ISSN: 2689-1204

Research Article

Journal of Applied Material Science & Engineering Research

Predicting the Fasting Plasma Glucose Level Using Two Linear Regression Equations from Body Temperature and Weight in the Early Morning as Inputs over a 14-Month Period for a type 2 Diabetes Patient Based on GH-Method: Math-Physical Medicine (No. 558)

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Submitted: 01 Dec 2021; **Accepted:** 08 Dec 2021; **Published:** 28 Dec 2021

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

Citation: *Gerald C Hsu (2021) Predicting the Fasting Plasma Glucose Level Using Two Linear Regression Equations from Body Temperature and Weight in the Early Morning as Inputs over a 14-Month Period for a type 2 Diabetes Patient Based on GH-Method: Math-Physical Medicine (No. 558). J App Mat Sci & Engg Res, 5(4), 01-07.*

Abstract

The author is a 27-year type 2 diabetes (T2D) patient, who has self-studied and researched diabetes, endocrinology, and chronic disease induced complications since 2010. He is a mathematician and engineer but not a medical doctor; therefore, he does his best to derive some mathematical equations or formulas with sufficient accuracy to describe the observed biomedical or biophysical phenomena.

His medical research work started with the task of collecting big data on his own biomarker values and lifestyle details. To date, he has collected and processed nearly 3 million data related to his health. The data in this article covers a few categories. Since 1/1/2012, he has accumulated data on his body weight in the early morning. Beginning on 1/2/2013, he measures his finger-piercing fasting plasma glucose (FPG) at the wakeup moment in the morning. In addition, starting on 5/8/2018, he measures his FPG using a continuous glucose monitoring (CGM) sensor device at 15-minute time intervals. 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 (104.6 mg/dL) and average sensor FPG (106.8 mg/dL) over the 3.5-year period from 5/8/2018 to 11/27/2018 is a mere 2%.***

In addition, since 10/1/2020, he measures his ***body temperature (BT)*** *and finger blood oxygen levels at the wake-up moment in the morning as biomarkers to monitor for possible COVID-19 infection. Currently, he has over one year's worth of data on his BT and wondered which primary biomarkers would have a connection. 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%,*** *over the one-year period from 11/21/2020 to 11/21/2021.*

Several years ago, he identified a strong correlation (≥ 90%) existing between his finger FPG and body weight (Weight).

In this article, he decided to use his CGM sensor FPG as the dependent variable Y and BT along with body weight as the independent variables X to conduct a space-domain regression analysis. The purpose is to develop a series of linear equations using BT and Weight as the inputs to quickly determine the desired output, his guesstimate sensor FPG value having a high prediction accuracy percentage without applying either finger-piercing device or CGM sensor device to measure his FPG level in the morning.

In summary, there are 3 observed conclusions as follows:

(1) There are no observed high correlation (-43%) existing between his measured BT and Weight. Furthermore, from the two-regression predicted FPG via BT and Weight as individual inputs, both have different and are not highly correlated ***(69% for FPG via BT and 12% for FPG via Weight)*** *with his measured FPG over this 14-month period. However,* ***the average regression predicted FPG, i.e. (FPG via BT + FPG via weight) / 2, has a high correlation of 82% (variance 67%) with his measured FPG over the same period.***

*(2) The regression model derived three average predicted FPG data: FPG via BT, FPG via Weight, and average predicted FPG. They have **extremely high** prediction accuracies (96%-99%) in comparison with the average measured FPG value. This means that the 3 predicted FPG equations are accurate enough for the time period. **The regression predicted FPG equations are listed as follows:***

Body Weight Case
Predicted finger FPG (Y)
= 4.314 * Weight (X) - 629.34

Body Temperature Case
Predicted sensor FPG (Y)
= 51.85 * BT (X) - 4970.28
(3) In conclusion, the average predicted FPG equation is the most suitable for predicting his FPG value (either sensor FPG or finger FPG values). Therefore, he can guesstimate an accurate FPG value using his BT and Weight as inputs, without applying either finger-piercing or CGM sensor devices for measuring his FPG value in the morning.

Introduction
The author is a 27-year type 2 diabetes (T2D) patient, who has self-studied and researched diabetes, endocrinology, and chronic disease induced complications since 2010. He is a mathematician and engineer but not a medical doctor; therefore, he does his best to derive some mathematical equations or formulas with sufficient accuracy to describe the observed biomedical or biophysical phenomena.

