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Research Article

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A *Summary Report* Utilizing Math-Physical Medicine Models and Statistical Regression Models to Derive Practical Prediction *Equations of Selected Biomarkers* for Glucoses, A1C, Diabetes, and Risk Probabilities of Having Certain Chronic Disease Complications from the Collected Data of a Type 2 Diabetes Patient based on GH-Method: Math-Physical Medicine (No. 560)

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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

In the author's previous medical research reports, he mainly applied physics theories, engineering models, mathematical equations, and computer science tools, including trend and pattern analysis, big data analytics and artificial intelligence (AI) techniques, as well as some statistical approaches to explore and interpret various biophysical phenomena. His ***physics and engineering methodologies*** *include wave theory, energy theory, quantum mechanics, optical physics, linear elasticity theory, and finite element method. His* ***mathematics methodologies*** *include topology, nonlinear algebra, geometric algebra, perturbation theory, Fourier transform, trend and pattern analyses, statistics, and probability theory.*

*However, the majority of medical research papers he has read thus far are primarily based on statistics tools, such as regression analysis, probability calculation, etc. As a result, he decided to dedicate the month of November 2021 using the same statistical regression models similar to other traditional medical papers to analyze his collected biomarkers to verify the relationship validity of his previous research results based on his developed math-physical models. During the month, he conducted 18 regression studies in papers No. 540 -544, No. 546-553, and No. 555-559. In the regression studies, he selected some basic statistical tools, such as correlation, variance, significance F value, p-value, and regression analyses (linear and nonlinear, single or multiple variables), to study the behaviors and relationships of his collected biomarkers. The regression model mentioned above is a statistical model that uses values such as mean, standard deviation, correlation, variance, significance F, p-value, and the equation of "Y = y-intercept + slope*X". These regression models include linear and nonlinear regression. The nonlinear regression models include exponential, logarithmic, polynomial, and power. Since 1/1/2012, the author has collected ~3 million data regarding his health conditions, lifestyle details, internal organs, and chronic diseases.*

From an academic viewpoint, strictly speaking, the statistical regression models are just a subset of mathematics category of his developed GH-method: math-physical medicine methodology.

In this particular paper, he adopted ***a "straight-line" pathway*** *starting from* ***body temperature and body weight*** *using regression model to arrive at the fasting plasma glucose* ***(FPG)*** *value; and from carbs/sugar intake amount and post-meal walking k-steps using linear elastic glucose theory (LEGT) model to arrive at the postprandial plasma glucose* ***(PPG)*** *value. He then applied the FPG value and PPG value to calculate his daily estimated average glucose* ***(eAG)*** *level which can be further converted into Hemoglobin A1C* ***(HbA1C or A1C)*** *value using the regression model. Traditionally, A1C values are frequently used to determine the severity of diabetes. After combining the other vital biomarker values, such as blood pressure and blood lipids with the selected lifestyle details, along with the regression model, he can then guesstimate the risk probabilities to develop certain chronic disease complications such as* ***CVD/Stroke and Cancers.***

His selected 6 cases include the following biomarkers:

(1) Sensor FPG via body temperature and body weight
(2) Sensor PPG vs. carbs/sugar and post-meal walking k-steps
(3) Sensor eAG via sensor FPG and sensor PPG
(4) Sensor A1C via sensor eAG
(5) CVD risk probability versus diabetes via 4 medical conditions & 6 lifestyle details (Metabolism Index model)
(6) Cancer risk probability versus CVD risk via 4 medical conditions & 6 lifestyle details (Metabolism Index model)

In summary, by using the collected 14-month data (from 10/1/2020 to 11/24/2021) as the inputs, his research results have identified the following comparison between the predicted biomarker value versus the measured biomarker value in the format of (correlation%, variance%):

(7) Sensor FPG: (87%, 67%)
(8) Sensor PPG: (44%, 19%)
(9) Sensor eAG: (57%, 33%)
(10) Sensor A1C: (61%, 37%)
(11) CVD risk: (31%, 10%)
(12) Cancer risk: (100%, 100%)

It should be noted that the CVD risk is based on 4 medical conditions of weight, glucose, blood pressure, and blood lipids, while the cancer risk is based on overall metabolism index (MI) model, including 4 medical conditions and 6 lifestyle details. Therefore, these 2 correlations and 2 variances are not closely related to the other 4 biomarker results: FPG, PLG, eAG, and A1C.

