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Using Regression Analysis Models to Explore the Possible Hidden Linkage between Finger-Pierced Fasting Plasma Glucose and Three Blood Pressure Components over an Approximate 8-Year Period for a type 2 Diabetes Patient based on GH-Method: Math-Physical Medicine (No. 552)

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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

When the author woke up on 11/14/2021 around 07:20AM, he felt lightheaded, nauseated, and had cold-sweat. Being a long-time type 2 diabetes (T2D) patient of over 27 years, he immediately noticed and guessed that it could be a symptom of hypoglycemia or low blood sugar. However, his continuous glucose monitoring (CGM) sensor device showed a normal glucose reading of 102 mg/dL. He then measured his blood pressure (BP) and was shocked to find the low readings for SBP/DBP/HR of 79/47/37. These extremely low readings are considered almost dangerous and in the abnormal range for the combined conditions of hypotension (low blood pressure) and bradycardia (slow heart rate). These kinds of low readings lasted for ~2 hours.

This incident peaked his curiosity which caused an immediate interest to identify the relationship existing between glucose, especially fasting plasma glucose (FPG), and three blood pressure components systolic blood pressure (SBP), diastolic blood pressure (DBP), and heart rate (HR). He then started to explore and read several published medical papers regarding this specific subject.

In this article, it describes the research efforts and findings by using his own biophysical data from the approximate 8-year period from 1/1/2014 to 11/18/2021. To reduce his data preparation workload for the following task of regression study, he further subdivided the daily data into ***16 semi-annual perods*** *with the corresponding biomarker results. In his data table, he labeled them as WY2014, CY2021, etc., where "W" indicates the* ***"Warmer"*** *semi-annual period from April 1st through September 30th of each year. Whereas "C" indicates the* ***"Cooler"*** *semi-annual period from October 1st of one year through March 31st of the next year. In this way, he can then reduce the observation data amount from 2,879 days to only 16 semi-annual periods. As a benefit of organizing the data this way, he could also observe whether ambient (weather) temperature has any influence on his BP and FPG.*

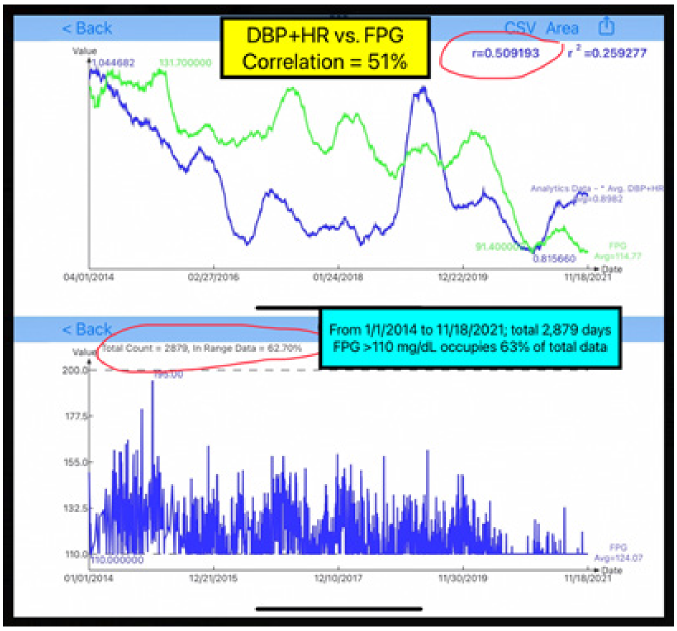
Of course, at the end of his research and for comparison purposes, he also conducted an additional time-domain analysis of the FPG and BP along with the regression analysis calculations of both correlation (R) and variance (R^2 or R square) ***based on the daily data of BP and FPG.***

Incidentally, the FPG values used in the study are ***finger-piercing FPG, not CGM sensor FPG,*** *because he began utilizing a CGM device on 5/8/2018.*

In summary, the author's time-domain analysis and space-domain regression analysis for exploring the possible relationships existing between FPG and three BP components provide the following five observations:

(1) It appears that none of the three BP components, SBP, DBP, and HR individually, have a very strong correlation or significant contribution to FPG. FPG has shown two moderate correlations with DBP (R=44%) and HR (R=42%).