His medical research work started with the task of collecting big data on his own biomarker values and lifestyle details. To date, he has collected and processed nearly 3 million data related to his health. The data in this article covers a few categories. Since 1/1/2012, he has accumulated data on his body weight in the early morning. Beginning on 1/2/2013, he measures his finger-piercing fasting plasma glucose (FPG) at the wakeup moment in the morning. In addition, starting on 5/8/2018, he measures his FPG using a continuous glucose monitoring (CGM) sensor device at 15-minute time intervals. 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 (104.6 mg/dL) and average sensor FPG (106.8 mg/dL) over the 3.5-year period from 5/8/2018 to 11/27/2018 is a mere 2%.***

In addition, since 10/1/2020, he measures his **body temperature (BT)** and finger blood oxygen levels at the wakeup moment in the morning as biomarkers to monitor for possible COVID-19 infection. Currently, he has over one year's worth of data on his BT and wondered which primary biomarkers would have a connection. 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%,*** over the one-year period from 11/21/2020 to 11/21/2021.

Several years ago, he identified a strong correlation (≥ 90%) existing between his finger FPG and body weight (Weight).

In this article, he decided to use his CGM sensor FPG as the dependent variable Y and BT along with body weight as the independent variables X to conduct a space-domain regression analysis. ***The purpose is to develop a series of linear equations using BT and Weight as the inputs to quickly determine the desired output, his guesstimate sensor FPG value having a high prediction accuracy percentage without applying either finger-piercing device or CGM sensor device to measure his FPG level in the morning.***

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 or 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.

Excerpt from One Paper Regarding Body Temperature and Glucose

The following article is written and published by Dr. Ben Bikman on October 7, 2020. It describes how glucose levels impact our body temperature, and how glucose spikes can lead to elevated body temperature.

"*In the never-ending pursuit of homeostasis, our bodies work to regulate countless processes. Paramount among these is body temperature. Even a body temperature shift of a few degrees can* *be catastrophic for our health; enzymes slow down, electrolytes get too low, and hormones don't work as well [1]. Unfortunately, temperature regulation in the body is disrupted when metabolic function is disrupted and glucose levels are elevated.*

The heat we produce in our bodies is the result of countless chemical reactions occurring in every cell. This heat production is generally matched with an equal heat dissipation, ensuring body temperature stays in a narrow range. Human bodies have a unique advantage over other terrestrial mammals—our naked skin is a superior thermoregulator, allowing us greater heat dissipation than other animals. Interestingly, glucose, a seemingly innocent nutrient, gets in the way.

Of course, the most obvious instance is elevated glucose in diabetes, where we see this phenomenon quite readily. Whether it's type 1 or type 2, people with diabetes have a harder time keeping body temperature in control [2]. This phenomenon is particularly evident with exercise in diabetes. During exercise, the increased physical exertion results in greater heat production, which is generally accounted for by a comparable increase in heat loss. However, the "heat loss" side of the equation is compromised with diabetes. Indeed, during a bout of exercise, someone with diabetes will keep up to 54% more heat than a comparably sized person without diabetes [2, 3]!

Importantly, the problem of glucose-induced changes in body temperature isn't simply a consequence of chronically elevated glucose levels. Even in healthy people without diabetes, acute spikes in glucose, either by glucose infusion or excessive carbohydrate consumption, body temperature climbs [4, 5].

The blood vessel is at the core of the problem with poor body temperature control and high glucose levels. To effectively remove heat from the body, we need a hemodynamic shift that arises from coordinated changes in the size of blood vessels throughout the body—blood vessels in the core of the body constrict, and those at the periphery (i.e., skin) dilate. These changes allow the body to transfer the heat from deep within the body to the skin and eventually to the air around the body.

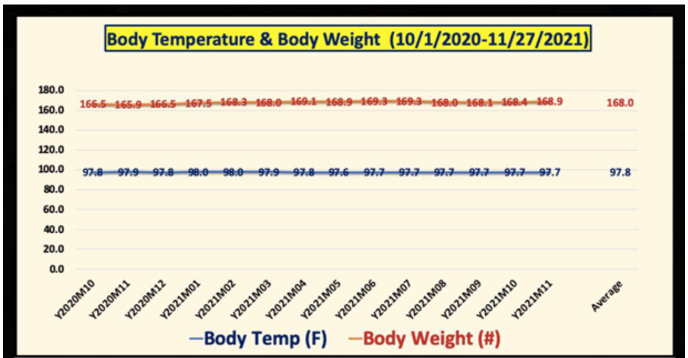
Beyond the discomfort of being hot and sweaty, having a high body temperature can compromise optimal function, including one of the most important things we do for our health: sleep. Increased body temperature, especially through reduced heat dissipation, is one of the most common causes of "frequent waking" insomnia [6]. Thus, it's little surprise that consuming a high-carbohydrate load before bed, and the commensurate blood glucose and body temperature spike, results in more frequent waking and worse sleep [7].