The general conclusion from this study is that the author can obtain a set of fairly accurate predicted diabetes biomarker values, including FPG, PPG, eAG, and A1C, from the 4 basic measured inputs, body temperature, body weight, carbs/sugar intake amount, and post-meal walking steps, without utilizing any glucose measurement devices, either a finger-piercing device or a continuously glucose monitoring (CGM) device. In a practical sense, ***he measured his body temperature using a thermometer, determined body weight using a weight scale, calculated carbs/sugar intake amount using meal photo and developed optical physics AI software on his iPhone, and tracked walking steps using a pedometer on a Fitbit watch.*** *From the above-described measurement devices and his developed software, he can achieve an accurate predicted glucoses (with a 98% prediction accuracy) and HbA1C value (with a 91% prediction accuracy) using* ***these derived mathematical equations.*** *With accurate predicted glucoses, he can expect to lower his risk probabilities of developing cardiovascular disease (CVD), stroke, chronic kidney disease (CKD), diabetic retinopathy (DR), neuropathy, cancers, dementia, and others.*

This article describes how he controls his T2D conditions based on a stringent lifestyle management program and how he successfully reduced his A1C level from 10% in 2010 to 5.8% in 2021 without taking any diabetes medication.

Introduction

In the author's previous medical research reports, he mainly applied physics theories, engineering models, mathematical equations, and computer science tools, including trend and pattern analysis, big data analytics and artificial intelligence (AI) techniques, as well as some statistical approaches to explore and interpret various biophysical phenomena. ***His physics and engineering methodologies*** include wave theory, energy theory, quantum mechanics, optical physics, linear elasticity theory, and finite element method. His ***mathematics methodologies*** include topology, nonlinear algebra, geometric algebra, perturbation theory, Fourier transform, trend and pattern analyses, statistics, and probability theory.

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applied the FPG value and PPG value to calculate his daily estimated average glucose ***(eAG)*** level which can be further converted into Hemoglobin A1C ***(HbA1C or A1C)*** value using the regression model. Traditionally, A1C values are frequently used to determine the severity of diabetes. After combining the other vital biomarker values, such as blood pressure and blood lipids with the selected lifestyle details, along with the regression model, he can then guesstimate the risk probabilities to develop certain chronic disease complications such as CVD/Stroke and Cancers.

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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 greater detail, "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".

The Author'S Case of Diabetes and Complications

The author has been a severe type 2 diabetes (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, 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, 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 good 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 continuous glucose monitoring (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 12 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 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.

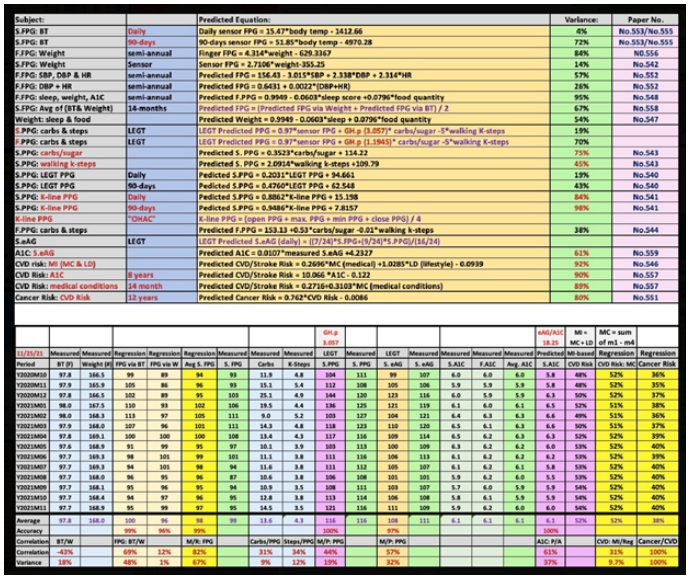
To date, he has collected ~3 million data regarding his medical conditions and lifestyle details. In addition, he has written 560 medical papers and published 500+ articles in 100+ various medical journals, including 10 special editions with selected 20-25 papers for each edition. Moreover, he has given ~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 shows the equation table (upper diagram). It contains 23 equations with its majority from the regression models along with the analysis results (lower diagram) of FPG, PPG, eAG, A1C, CVD risk, and cancers risk, using input data collected within a 14-month period from 11/1/2020 through 11/24/2021. In the lower diagram of Figure 1, the analysis results are further demonstrated in Figure 2 through Figure 6.



