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Using Regression Analysis Model to Explore the Relationship Between the CGM Sensor Measured Fasting Plasma Glucose from Sleeping Hours and Measured Body Temperature in the Early Morning Over a One-Year Period for a Type 2 Diabetes Patient Based on GH-Method: Math-Physical Medicine (No. 555)

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Note: *Readers who want to get a quick overview can read the abstract, results and graphs sections.*

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Abstract

The author began measuring his finger-piercing fasting plasma glucose (FPG) at the wakeup moment starting on the morning of 1/1/2012. In addition, he started measuring his FPG using a continuous glucose monitoring (CGM) device at 15-minute time intervals beginning on 5/8/2018. His sensor FPG uses the average glucose value between 12:00 midnight and 07:00 AM for a total of 29 glucose values. Incidentally, the difference between his average finger FPG and average sensor FPG is a mere 1%.

Since 10/1/2020, he has been measuring his daily ***body temperature (BT)*** *and blood oxygen levels at the wakeup moment in the early morning as an additional daily biomarker to monitor for possible COVID-19 infection. Currently, he has over one year's worth of data on his BT. He wondered which primary biomarkers would have a connection with BT. Through a quick and easy time-domain analysis, he identified that his FPG has an extremely high correlation with BT,* ***using the 90-days moving average data, finger FPG vs. BT at 73%, and using the 90-days moving average data, sensor FPG vs. BT at 85%****, for the one-year period from 11/21/2020 to 11/21/2021. Therefore, he decided to use his CGM sensor FPG as the dependent variable Y and his BT as the independent variable X to conduct a space-domain regression analysis.*

In this particular article, he has also compared the regression analysis results from using his daily data (in current paper No. 555) and the 90-days moving average data (in paper No. 535).

In summary, his CGM sensor FPG and BT have a high correlation of 85% with a variance of 72% ***using the 90-days moving average data*** *from 366 observation days. However, his CGM sensor FPG and BT have a low correlation of 20% with a variance of 4%* ***using the daily average data*** *from the same 366 observation days. This finding is expected due to the statistical nature of* ***a daily data curve which fluctuates more and is not synchronized compared with a 90-days moving average data curve, under normal circumstances. Besides, the peaks and nadirs of a daily data waveform would be "smoothed off" in its corresponding moving average data waveform.***

His predicted CGM sensor FPG using his BT as input in both daily and moving average cases have achieved the prediction accuracies of 100%. Despite having different values of correlation and variance, the regression predicted FPG equations from the daily data and moving average data are observed as a linear variance (R^2) of 1.0 or 100% in their trend-line equations. The two-regression predicted Sensor FPG equations are:

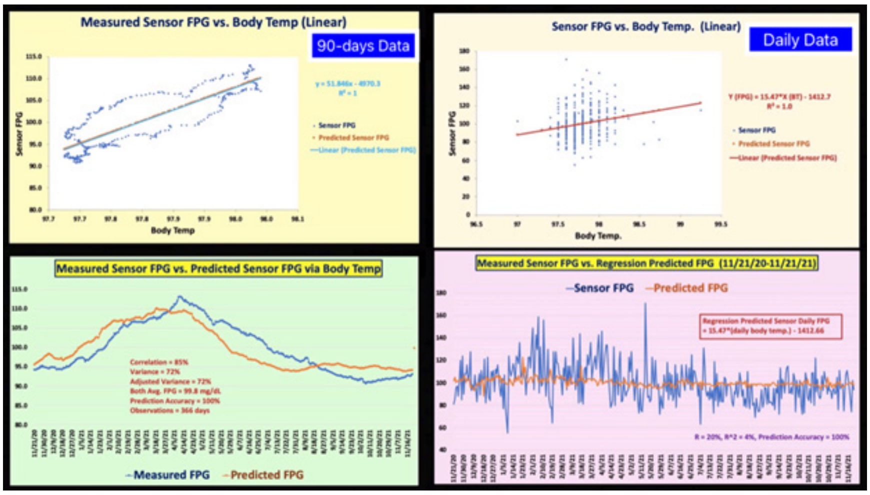
Daily Data Case
Predicted sensor FPG (Y)
= 15.47 * BT (X) - 1412.6t

90-days Moving Average Data Case
Predicted sensor FPG (Y)
= 51.85 * BT (X) - 4970.28

The significance F-values and p-values are extremely small, near zero, in both cases of ***the daily data and moving average data. This indicates that the data in the two datasets are statistically significant.***

Simply put, based on the data from 11/21/2020 to 11/21/2021, his average FPG value during sleep has a tight connection with his BT in the early morning, especially under the moving average data case.

Therefore, the author can guesstimate his fasting glucose value once he knows his BT value. *For verification purpose, using his morning biomarkers of 11/24/2021 as an example, he is able to predict his FPG at 103 mg/dL using the input of his body temperature of 97.9-degree Fahrenheit. His measured FPG level was exactly at 103 mg/dL!*



Introduction

The author began measuring his finger-piercing fasting plasma glucose (FPG) at the wakeup moment starting on the morning of 1/1/2012. In addition, he started measuring his FPG using a continuous glucose monitoring (CGM) device at 15-minute time intervals beginning on 5/8/2018. His sensor FPG uses the average glucose value between 12:00 midnight and 07:00 AM for a total of 29 glucose values. Incidentally, the difference between his average finger FPG and average sensor FPG is a mere 1%.