So, if you're "feeling the heat," it might be time to check your glucose levels."

From this excerpt of Dr. Bikman's biochemical alphabetic descriptions, the author has learned that elevated glucose can definitely create higher body temperature. In addition, from his own numerical and quantitative data and math-physical analysis, he can also prove the close linkage between FPG and body temperature via very high correlation coefficients and variances of two datasets: sensor FPG and finger FPG versus his body temperature measured in early morning. Although the majority of his body temperatures in early morning fall into a very narrow range of 97.1 to 97.9 degree Fahrenheit, even an 0.1 degree of body temperature change can be associated with a visible FPG change.

Results

Figure 1 displays the input data table and regression analysis results (bottom diagram) and the comparison of his measured BT along with body weight during the selected 14-month period (upper diagram).



11/27/21	Measured	Measured	11/27/21	Regression	Regression	Regression	Measured
Period	Body Temp (F)	Body Weight (#)	Period	S. FPG via BT	S. FPG via W	Avg S. FPG	Measured S. FPG
Y2020M10	97.8	166.5	Y2020M10	99	89	94	93
Y2020M11	97.9	165.9	Y2020M11	105	86	96	93
Y2020M12	97.8	166.5	Y2020M12	102	89	95	103
Y2021M01	98.0	167.5	Y2021M01	110	93	102	106
Y2021M02	98.0	168.3	Y2021M02	113	97	105	111
Y2021M03	97.9	168.0	Y2021M03	107	96	101	111
Y2021M04	97.8	169.1	Y2021M04	100	100	100	108
Y2021M05	97.6	168.9	Y2021M05	91	99	95	97
Y2021M06	97.7	169.3	Y2021M06	98	101	99	101
Y2021M07	97.7	169.3	Y2021M07	94	101	98	94
Y2021M08	97.7	168.0	Y2021M08	96	95	96	87
Y2021M09	97.7	168.1	Y2021M09	95	96	95	94
Y2021M10	97.7	168.4	Y2021M10	94	97	96	95
Y2021M11	97.7	168.9	Y2021M11	95	99	97	95
Average	97.8	168.0	Average	100	96	98	99
Accuracy			Accuracy	99%	96%	99%	
Correlation	BT/W		Correlation	FPG: BT/W		M/R: FPG	
Correlation	-43%		Correlation	69%	12%	82%	
Variance	18%		Variance	48%	1%	67%	

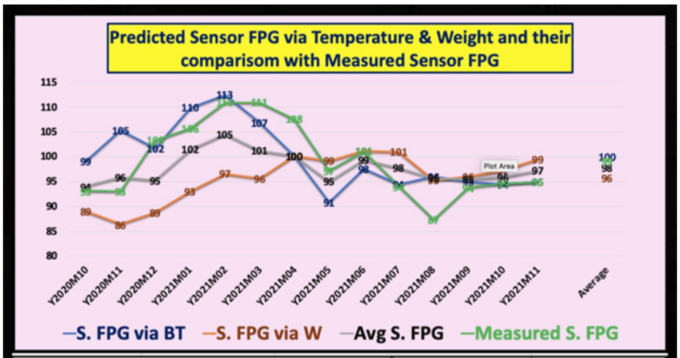
Figure 1: Input data table and regression analysis results of body temperature (BT) and weight over a 14-month period

The regression predicted FPG equations are listed as follows:

Body weight case
Predicted finger FPG (Y)
= 4.314 * Weight (X) - 629.34

Body temperature case
Predicted sensor FPG (Y)
= 51.85 * BT (X) - 4970.28

Figure 2 shows the comparison among 4 FPG curves: Predicted FPG via BT, Predicted FPG via weight, average predicted FPG, and measured FPG.



