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Type 2 diabetes control using accurate prediction tools for various biomarkers based on GH-Method: math-physical medicine (No. 474)

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Abstract

The author utilizes his research results accumulated since 2015 to summarize some key points regarding type 2 diabetes (T2D) control. This paper is aimed at family clinical practice and public health via lifestyle medicine. The approaches and formulas outlined in this article are based on his collected ~2 million data of his medical and health conditions over a period of 6 years from 7/1/2015 through 6/30/2021. He utilized his developed 4 prediction tools for various basic biomarkers for T2D patients, including body weight, fasting plasma glucose (FPG), postprandial plasma glucose (PPG), and HbA1C. All of the predicted results are then compared against his measured 4 biomarkers during the same time period. His research methodology is based on his developed GH-Method: math-physical medicine approach instead of the traditional biochemical medicine approach. Of course, all of the math-physical medicine derived results have quantitative proof and reliable support from biochemical medicine viewpoints.

In summary, either on a daily basis or a longer time period, all of the predicted biomarker data curves versus the measured biomarker data curves have extremely high correlation coefficients, moving up and down in unison, and high prediction accuracy, where the two datasets have almost identical average results. The following table summarizes the correlation coefficients and prediction accuracies in the format of (Correlation; Accuracy):

Weight	***:***	***(87%; 99%)***
FPG	***:***	***(99.8%; 100%)***
PPG	***:***	***(88%; 99.8%)***
Daily eAG	***:***	***(91%; 99.8%)***

These results have proven that the Prediction models are highly accurate with the ending average results as well as the moving patterns of data curves. For the author himself, who had severe T2D without any diabetic medication interventions from 12/8/2015 to 6/30/2021, this set of prediction tools has demonstrated the usefulness and effectiveness on his T2D control. Therefore, other diabetes patients can also confidently utilize these tools to manage their conditions.

Introduction

The author utilizes his research results accumulated since 2015 to summarize some key points regarding type 2 diabetes (T2D) control. This paper is aimed at family clinical practice and public health via lifestyle medicine. The approaches and formulas outlined in this article are based on his collected ~2 million data of his medical and health conditions over a period of 6 years from 7/1/2015 through 6/30/2021. He utilized his developed 4 prediction tools for various basic biomarkers for T2D patients, including body weight, fasting plasma glucose (FPG), postprandial plasma glucose (PPG), and HbA1C. All of the predicted results are then compared against his measured 4 biomarkers during the same time period. His research methodology is based on his developed GH-Method: math-physical medicine approach instead of the traditional biochemical medicine approach. Of course, all of the math-physical medicine derived results have quantitative proof and reliable support from biochemical medicine viewpoints.

Preface

The author has been a sever T2D patient since 1996. He 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 and albumin-creatinine ratio (ACR) at 116. He also suffered from five cardiac episodes within a decade. In 2010, three independent physicians warned him regarding his needs of kidney dialysis treatment and his future high risk of dying from his severe diabetic complications. Oth-

er than cerebrovascular disease (stroke), he has suffered most of 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), fasting plasma glucose (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) 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 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 heavier traveling period.

During 2020 with a COVID-19 quarantined lifestyle, not only has he published approximately 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 6.2% A1C value, without having any medication interventions or insulin injections. These good results are due to his non-traveling, low-stress, and regular daily life routines. Of course, his knowledge of chronic diseases, practical lifestyle management experiences, and his developed various high-tech tools contribute to his excellent health status since 1/19/2020.

On 5/5/2018, he applied a continuous glucose monitoring (CGM) sensor device on his upper arm and checks his 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 his CGM sensor glucose at time-interval of 15 minutes (96 data per day). By the way, the difference of average sensor glucoses between 5-minutes interval and 15-minutes interval is only 0.3% (averaged glucose of 114.96 mg/dL for 5-minutes and averaged glucose of 115.35 mg/dL for 15-minutes during 2/19/20-7/6/21).

