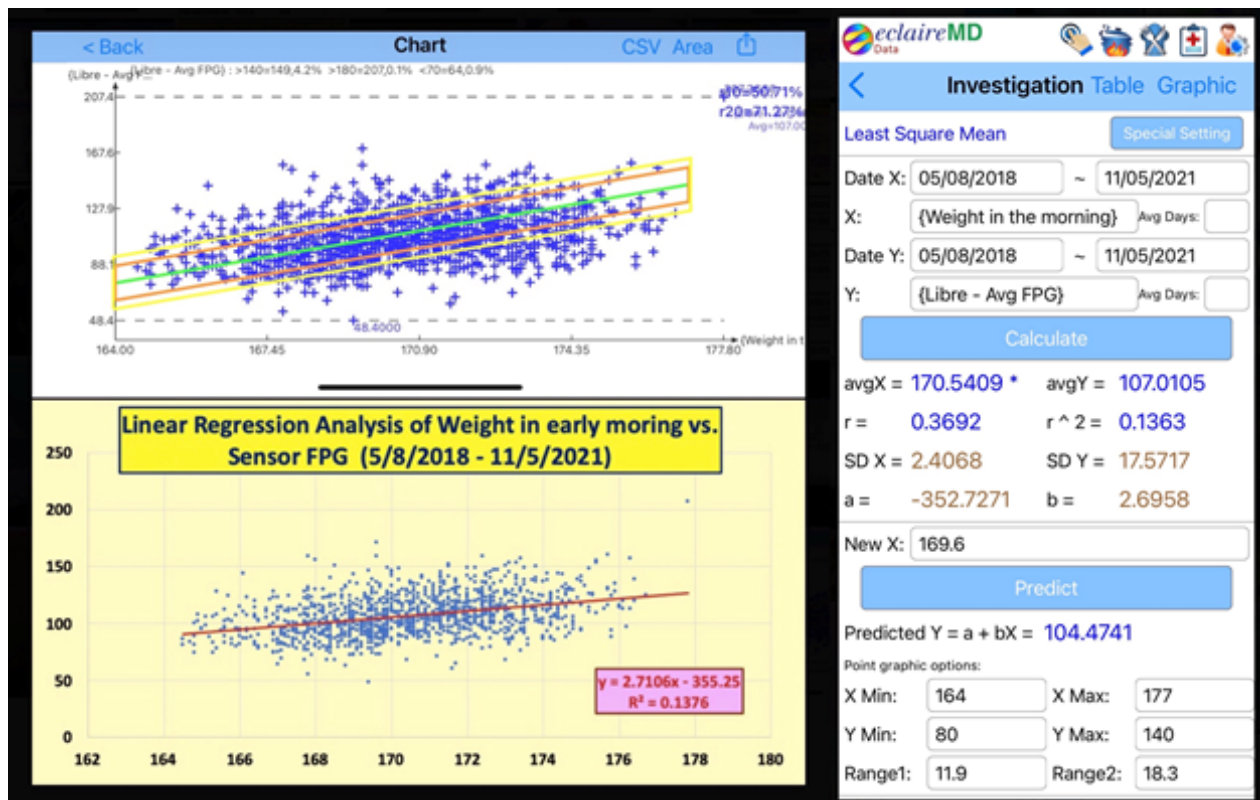


Figure 1: Time-domain analysis results diagram of both daily weight and FPG (lower R and R²) and 90-days moving average weight and FPG (higher R and R²)