Biomarkers (10/1/2020 -11/27/2020)	Correlation	Variance
Body Weight vs. Body Temperature	-43%	18%
Predicted Sensor FPG using Body Temperature	69%	48%
Predicted Sensor FPG using Body Weight	12%	1%
Averaged Sensor FPG based on Temp & Weight	82%	67%
Measured Sensor FPG	100%	100%

Figure 2: Three regression predicted FPG curves and the measured FPG curve with the Comparison table of correlation and variance

Figure 3 signifies the direct comparison of measured FPG versus average regression predicted FPG. Their correlation is 82% with a variance of 67%, which can be observed from the waveform similarity of the two curves in Figure 3.

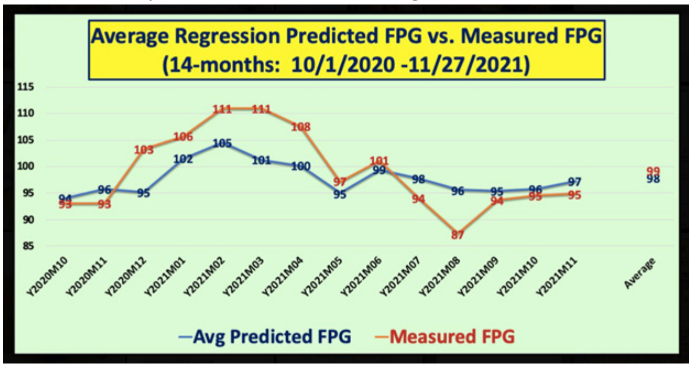


Figure 3: Direct Comparison of average predicted FPG versus measured FPG over 14 months

Figure 4 illustrates three comparison of correlation results among weight vs. sensor FPG (72%), weight vs. Finger FPG (75%), and sensor FPG vs. finger FPG (89%) within the same time-window from 8/8/2018 to 11/28/2021. It should be pointed out that the average glucoses difference sensor FPG and finger FPG during this period is a mere 2%. This means that *in his analysis, the average data of sensor FPG and finger FPG are interchangeable.*

Figure 4: Comparison of weight vs. both sensor FPG and finger FPG, and comparison between sensor FPG and finger FPG

Figure 5 reflects two predicted FPG equations of sensor FPG via body temperature over 1 year and finger FPG via body weight over 8 years. Both results have shown extremely high correlation of 84%.

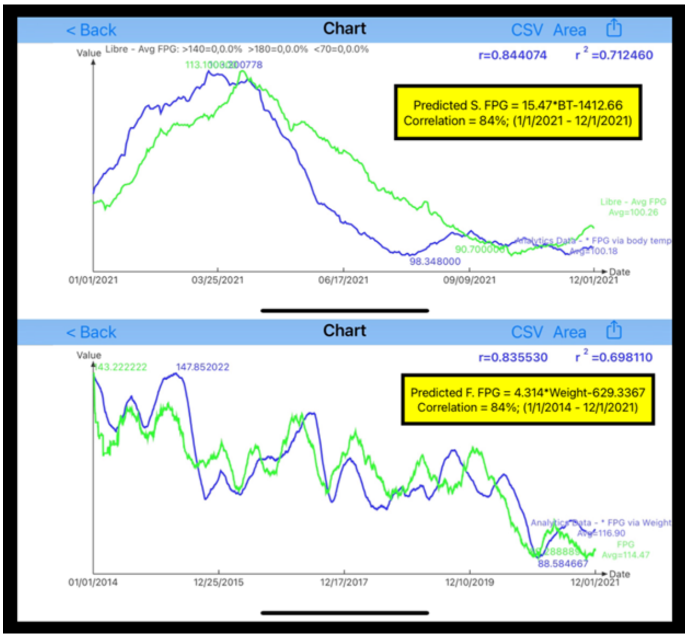


Figure 5: Predicted equations of S. FPG via body temperature over 1 year (top); and F. FPG via body weight over 8 years (bottom); both have high correlation of 84%

It is obvious that all calculated correlation coefficients are very high (72%-84%) between FPG versus either body temperature or body weight with long enough and different time windows. Furthermore, the glucose difference between finger FPG and sensor FPG is a mere 2%; therefore, the author does not need to distinguish sensor FPG and finger FPG.