Therefore, over the past 11 years, he could study and analyze the collected 2 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, using optical physics, artificial intelligence (AI), and neuroscience.
- 2017: Complications due to macro-vascular research, such as Cardiovascular disease (CVD), coronary heart diseases (CHD) and stroke, using pattern analysis and segmentation analysis.
- 2018: Complications due to micro-vascular research such as kidney, bladder, foot, and eye issues.
- 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 fungal infection, and linkage between metabolism and immunity, learning about certain infectious diseases, such as COVID-19.
- 2021: Applications of linear elastic glucose theory (LEGT) and perturbation theory on medical research subjects, such as chronic diseases and their complications, cancer, and dementia.

Again, to date, he has collected more than two million data regarding his medical conditions and lifestyle details. In addition, he has written 473 medical papers and published ~400 paper in 100+ various medical journals. Moreover, he has also given ~120 presentations at ~65 international medical conferences. He has continuously dedicated his time and efforts on his medical research work and shared his findings and learnings with other patients worldwide.

Method and Results

The author will describe his method, data collection, and prediction results in the following sub-sections using a chronological order. Most numbers cited in this article are the average number with a period of 6 years from 7/1/2015 to 6/30/2021. Furthermore, all of glucose readings used are based on the finger-pierced method, not the CGM sensor collected glucose readings.

Weight

Every morning when he wakes up, he immediately measures his FPG, blood pressure, body temperature, and body weight; and then enter those data into his iPhone which holds his developed eclaireMD software.

He developed a predicted weight model in his software which is based on his collected food quantity (3 meals plus snacks/fruits in between meals) and his daily amount of bowel movement.

The lower diagram in Figure 1 shows the comparison between his measured weight (172 lbs.) and predicted weight (170 lbs.) which have a correlation coefficient (Correlation or "R") of 87% and a prediction accuracy (Accuracy) of 99%.

FPG

He has identified a remarkably close relationship and strong connection between his early morning's body weight and his early morning's FPG. Both his weight gain during daytime and weight loss during night sleeping hours are a near constant value which is located within the range of 1.7 lbs to 2.2 lbs. However, his morning body weight, before his breakfast, has an extremely high correlation of 70% to 90% with his early morning FPG value, depending upon the selected time window of data. Once he establishes the ratio of FPG versus body weight, he would then know his FPG level.

He has developed a predicted FPG model in the software which uses statistics tools (least square mean and standard deviation) and based on inputs from his body weight of previous 90 days along with four modification factors of sleep, stress, physical illness, weather and ambient temperature.

The middle diagram in Figure 1 depicts the comparison between his measured weight (172 lbs.) and measured FPG (113 mg/dL) which have a correlation coefficient (Correlation or R) of 74%.

The lower diagram in Figure 1 illustrates the comparison between his measured FPG (113 mg/dL) and predicted FPG (113 mg/dL) which have a correlation of 99.8% and a prediction accuracy of 100%.