Subject:		Predicted Equation:	Variance:	Paper No.
S.FPG: BT	Daily	Daily sensor FPG = 15.47*body temp - 1412.66	6%	No.553/No.555
S.FPG: BT	90-days	90-days sensor FPG = 51.85*body temp - 4970.28	72%	No.553/No.555
F.FPG: Weight	semi-annual	Finger FPG = 4.314*weight - 629.3367	84%	N0.556
S.FPG: Weight	Sensor	Sensor FPG = 2.7106*weight-355.25	14%	No.542
F.FPG: SBP, DBP & HR	semi-annual	Predicted FPG = 156.43 - 3.015*SBP + 2.338*DBP + 2.314*HR	57%	No.552
F.FPG: DBP + HR	semi-annual	Predicted FPG = 0.6431 + 0.0022*(DBP+HR)	26%	No.552
F.FPG: sleep, weight, A1C	semi-annual	Predicted F.FPG = 0.9949 - 0.0603*sleep score +0.0796*food quantity	95%	No.548
S.FPG: Avg of (BT& Weight)	14-months	Predicted FPG = (Predicted FPG via Weight + Predicted FPG via BT) / 2	67%	No.558
Weight: sleep & food		Predicted Weight = 0.9949 - 0.0603*sleep + 0.0796*food quantity	54%	No.547
S.PPG: carbs & steps	LEGT	LEGT Predicted PPG = 0.97*sensor FPG + GH.p (3.057)* carbs/sugar -5*walking K-steps	19%	
F.PPG: carbs & steps	LEGT	LEGT Predicted PPG = 0.97*sensor FPG + GH.p (1.1945)* carbs/sugar -5*walking K-steps	70%	
S.PPG: carbs/sugar		Predicted S. PPG = 0.3523*carbs/sugar + 114.22	75%	No.543
S.PPG: walking k-steps		Predicted S. PPG = 2.0914*walking k-steps +109.79	45%	No.543
S.PPG: LEGT PPG	Daily	Pedicted S.PPG = 0.2031*LEGT PPG + 94.661	19%	No.540
S.PPG: LEGT PPG	90-days	Pedicted S.PPG = 0.4760*LEGT PPG + 62.548	43%	No.540
S.PPG: K-line PPG	Daily	Pedicted S.PPG = 0.8862*K-line PPG + 15.198	84%	No.541
S.PPG: K-line PPG	90-days	Pedicted S.PPG = 0.9486*K-line PPG + 7.8157	98%	No.541
K-line PPG	"OHAC"	K-line PPG = (open PPG + max. PPG + min PPG + close PPG) / 4		
F.PPG: carbs & steps		Predicted F.PPG = 153.13 +0.53*carbs/sugar -0.01*walking k-steps	38%	No.544
S.eAG	LEGT	LEGT Predicted S.eAG (daily) = ((7/24)*S.FPG+(9/24)*S.PPG)/(16/24)		
A1C: S.eAG		Predicted A1C = 0.0107*measured S.eAG +4.2327	61%	No.559
CVD risk: MI (MC & LD)		Predicted CVD/Stroke Risk = 0.2696*MC (medical) +1.0285*LD (lifestyle) - 0.0939	92%	No.546
CVD Risk: A1C	8 years	Predicted CVD/Stroke Risk = 10.066 *A1C - 0.122	90%	No.557
CVD Risk: medical conditions	14 month	Predicted CVD/Stroke Risk = 0.2716+0.3103*MC (medical conditions)	89%	No.557
Cancer Risk: CVD Risk	12 years	Predicted Cancer Risk = 0.762*CVD Risk - 0.0086	80%	No.551