However, FPG has displayed an extremely low correlation with SBP (R=14%); therefore, in conclusion, FPG almost has no relationship with SBP. This is the main reason of excluding SBP in his daily data analysis. ***It should be noted that all of the calculated p-values and significance F values are relatively small, but still slightly greater than 5%.*** *This means that all data used in this analysis are* ***"somewhat"*** *statistically significant.*
(2) However, by combining three of them together, the total BP value has demonstrated a substantial correlation with FPG; therefore, the combination of 3 BP components make significant contribution (R=76%) to FPG.
(3) A general graphic observation of time-domain results illustrate that the regression model predicted dependent variable (Predicted FPG) curve is relatively smoother and less-bumpy than the measured FPG curve due to the nature of the statistical regression model.
(4) The author has obtained ***a slightly different conclusion*** *from the predicted FPG curve versus the measured FPG curve* ***using his daily biomarker data****. His space-domain linear regression model has reached a correlation of 48% and a variance of 23%, while the time-domain model has achieved a correlation of 51% and a variance of 26%. Although the two sets of values are not identical, but they are extremely close to each other. In addition,* ***there are no observed difference on the measured daily BP values due to either warmer or cooler ambient (weather) temperatures.***
(5) Nevertheless, the correlation values of 48% or 51% are still not high enough to indicate the existence of a strong relationship, just a moderate level, existing between the Measured daily DBP+HR and Predicted daily DBP+HR. ***It should also be noted that in the daily biomarker data analysis, his BP includes DBP and HR only, while excluding SBP.***
(6) During the approximate 8-year period, ***the percentage of hyperglycemia (above 110 mg/dL) of his FPG is 63% which is concentrated during a longer period of 2014-2019.*** *During the COVID-19 period of 2020-2021, he successfully maintained his FPG below 110 mg/dL due to his lifestyle management without medication intervention. Therefore, this study still offers useful and beneficial information for other T2D patients who have similarly higher FPG values (above 110 mg/dL) from time to time.*



Introduction

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Of course, at the end of his research and for comparison purposes, he also conducted an additional time-domain analysis of the FPG and BP along with the regression analysis calculations of both correlation (R) and variance (R^2 or R square) ***based on the daily data of BP and FPG.***

Incidentally, the FPG values used in the study are ***finger-piercing FPG, not CGM sensor FPG***, because he began utilizing a CGM device on 5/8/2018.

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 a time-domain analysis of his ***combined daily DBP and HR daily curve versus*** the daily FPG curve over an approximate 8-year period (2,879 days) from 1/1/2014 to 11/18/2021. It should be pointed out that the correlation between these two curves is 51% and ***his FPG hyperglycemia (above 110 mg/dL) occupies 63% (1,805 days) of the total data population of 2,879 days.***

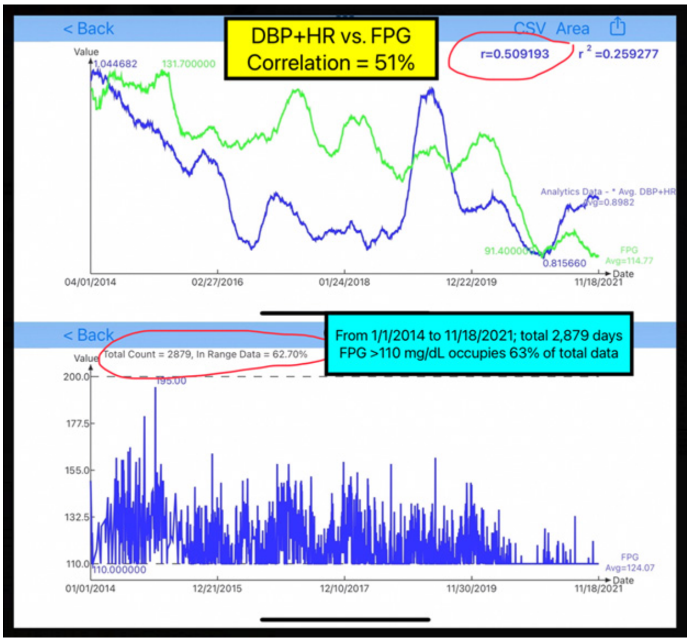

Figure 1: Time-domain analysis of daily FPG vs. daily DBP+HR and 63% of FPG's hyperglycemia