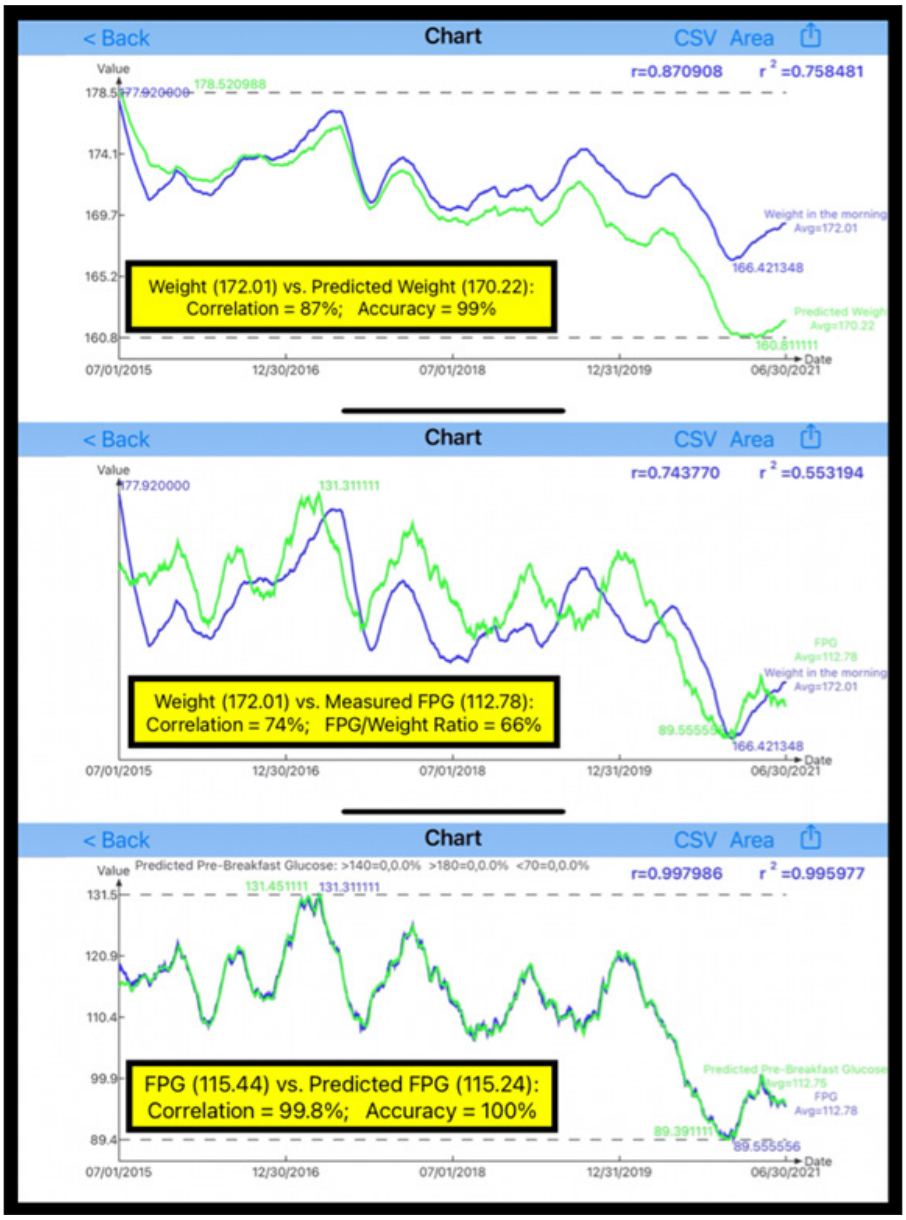


Figure 1: Weight & FPG in early morning during 2015 – 2021

PPG

He has identified PPG having a positive correlation with carbs/sugar intake amount, meaning higher carbs/sugar results into elevated PPG, and a negative correlation with post-meal walking steps, where increased steps result into lower PPG.

FPG & initial PPG

From the observation of his collected big data of glucose readings, he can clearly see the initial PPG value of his breakfast (i.e., at 0-minute of a 180-minute duration). It is usually about 8 mg/dL to 11 mg/dL higher than his FPG value in the early morning when the time gap between his wakeup moment and his first-bite of breakfast falls within a time frame of 30 minutes to 45 minutes. This biophysical phenomenon can be explained via a neuro-scientific viewpoint. The FPG at the wakeup moment does not have any influences from either food or exercise. But, when one wakes up from sleeping, the brain detects it immediately that the body needs glucose to support its daily activities. Therefore, the brain issues a marching order to the liver for production or release of glucose from muscles and pancreas for insulin secretion via beta cells or glucagon through alpha cells.

The initial PPG values for his lunch and dinner are higher than the initial PPG value of his breakfast. This is due to his between-meal glucose levels that are generally higher than his FPG in the early morning due to the intake of snacks or fruits between-meals. He has identified that the gap between his initial daily PPG and FPG (18 mg/dL) is 2x larger than the gap between his initial breakfast PPG and FPG (9 mg/dL).

Predicted PPG

T2D patients can use their intended food intake amount and their planned post-meal exercise level to construct or predict the PPG value beforehand. The following section lists his developed linear elastic glucose theory (LEGT) based on his GH-Method: math-physical medicine.