11/25/21	Measured	Measured	Regression	Regression	Regression	Measured	Measured	Measured	GH.p 3.057	Measured	LEGT	Measured	Measured	Measured	Measured	eAG/A1C 18.25	MI = MC + LD	MC = sum of m1 - m4	
Period	BT (F)	Weight (#)	FPG via BT	FPG via W	Avg S. FPG	S. FPG	Carbs	K-Steps	S.PPG	S. PPG	S. eAG	S. eAG	S.A1C	F.A1C	Avg. A1C	S.A1C	CVD Risk	CVD Risk: MC	Cancer Risk
Y2020M10	97.8	166.5	99	89	94	93	11.9	4.8	104	111	99	107	6.0	6.0	6.0	5.8	48%	52%	36%
Y2020M11	97.9	165.9	105	86	96	93	15.1	5.4	112	108	105	106	5.9	5.9	5.9	5.8	48%	52%	35%
Y2020M12	97.8	166.5	102	89	95	103	25.1	4.9	144	120	123	116	6.0	5.9	5.9	6.3	50%	52%	37%
Y2021M01	98.0	167.5	110	93	102	106	19.5	4.4	136	125	121	119	6.1	6.0	6.1	6.5	52%	51%	38%
Y2021M02	98.0	168.3	113	97	105	111	9.0	5.2	103	127	104	121	6.4	6.3	6.3	6.6	49%	51%	36%
Y2021M03	97.9	168.0	107	96	101	111	14.3	4.8	118	123	110	120	6.5	6.1	6.3	6.6	50%	51%	37%
Y2021M04	97.8	169.1	100	100	100	108	13.4	4.3	117	116	109	114	6.5	6.2	6.3	6.5	52%	52%	39%
Y2021M05	97.6	168.9	91	99	95	97	10.1	3.9	103	113	100	109	6.3	6.2	6.2	6.0	53%	52%	40%
Y2021M06	97.7	169.3	98	101	99	101	11.1	3.8	111	116	106	113	6.1	6.2	6.2	6.2	53%	52%	39%
Y2021M07	97.7	169.3	94	101	98	94	11.6	3.8	111	112	105	107	6.1	6.2	6.1	5.8	53%	52%	40%
Y2021M08	97.7	168.0	96	95	96	87	10.6	3.8	106	108	101	101	5.9	6.2	6.0	5.5	53%	52%	40%
Y2021M09	97.7	168.1	95	96	95	94	10.9	3.5	108	111	103	107	5.7	6.0	5.9	5.9	54%	52%	40%
Y2021M10	97.7	168.4	94	97	96	95	12.8	3.8	113	114	106	108	5.8	6.1	5.9	5.9	54%	52%	40%
Y2021M11	97.7	168.9	95	99	97	95	14.5	3.5	121	116	111	109	5.9	6.2	6.0	6.0	54%	52%	40%
Average	97.8	168.0	100	96	98	99	13.6	4.3	116	116	108	111	6.1	6.1	6.1	6.1	52%	52%	38%
Accuracy			99%	96%	99%				100%		97%					100%			
Correlation	BT/W		FPG: BT/W		M/F: FPG		Carbs/FPG	Steps/FPG	M/F: PPG		M/F: PPG					A1C: P/A		CVD: MI/Reg	Cancer/CVD
Correlation	-43%		69%	12%	82%		31%	34%	44%		57%					61%		31%	100%
Variance	18%		48%	1%	67%		9%	12%	19%		32%					37%		9.7%	100%

Figure 1: Derived equations and results data table over 14-month period from 10/1/2020 to 11/24/2021

Figures 2 depicts body temperature (BT), body weight (BW), and FPG (including the predicted FPG and measured FPG). In time-domain diagrams, we can observe that the correlation is 73% between FPG and BT while the correlation is 84% between FPG and body weight. The correlation and data accuracy between finger FPG and sensor FPG are 89% and 98%, respectively. The final results of the regression predicted FPG based on the average BT and BW have 82% correlation and 100% prediction accuracy.