Figure 2 shows the data table and Figure 3 illustrates the graphic results of regression analysis model between the dependent variable of FPG versus three BP components, SBP, DBP, and HR ***individually.***

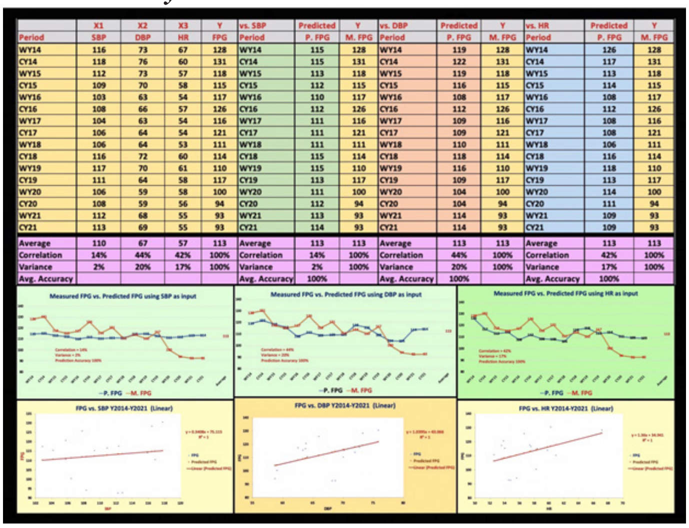

Figure 2: Data table and regression analysis results of FPG vs. 3 BP components individually

From both Figures 2 and 3, the correlation between FPG and DBP/HR are moderate (44% / 42%), while FPG vs. SBP is extremely low (only 14%). The linear regression model for three components vs. FPG have already achieved a perfect variance of 1.0. As a result, there is no need to perform nonlinear regression calculations.

Figure 3 reflects the comparison of measured FPG versus regression predicted FPG using three BP components as inputs, which are three BP independent variables X. *It has attained a higher correlation of 76% and variance of 57%. Both Significance F and p-values are exceptionally low with less than 0.05 or 5%.* Incidentally, the predicted FPG curve is smoother than the measured FPG curve.

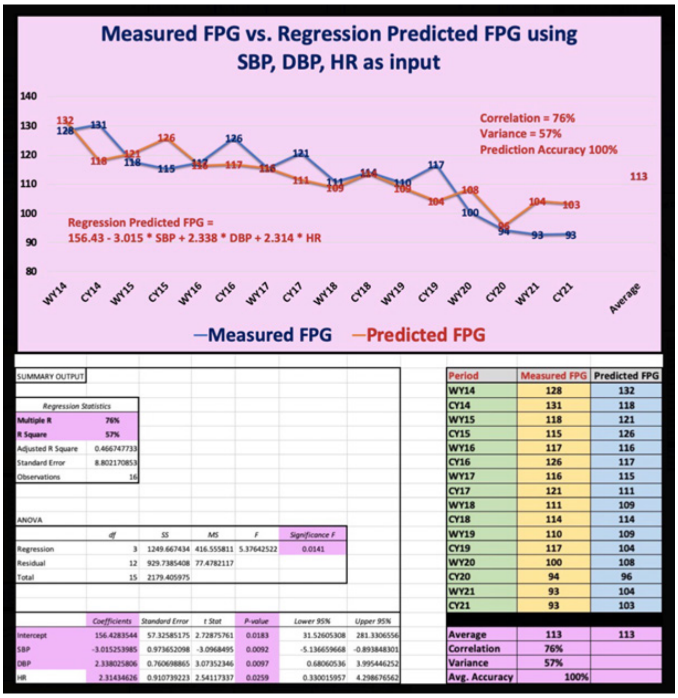

Figure 3: Data table and regression analysis results of FPG vs. combined BP values