LEGT

Using two perturbation factors, both of carbohydrates and sugar intake amount in grams and post-meal walking steps in K-steps, his developed LEGT equation is:

Predicted PPG = Baseline PPG + food induced incremental PPG + exercise induced incremental PPG
or,

Predicted PPG = (FPG * GH.f) + Food intake increased PPG
+ Exercise reduced PPG = (FPG * GH.f) + (Carbs/sugar * GH.p) + (Walking k-steps * GH.w)

Where
GH.f = 0.5 to 1.5 (1.0 for here)
GH.p = 0.5 to 6.0 (1.66 for here) GH.w = -2.0 to -6.0 (-5.0 for here)
Therefore,

His Predicted PPG = (112.78*1.0) + (14.32*1.657) + (4.253*(-5.0)) = 112.78 + 23.73 - 21.27 = **115.24 mg/dL**

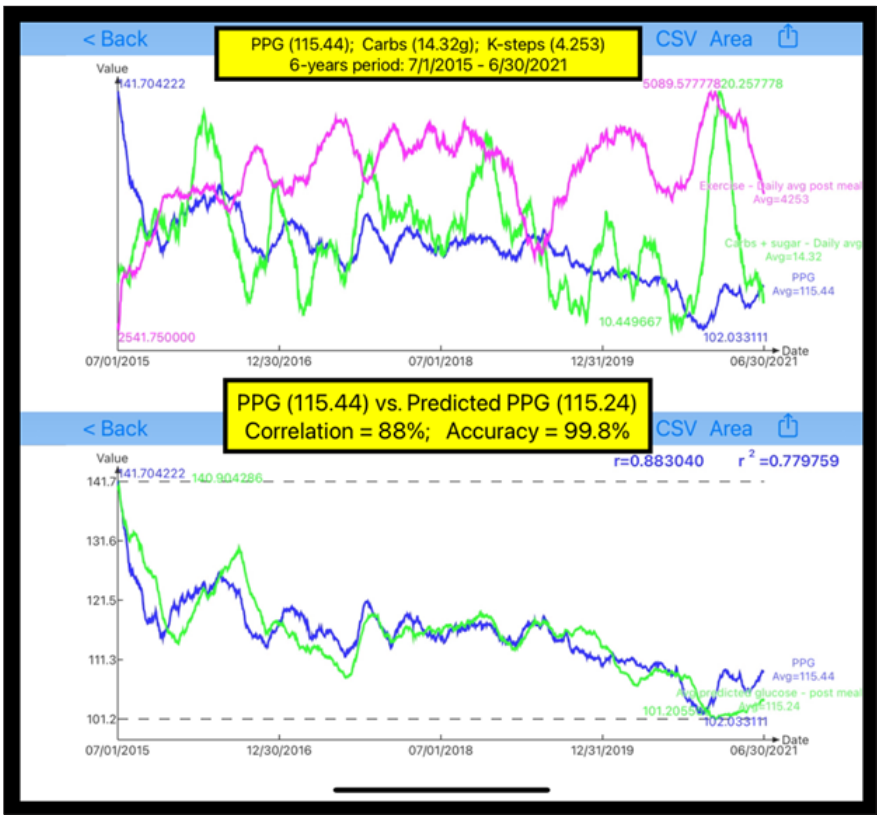


Figure 2: PPG and Carbs/sugar intake amount with walking exercise level during 2015 – 2021

The upper diagram in Figure 2 establishes the measured PPG (115.44 mg/dL), carbs/sugar intake amount (14.32 grams per meal) and post-meal walking k-steps (4.253 thousand steps after each meal).

The lower diagram in Figure 2 reflects the comparison between his measured PPG (115.44 mg/dL) and predicted FPG (115.24 mg/dL) which have a correlation of 88% and a prediction accuracy of 99.8%.