Since 10/1/2020, he has been measuring his daily ***body temperature (BT)*** and blood oxygen levels at the wakeup moment in the early morning as an additional daily biomarker to monitor for possible COVID-19 infection. Currently, he has over one year's worth of data on his BT. He wondered which primary biomarkers would have a connection with BT. Through a quick and easy time-domain analysis, he identified that his FPG has an extremely high correlation with BT, using the 90-days moving average data, finger FPG vs. BT at 73%, and ***using the 90-days moving average data, sensor FPG vs. BT at 85%***, for the one-year period from 11/21/2020 to 11/21/2021. Therefore, he decided to use his CGM sensor FPG as the dependent variable Y and his BT as the independent variable X to conduct a space-domain regression analysis.

In this particular article, he has also compared the regression analysis results from using his daily data (in current paper No. 555) and the 90-days moving average data (in paper No. 535).

Methods

MPM Background

To learn more about the author's developed GH-Method: math-physical medicine (MPM) methodology, readers can select the following three papers 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, 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".

His Case of T2D and Complications

The author has been a severe T2D patient since 1996 and weighed 220 lbs. (100 kg, BMI 32.5) at that time. By 2010, he still weighed 198 lbs. (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, 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 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 heavy travel period.

During 2020 and 2021 with a strict COVID-19 quarantine 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 satisfactory 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 CKD, bladder, foot, and eye issues such as 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, 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.

Regression Analysis Models

In this study, he will not repeat the detailed introduction of the regression analysis in the Method section because it is available in many statistics' textbook. It should be noted that in regression analysis, the correlation coefficient R should be > 0.5 or 50% to indicate a strong inter-connectivity and the p-value should be < 0.05 to be considered as statistically significant.

Results

Figure 1 displays two time-domain analysis results of ***his daily sensor FPG vs. daily BT (correlation = 20%) and his 90-days moving average sensor FPG vs. 90-days moving average BT (correlation = 84%) using the 90-days average values*** over a one-year period (366 days) from 11/21/2020 to 11/21/2021.

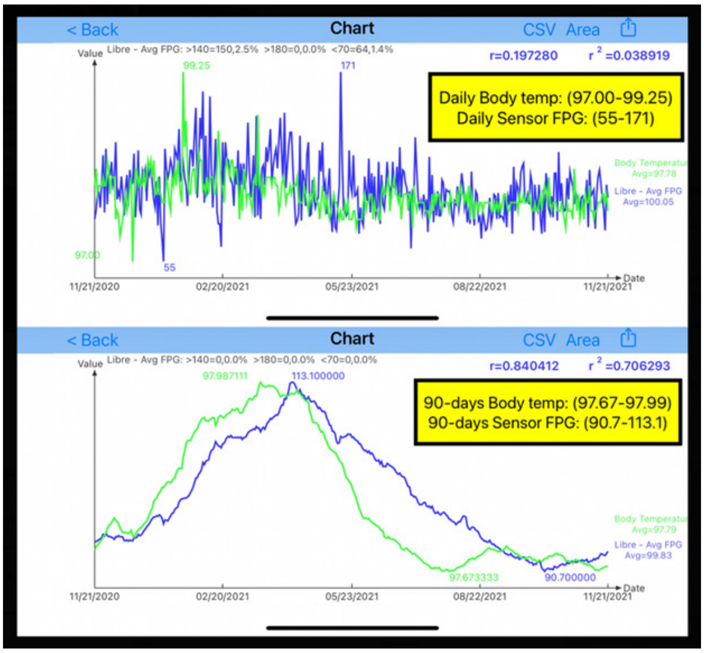


Figure 1: Time-domain analysis of measured daily data curves (top diagram) and 90-days moving averaged data curves (bottom diagram) of sensor FPG vs. body temperature (BT)

The data ranges of FPG & BT biomarkers in each case (daily vs. 90-days) are listed as follows:

Daily Case
BT (degree F): (97.00-99.25)
FPG (mg/dL): (55-171)

90-Days Case
BT (degree F): (97.67-97.99)
FPG (mg/dL): (91-113)

Figure 2 shows the regression analysis data and results table (top diagram) and time-domain plot between sensor FPG and BT (bottom diagram) between the dependent variable Y of his daily CGM sensor FPG versus the independent variable X of the daily BT. The data table illustrates correlation, variance, significance F, p-value, y-intercept, and slope of the trend-line.

