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Research Article

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Using Regression Analysis Model to Explore the Hidden Linkage between the CGM Sensor Measured Fasting Plasma Glucose from Sleeping Hours and Body Temperature in Early Morning (both are 90-Days Moving Average Values) over a One-Year Period from 11/21/2020 to 11/21/2021 for a type 2 Diabetes Patient Based on GH-Method: Math-Physical Medicine (No. 553)

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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 started to measure his finger-piercing fasting plasma glucose (FPG) at his wakeup moment in the morning starting on 1/1/2012. In addition, he began to measure his FPG using a continuous glucose monitoring (CGM) device at each 15-minute time interval since 5/8/2018. His sensor 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%.

During the period of 2015-2017, he investigated the correlation between his postprandial plasma glucose (PPG) and its 19 influential factors. He identified that both warmer or colder ambient weather temperature affects PPG level. However, the role of the ambient weather temperature is not like the carbs/sugar intake amount or the post-meal exercise that serve as the primary influential factors of PPG. The temperature only provides a secondary and weaker influential factor of the PPG formation.

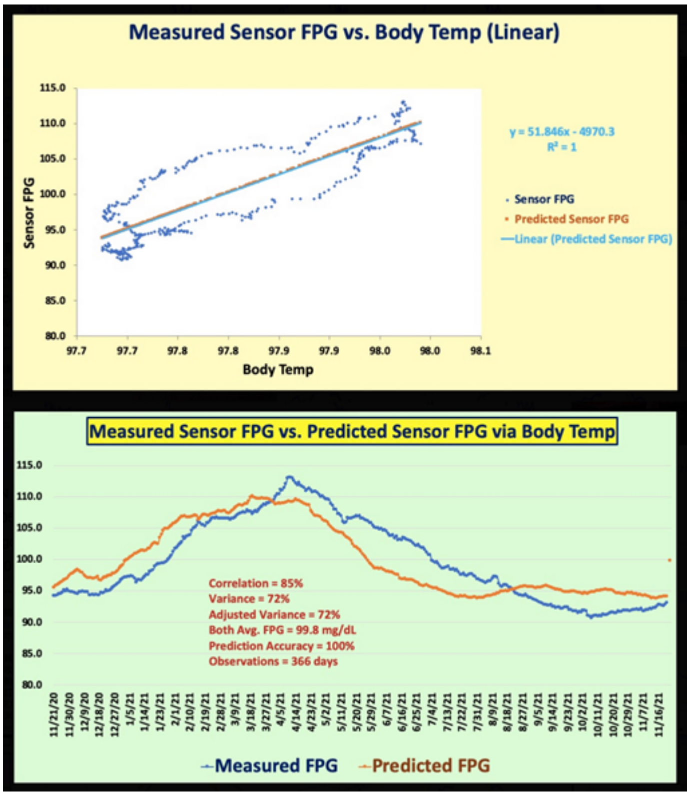
*Starting from 10/1/2020, he set out to measure his daily body temperature (BT) at his wakeup moment in the early morning as an additional daily biomarker to monitor for COVID-19 infection. Currently, he has collected more than one-year data of his body temperature. He wondered which primary biomarkers would have a connection with his BT. Through a quick and easier time-domain analysis, he identified that his FPG has a very high correlation with BT, **finger FPG vs. BT at 73% and sensor FPG vs. BT at 85%, using 90-days moving average values** during 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 summary, his CGM sensor FPG and BT have a high correlation of 85% and variance of 72% using data from 366 observation days. His predicted CGM sensor FPG using his BT as input to achieve a prediction accuracy of 100% is shown in the time-domain diagram with highly comparable waveforms. The predicted FPG equation has a linear variance (R^2) of 1.0 or 100%:

Predicted sensor FPG (Y)
= 51.846 * BT (X) - 4970.3

The significance F and p-values are extremely small, near zero, which indicates that the data in the dataset are statistically significant.

*Simply put, based on the data from 11/21/2020 to 11/21/2021, **his average FPG value during sleep has an extremely tight relationship with BT in the early morning. As a result, he can guess his FPG value once he knows the BT.***



Introduction

The author started to measure his finger-piercing fasting plasma glucose (FPG) at his wakeup moment in the morning starting on 1/1/2012. In addition, he began to measure his FPG using a continuous glucose monitoring (CGM) device at each 15-minute time interval since 5/8/2018. His sensor 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%.

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Starting from 10/1/2020, he set out to measure his daily body temperature (BT) at his wakeup moment in the early morning as an additional daily biomarker to monitor for COVID-19 infection. Currently, he has collected more than one-year data of his body temperature. He wondered which primary biomarkers would have a connection with his BT. Through a quick and easier time-domain analysis, he identified that his FPG has a very high correlation with BT, finger FPG vs. BT at 73% and sensor FPG vs. BT at 85%, using 90-days moving average values during 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.

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 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 finger FPG vs. body temperature (correlation = 73%) and CGM sensor FPG vs. body temperature (correlation = 85%) using 90-days average values*** over a one-year period (366 days) from 11/21/2020 to 11/21/2021.