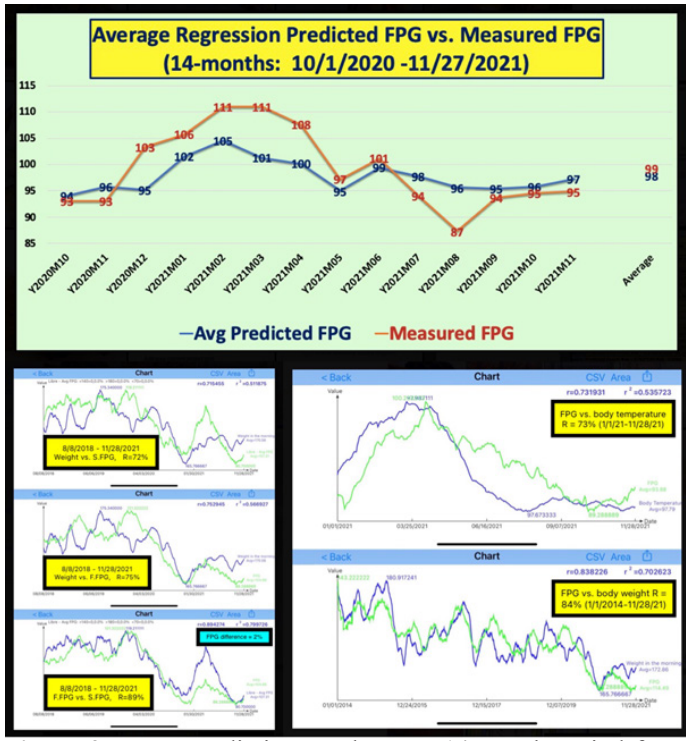


Figure 2: FPG prediction results over 14-month period from 10/1/2020 to 11/24/2021

Figure 3 illustrates a correlation of 80% between the LEGT predicted PPG and measured PPG over a period from 8/8/2018

through 11/27/2021 (upper diagram). The lower diagram reflects the LEGT predicted PPG equation as follows:

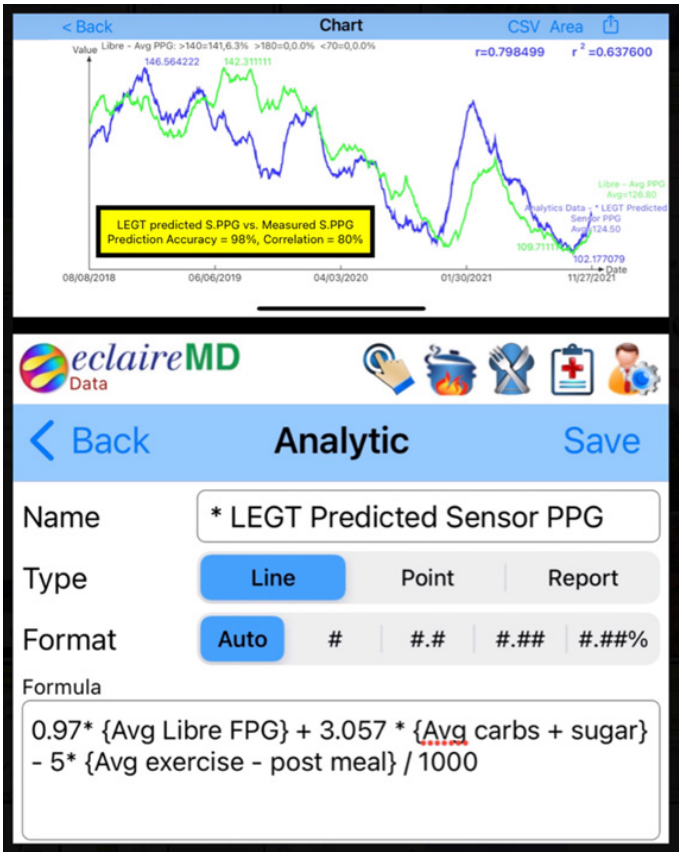


Figure 3: LEGT PPG equation and results (8/8/2018 - 11/27/2021)

LEGT predicted PPG =
0.97*FPG + 3.057*carbs - 5*k-steps

Figure 4 reveals a 61% correlation and 100% prediction accuracy between the regression predicted A1C via measured daily eAG and the measured A1C.