The derived linear regression equation with multiple variables is expressed as follows:

Regression predicted FPG =
156.43 - 3.015*SBP + 2.338*DBP + 2.314*HR

Figure 4 reveals the data table and Figure 5 specifies the graphic results of regression analysis model between the dependent variable Y of ***daily FPG versus three daily BP components, and DBP+HR.*** The big daily data is expressed via 16 semi-annual periods to reduce the burden of data preparation for regression analysis.

11/18/21	X2	X3	11/18/21	X	Y	11/18/21	Predicted	
Period	DBP	HR	Period	DBP + HR	FPG	Period	Predicted BP	Measured BP
WY14	73	67	WY14	1.02	128	WY14	0.93	1.02
CY14	76	60	CY14	0.98	131	CY14	0.94	0.98
WY15	73	57	WY15	0.93	118	WY15	0.91	0.93
CY15	70	58	CY15	0.93	115	CY15	0.90	0.93
WY16	63	54	WY16	0.84	117	WY16	0.91	0.84
CY16	66	57	CY16	0.88	126	CY16	0.92	0.88
WY17	63	54	WY17	0.85	116	WY17	0.90	0.85
CY17	64	54	CY17	0.85	121	CY17	0.91	0.85
WY18	64	53	WY18	0.84	111	WY18	0.89	0.84
CY18	72	60	CY18	0.95	114	CY18	0.90	0.95
WY19	70	61	WY19	0.95	110	WY19	0.89	0.95
CY19	64	58	CY19	0.88	117	CY19	0.90	0.88
WY20	59	58	WY20	0.85	100	WY20	0.87	0.85
CY20	59	56	CY20	0.83	94	CY20	0.85	0.83
WY21	68	55	WY21	0.88	93	WY21	0.85	0.88
CY21	69	55	CY21	0.88	93	CY21	0.85	0.88
Average	67	57	Average	0.90	113	Average	0.90	0.90
Correlation	44%	42%	Correlation	48%	100%	Correlation	48%	100%
Variance	20%	17%	Variance	23%	100%	Variance	23%	100%
Avg. Accuracy			Avg. Accuracy			Avg. Accuracy	100%	

SUMMARY OUTPUT

Regression Statistics	
Multiple R	48%
R Square	23%
Adjusted R Square	18%
Standard Error	0.050813497
Observations	16

ANOVA

	df	SS	MS	F	Significance F
Regression	1	0.010913393	0.010913393	4.226701975	0.059
Residual	14	0.036148161	0.002582012		
Total	15	0.047061554			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	0.6431	0.123345065	5.213796575	0.000	0.378547223	0.907644927
FPG	0.0022	0.001088454	2.055894446	0.059	-9.67551E-05	0.004572248

Figure 4: Data table and regression analysis results of 16 semi-annual FPG data vs. daily DBP+HR values

From Figures 4 and 5, the correlation between FPG and DBP+HR is moderate (48%), while the variance is 23%. The linear regression model for daily DBP+HR vs. daily FPG has already reached a perfect variance of 1.0. As a result, there is no need to perform the nonlinear regression calculations.

Figure 5 indicates the comparison of ***measured daily DBP+HR versus regression predicted daily DBP+HR using the daily FPG as inputs*** (independent variables X). It has achieved another moderate correlation of 51% and variance of 26%. However, these R and R^2 values of the combined DBP+HR are slighter higher than their independent R values of 44% with DBP and 42% with HR. Both Significance F and p-values of 0.06 are remarkably close to the boundary of 0.05 or 5%. Again, the predicted DBP+HR curve is smoother than the measured DBP+HR curve.