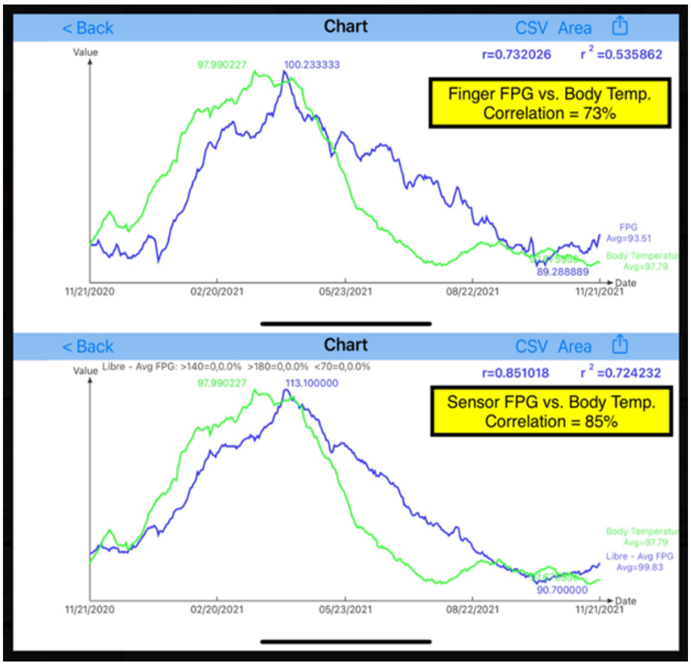

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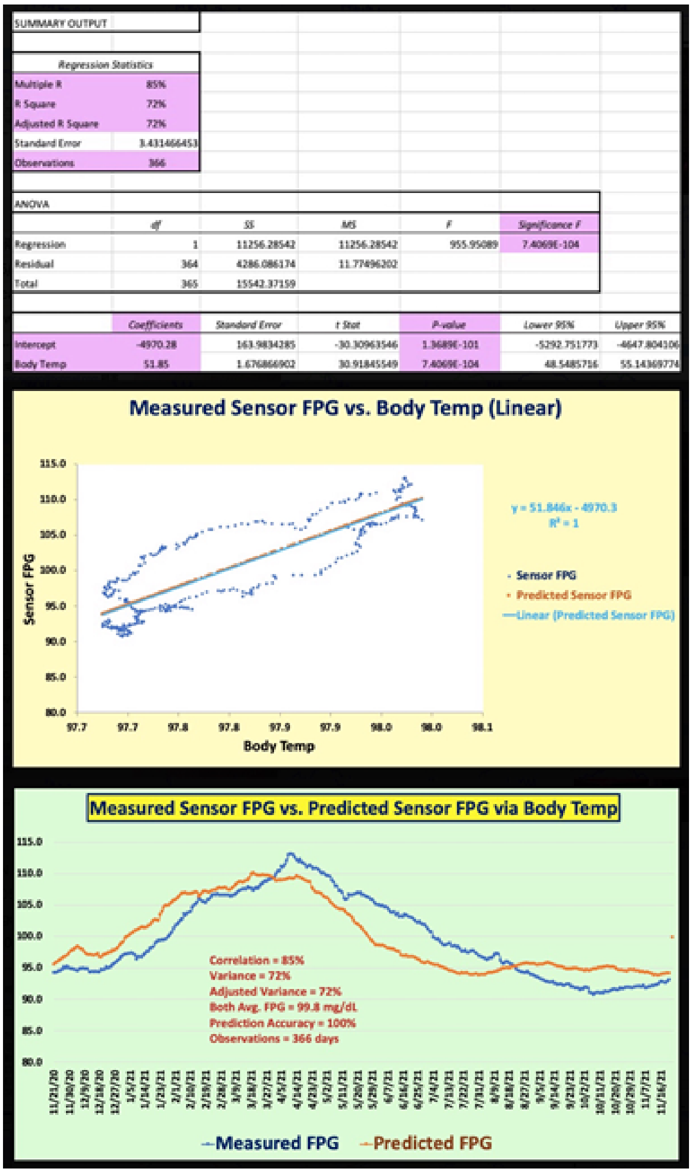
Figure 2 shows the data table and the graphic results of the regression analysis model between the dependent variable Y of his CGM sensor FPG versus the independent variable X of BT.



SUMMARY OUTPUT	
Regression Statistics	
Multiple R	85%
R Square	72%
Adjusted R Square	72%
Standard Error	3.431466453
Observations	366

ANOVA					
	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	11256.28542	11256.28542	955.95089	7.4069E-104
Residual	364	4286.086174	11.77496202		
Total	365	15542.37159			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	-4970.28	163.9834285	-30.30963546	1.3689E-101	-5292.751773	-4647.804106
Body Temp	51.85	1.676866902	30.91845549	7.4069E-104	48.5485716	55.14369774

Figure 2: Regression analysis data, space-domain linear plot between sensor FPG and body temperature, and time-domain between measured FPG vs. predicted FPG

In the top diagram, it illustrates the regression analysis related data.

The middle diagram reveals the space-domain's linear regression plot of the sensor FPG (blue dots) versus predicted sensor FPG (dark brown dots) with a trend-line (light blue straight line). The trend-lines equation is listed as follows:

Predicted sensor FPG
= 51.846 * X - 4970.3

At the bottom, it reflects the time-domain diagram of measured FPG versus regression predicted FPG using BT as the input X variable.

Conclusions

In summary, his CGM sensor FPG and BT have a high correlation of 85% and variance of 72% using data from 366 observation days. His predicted CGM sensor FPG using his BT as input to achieve a prediction accuracy of 100% is shown in the time-domain diagram with highly comparable waveforms. The predicted FPG equation has a linear variance (R^2) of 1.0 or 100%:

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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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