Figure 6 reveals the FPG Density distribution diagram during 2 different periods:

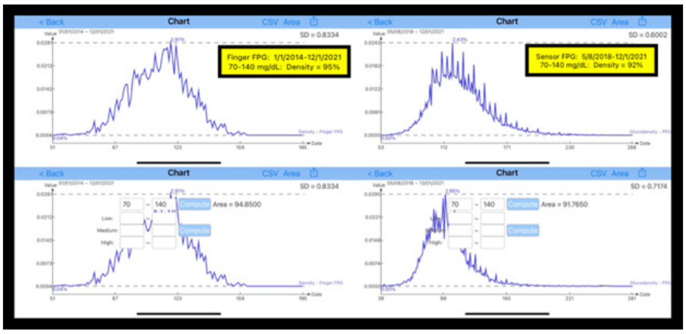


Figure 6: FPG Density distribution diagram during 2 different periods

Finger FPG (1/1/2014-12/1/2021): within 70-140 mg/dL; density = 95 %

Sensor FPG (5/8/2018-12/1/2021): within 70-140 mg/dL; density = 92 %

Figure 7 indicates the Body temperature Density distribution diagram during the period of 10/1/2020-12/1/2021.

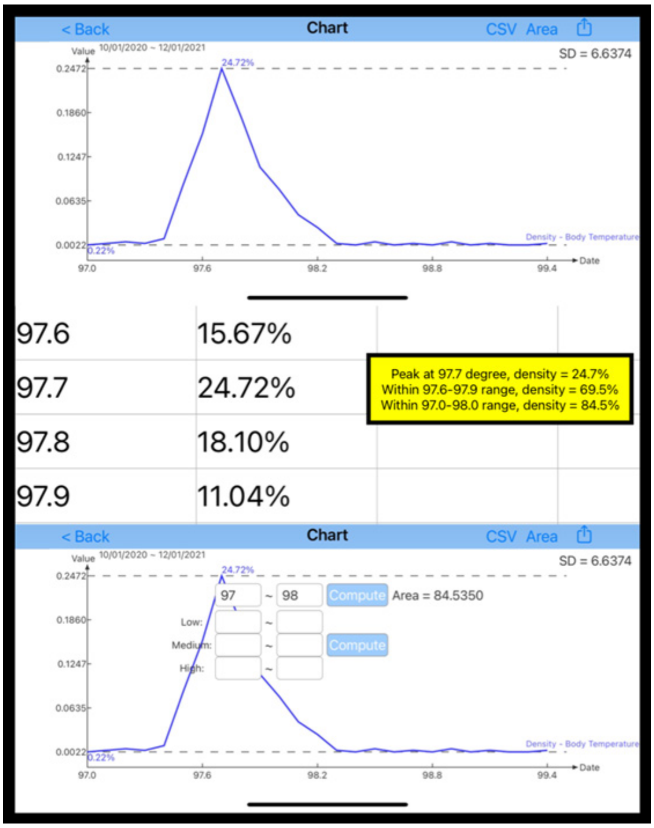


Figure 7: Body temperature Density distribution diagram during the period of 10/1/2020-12/1/2021

The peak body temperature:
density = 24.7 % at BT= 97.7 °F

Within a range of 97.6-97.9 °F:
density = 69.5 %

Within a range of 97.0-98.0 °F:
density = 84.5 %

Conclusions

In summary, there are 3 observed conclusions as follows:

(1) There are no observed high correlation (-43%) existing between his measured BT and Weight. Furthermore, from the two-regression predicted FPG via BT and Weight as individual inputs, both have different and are not highly correlated ***(69% for FPG via BT and 12% for FPG via Weight)*** with his measured FPG over this 14-month period. However, ***the average regression predicted FPG, i.e. (FPG via BT + FPG via weight) / 2, has a high correlation of 82% (variance 67%) with his measured FPG over the same period.***

(2) The regression model derived three average predicted FPG data: FPG via BT, FPG via Weight, and average predicted FPG. They have ***extremely high prediction accuracies (96%-99%)*** in comparison with the average measured FPG value. This means that the 3 predicted FPG equations are accurate enough for the time period. ***The regression predicted FPG equations are listed as follows:***

Body weight case
Predicted finger FPG (Y)
= 4.314 * Weight (X) - 629.34

Body temperature case
Predicted sensor FPG (Y)
= 51.85 * BT (X) - 4970.28

(3) In conclusion, the average predicted FPG equation is the most suitable for predicting his FPG value (either sensor FPG or finger FPG values). Therefore, he can guesstimate an accurate FPG value using his BT and Weight as inputs, without applying either finger-piercing or CGM sensor devices for measuring his FPG value in the morning.

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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