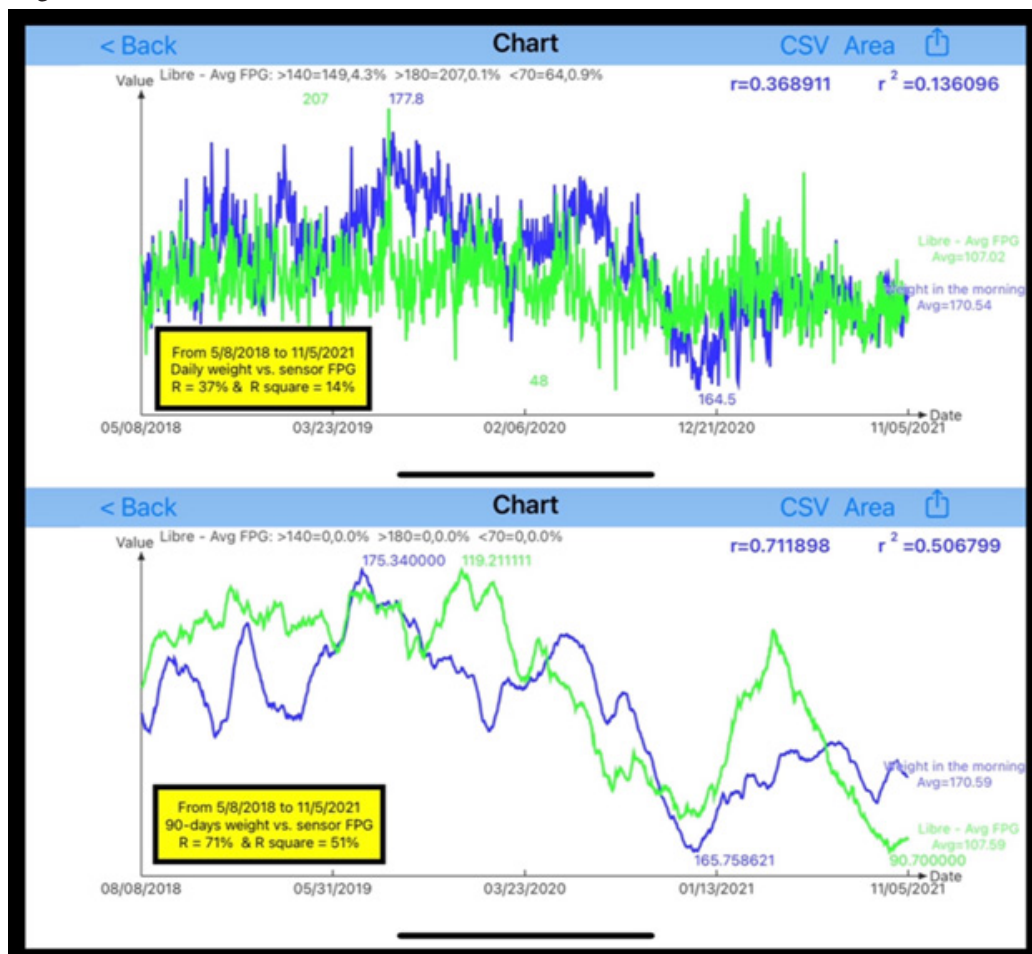


Figure 2: Spatial analysis and Linear regression analysis results diagram of both daily weight (input or independent variable) and average sensor FPG (output or dependent variable)

The diagram on the right-side shows the data table of his developed spatial analysis tool which includes X-values of **weight (independent variable)** and Y-values of sensor average **FPG (dependent variable)**, meal values, R, R², SD-X, SD-Y, plus a value and b value of the **linear regression formula of:**

$$Y = a + bX$$

or

$$Y = -352.7271 + 2.6958 X$$

On the bottom of the right-side diagram, a sample calculation is displayed with a predicted FPG using **X = 169.6 lbs. of weight as the input to obtain a predicted Y = 104.5 mg/dL of FPG as the output.**

The upper-left diagram reflects the results from his developed program of spatial-analysis tool. The orange-colored skewed (at ~37 degrees) rectangular box occupies 51% of the total data area while the yellow-colored skewed (at ~37 degrees) rectangular box occupies 71% of the total data area for the average PPG. These two selected percentages are corresponding to those two different statistics values of 51% (variance, R²) and 71% (correlation, R) in the corresponding time-domain analysis results.

The boundary of the two rectangular boxes for both X (weight) and Y (FPG) are:

$$X_{min} = 164 \text{ lbs.}$$

$$X_{max} = 177 \text{ lbs.}$$

$$(BMI = \sim 25)$$

$$Y_{min} = 80 \text{ mg/dL}$$

$$Y_{max} = 140 \text{ mg/Dl}$$

(Within normal range to pre-diabetes range)

The lower-left diagram depicts the results from his linear regression analysis. It should be pointed out that *the linear regression's blue-colored data cloud is identical to the blue-colored data cloud in the upper-left diagram of the spatial analysis.* The central red-colored and skewed line is the calculated trend-line from the linear regression analysis.

The linear regression trend-line's formula is

$$Y = 2.7106 X - 355.25$$

$$\text{with } R = 36.9\% \text{ and } R^2 = 13.6\%$$

(they are the same as the time-domain daily dataset, not i0-days moving averaged data)

Conclusions

In summary, these three approaches have their individual pros and cons. From a mathematical viewpoint, the second approach of spatial analysis is the same as the linear regression analysis, using mean, least square mean, standard deviation, correlation coefficient, variance, etc. However, the spatial analysis model offers advantages to application flexibility, clear graphic presentation, and associated result interpretation.

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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.eclaircmd.com.

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