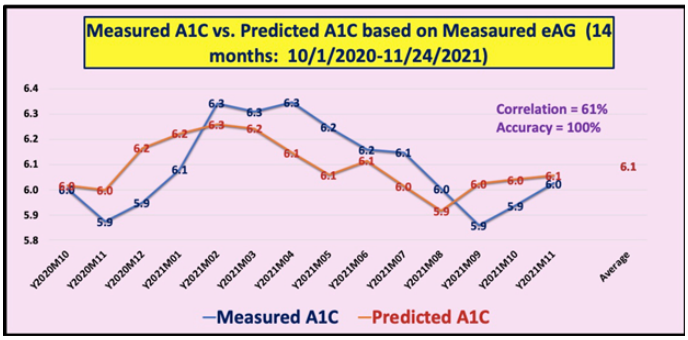


Figure 4: measured A1C versus regression predicted A1C over 14 months from 10/1/20 to 11/24/21

Figure 5 exhibits two diagrams for the regression predicted CVD versus calculated CVD risk based on 4 medical conditions. The upper diagram utilized a 14-month period from 10/1/2020 to 11/24/2021, whereas the lower diagram used an 8-year period from 2014 to 2021. Both diagrams show high correlations, i.e., high waveform similarities.

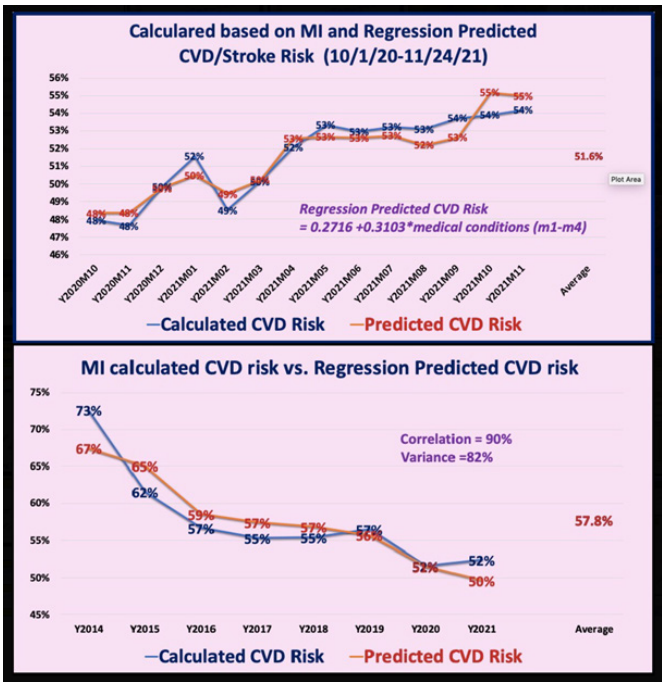


Figure 5: CVD risk (14 months and 8 years)

Figure 6 signifies the comparison between the regression predicted cancer risk versus calculated CVD risk based on the MI model (4 medical conditions plus 6 lifestyle details). This diagram utilized a 14-month period from 10/1/2020 to 11/24/2021.

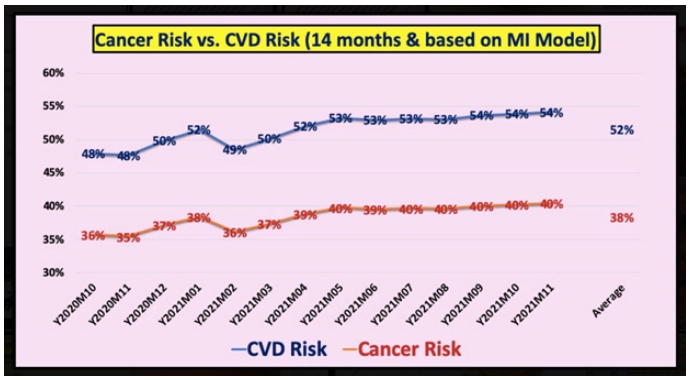
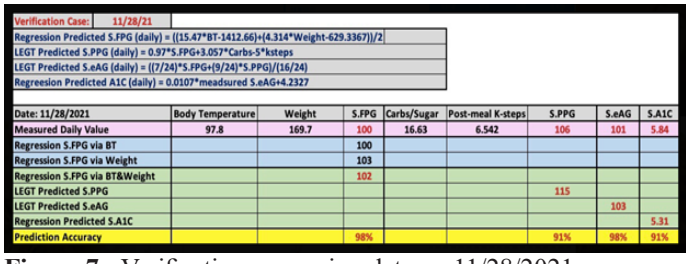


Figure 6: Cancer risk (14 months)

Figure 7 is a verification data table of 4 biomarker values, FPG, PPG, eAG, and A1C, using BT, BW, carbs, k-steps as inputs based on 11/28/2021. On that particular day, his BT in the early morning was 97.8-degree Fahrenheit, BW in the early morning was 169.7 lbs., carbs/sugar intake amount was 16.63 grams, and average post-meal walking was 6.542 k-steps. The following table lists the results comparison in the format of (measured, predicted, prediction accuracy %).