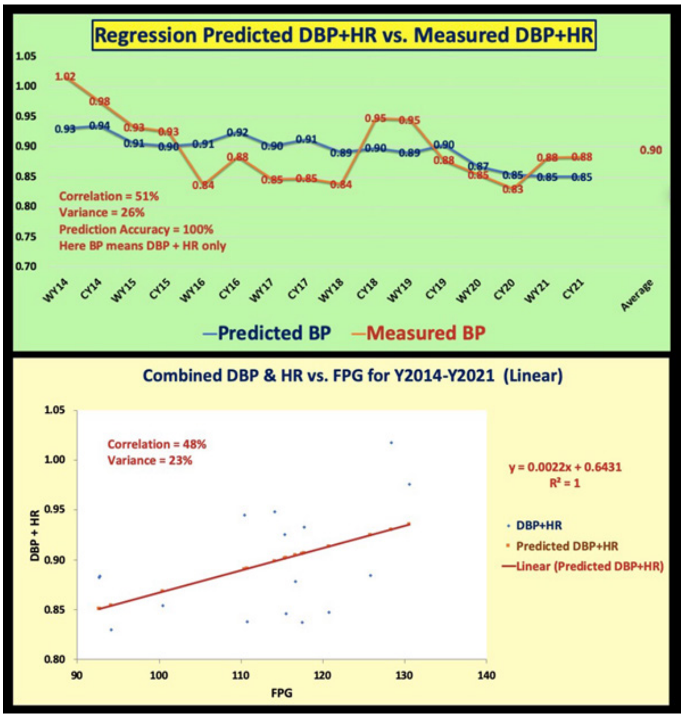

Figure 5: Regression analysis results of 16 semi-annual data between measured DBP+HR vs. predicted DBP+HR values using semi-annual FPG value as inputs

The derived linear regression equation with a single variable of combined DBP and HR is expressed as follows:

Regression predicted DBP+HR =
0.6431 + 0.0022*FPG

Conclusions

In summary, the author's time-domain analysis and space-domain regression analysis for exploring the possible relationships existing between FPG and three BP components provide the following five observations:

(1) It appears that none of the three BP components, SBP, DBP, and HR individually, have a very strong correlation or significant contribution to FPG. FPG has shown two moderate correlations with DBP (R=44%) and HR (R=42%). However, FPG has displayed an extremely low correlation with SBP (R=14%); therefore, in conclusion, FPG almost has no relationship with SBP. This is the main reason of excluding SBP in his daily data analysis. ***It should be noted that all of the calculated p-values and significance F values are relatively small, but still slightly greater than 5%.*** *This means that all data used in this analysis are* ***"somewhat"*** *statistically significant.*

(2) However, by combining three of them together, the total BP value has demonstrated a substantial correlation with FPG; therefore, the combination of 3 BP components make significant contribution (R=76%) to FPG.

(3) A general graphic observation of time-domain results illustrate that the regression model predicted dependent variable (Predicted FPG) curve is relatively smoother and less-bumpy than the measured FPG curve due to the nature of the statistical regression model.

(4) The author has obtained a ***slightly different conclusion*** from

the predicted FPG curve versus the measured FPG curve ***using his daily biomarker data.*** His space-domain linear regression model has reached a correlation of 48% and a variance of 23%, while the time-domain model has achieved a correlation of 51% and a variance of 26%. Although the two sets of values are not identical, but they are extremely close to each other. In addition, ***there are no observed difference on the measured daily BP values due to either warmer or cooler ambient (weather) temperatures.***

(5) Nevertheless, the correlation values of 48% or 51% are still not high enough to indicate the existence of a strong relationship, just a moderate level, existing between the Measured daily DBP+HR and Predicted daily DBP+HR. ***It should also be noted that in the daily biomarker data analysis, his BP includes DBP and HR only, while excluding SBP.***

(6) During the approximate 8-year period, ***the percentage of hyperglycemia (above 110 mg/dL) of his FPG is 63% which is concentrated during a longer period of 2014-2019.*** During the COVID-19 period of 2020-2021, he successfully maintained his FPG below 110 mg/dL due to his lifestyle management without medication intervention. Therefore, this study still offers useful and beneficial information for other T2D patients who have similarly higher FPG values (above 110 mg/dL) from time to time.

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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