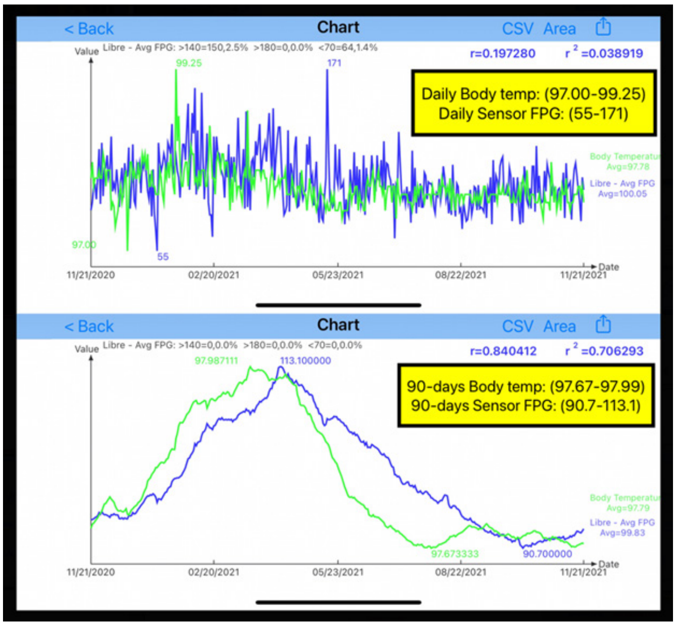


Figure 2: Regression analysis data and results table (top diagram) and time-domain plot between sensor FPG and body temperature (bottom diagram)

Figure 3 reveals the comparison of regression analysis results between using his daily data (left-side diagram) and using the 90-days moving average data (right-side diagram) as inputs. The upper portion is the space-domain's linear regression plot of the sensor FPG (blue dots) versus regression predicted sensor FPG (dark brown dots) with skewed trend-lines. The lower portion is the time-domain diagram of his measured sensor FPG versus the regression predicted FPG.

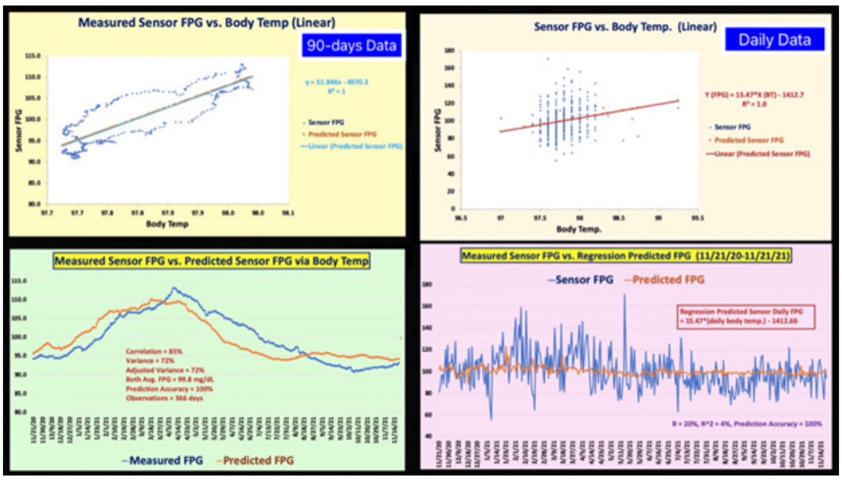


Figure 3: Regression analysis results of top-portion comparison of regression trend-lines from using daily data (right-side) and using 90-days average data (left-side) and bottom-portion comparison of measured FPG vs. predicted FPG from using daily data (right-side) and using 90-days average data (left-side)

The two trend-lines, regression prediction equations, are listed a

Daily Data Case
Predicted sensor FPG (Y)
= 15.47 * BT (X) - 1412.66

90-Days Moving Average Data Case
Predicted sensor FPG (Y)
= 51.85 * BT (X) - 4970.28

Verification

Figure 4 demonstrates a case of his regression model verification using his 11/24/2021 data.

Figure 4: Verification of both model applicability and result accuracy of regression predicted FPG equation on 11/24/2021

The top diagram is the results of both daily data and 90-days moving average data during the period ***from 11/21/2020 to 11/21/2021.*** The predicted FPG results are listed below:

For 11/21/2020-11/21/2921:
Daily case: FPG = 101.8726
90-days case: FPG = 105.5280
Average FPG: FPG = 103.7mg/dL

The bottom diagram is the results of both daily data and 90-days moving average data during the period from ***10/1/2020 to 11/23/2021.*** The predicted FPG results are listed below:

For 10/1/2020-11/23/2921:
Daily case: FPG = 100.6534
90-days case: FPG = 104.7203
Average FPG: FPG = 102.7mg/dL

The average value of 103.7 and 102.7 is 103.3 mg/dL which is his measured sensor FPG of 103 mg/dL in early morning (06:30 am) of 11/24/2021.

Conclusions

In summary, his CGM sensor FPG and BT have a high correlation of 85% with a variance of 72% ***using the 90-days moving average data*** from 366 observation days. However, his CGM sensor FPG and BT have a low correlation of 20% with a variance of 4% ***using the daily average data*** from the same 366 observation days. This finding is expected due to the statistical nature of ***a daily data curve which fluctuates more and is not synchronized compared with a 90-days moving average data curve, under normal circumstances. Besides, the peaks and nadirs of a daily data waveform would be "smoothed off" in its corresponding moving average data waveform.***

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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.

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