Verification Case:	11/28/21							
Regression Predicted S.FPG (daily) = ((15.47*BT-1412.66)+(4.314*Weight-629.3367))/2								
LEGT Predicted S.PPG (daily) = 0.97*S.FPG+3.057*Carbs-5*ksteps								
LEGT Predicted S.eAG (daily) = ((7/24)*S.FPG+(9/24)*S.PPG)/(16/24)								
Regression Predicted A1C (daily) = 0.0107*meadsured S.eAG+4.2327								
Date: 11/28/2021	Body Temperature	Weight	S.FPG	Carbs/Sugar	Post-meal K-steps	S.PPG	S.eAG	S.A1C
Measured Daily Value	97.8	169.7	100	16.63	6.542	106	101	5.84
Regression S.FPG via BT			100					
Regression S.FPG via Weight			103					
Regression S.FPG via BT&Weight			102					
LEGT Predicted S.PPG						115		
LEGT Predicted S.eAG							103	
Regression Predicted S.A1C								5.31
Prediction Accuracy			98%			91%	98%	91%

Figure 7: Verification case using data on 11/28/2021

Verification Data Table
Sensor FPG: (100, 102, 98%)
Sensor PPG: (106, 115, 91%)
Sensor eAG: (101, 103, 98%)
Sensor A1C: (5.84, 5.31, 91%)

Randomly selecting one day, the prediction accuracies for the 4 key diabetes biomarkers have achieved extremely high prediction accuracies in the range of 91%-98%.

Figure 7 offers a verification of the suitability of his derived mathematical equations and a validation of the accuracy of the predicted results.

Conclusions

In summary, by using the collected 14-month data (from 10/1/2020 to 11/24/2021) as the inputs, his research results have identified the following comparison between the predicted biomarker value versus the measured biomarker value in the format of (correlation%, variance%):

(1) Sensor FPG: (87%, 67%)
(2) Sensor PPG: (44%, 19%)
(3) Sensor eAG: (57%, 33%)
(4) Sensor A1C: (61%, 37%)
(5) CVD risk: (31%, 10%)
(6) Cancer risk: (100%, 100%)

It should be noted that the CVD risk is based on 4 medical conditions of weight, glucose, blood pressure, and blood lipids, while the cancer risk is based on overall metabolism index (MI) model, including 4 medical conditions and 6 lifestyle details. Therefore, these 2 correlations and 2 variances are not closely related to the other 4 biomarker results: FPG, PLG, eAG, and A1C.

The general conclusion from this study is that the author can obtain a set of fairly accurate predicted diabetes biomarker values, including FPG, PPG, eAG, and A1C, from the 4 basic measured inputs, body temperature, body weight, carbs/sugar intake amount, and post-meal walking steps, without utilizing any glucose measurement devices, either a finger-piercing device or a continuously glucose monitoring (CGM) device. *In a practical sense, he measured his body temperature using a thermometer, determined body weight using a weight scale, calculated carbs/sugar intake amount using meal photo and developed AI software on the iPhone, and tracked walking steps using a pedometer on a Fitbit watch.* From the above-described measurement devices and his developed software, he can achieve an accurate predicted glucoses (with a 98% prediction accuracy) and HbA1C value (with a 91% prediction accuracy) using these ***derived mathematical equations.***

With accurate predicted glucoses, he can expect to lower his risk probabilities of developing cardiovascular disease (CVD), stroke, chronic kidney disease (CKD), diabetic retinopathy (DR), neuropathy, cancers, dementia, and others.

This article describes how he controls his T2D conditions based on a stringent lifestyle management program and how he successfully reduced his A1C level from 10% in 2010 to 5.8% in 2021 without taking any diabetes medication.

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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