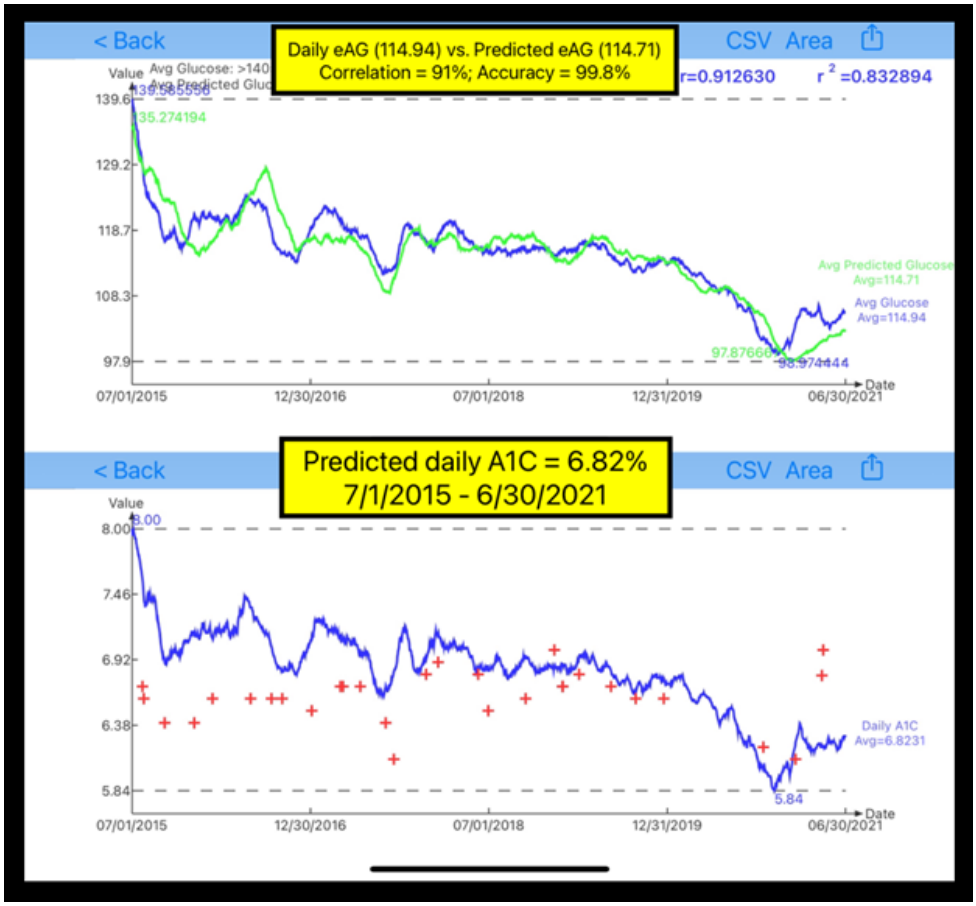
The above LEGT illustration has clearly demonstrated a simple linear elastic engineering model can accurately predict the complex biomedical phenomenon and outcomes of PPG.

Daily Glucose (eAG)

The author has chosen a simple arithmetic formula for his approximated daily glucose or "eAG" as the estimated Average Glucose which disregards all of the glucose values of between-meals time slot and pre-bed time slot. In fact, PPG plays a predominant role of HbA1C, while FPG has a predominant role of indicating the health state of pancreatic beta cells which also directly influence the HbA1C level.

The eAG formula is expressed as follows:

His Predicted Daily glucose (eAG) = (FPG*0.25 + PPG*0.75) = (112.78*0.25) + (115.44*0.75) = 28.195 + 86.58 = **114.78 mg/dL**



The upper diagram in Figure 3 indicates the measured eAG (114.94 mg/dL) and predicted eAG (114.71 mg/dL) which have a correlation of 91% and a prediction accuracy of 99.8%.

Predicted daily HbA1C

Finally, he has chosen a simple conversion factor (CF) of 16.846 to calculate his corresponding finger-based daily HbA1C value as follows:

Finger-based HbA1C = (finger eAG) / 16.846
Therefore,

Finger-based A1C = 114.94 / 16.846 = 6.82

Conclusion

In summary, either on a daily basis or a longer time period, all of the predicted biomarker data curves versus the measured biomarker data curves have extremely high correlation coefficients, moving up and down in unison, and high prediction accuracy, where the two datasets have almost identical average results. The following table summarizes the correlation coefficients and prediction accuracies in the format of (Correlation; Accuracy):

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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.