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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 + s-lope*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 AIC (HbA1C or A1C) value using the regression model. Traditionally, AIC 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

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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 \sim 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 \sim 120 presentations at \sim 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.

					Pred	Predicted Equation:									Variance: F		per No.		
S.FPG: BT	r		Daily		Daily	Daily sensor FPG = 15.47*body temp - 1412.66									4% No.5		53/No.555		
S.FPG: BT	r		90-di	rys				1.85*bod											53/No.555
F.FPG: W	eight		semi	annual	Finge	er FPG = 4	4.314*wei	ight - 629.	3367								84% N		NO.556
S.FPG: W	eight		Sens	or	Sens	Sensor FPG = 2.7106*weight-355.25								14%		No.542			
F.FPG: SB	P. DBP 8	HR	semi	annual	Pred	Predicted FPG = 156.43 - 3.015*SBP + 2.338*DBP + 2.314*HR							57%		No.552				
F.FPG: DE	SP + HR		semi	annual	Pred	Predicted FPG = 0.6431 + 0.0022*(DBP+HR)							26%		No.552				
F.FPG: sle	ep, weig	ht, AIC	semi	annual	Pred	Predicted F.PPG = 0.9949 - 0.0603*sleep score +0.0796*food quantity						95%		No.548					
S.FPG: Avg of (BT& Weight)			14-m	onths		Predicted FPG = (Predicted FPG via Weight + Predicted FPG via BT) / 2							67%		No.558				
Weight: sleep & food									0.0603*sleep + 0.0796*food quantity								54%		No.547
S.PPG: carbs & steps			LEGT				right = 0.9949 - 0.0003*sieep + 0.0796*1000 quantity rid PPG = 0.97*sensor FPG + GH.p (3.057)* carbs/sugar -5*walking K-steps									19%			
F.PPG: carbs & steps			LEGT					d PPG = 0.97*sensor FPG + GH.p (3.057)* carbs/sugar - 5*walking K-steps d PPG = 0.97*sensor FPG + GH.p (1.1945)* carbs/sugar - 5*walking K-steps									70%		
F.PPG: carbs & steps S.PPG: carbs/sugar			LEGI			Predicted PPG = 0.97*sensor PPG + GPLp (1.1945)* Carbs/sugar -5*walking K-steps Predicted S, PPG = 0.3523*carbs/sugar + 114.22						_	75%		No.543				
S.PPG: carbs/sugar S.PPG: walking k-steps						Predicted 5. PPG = 0.3523*carbs/sugar + 114.22 Predicted 5. PPG = 2.0914*walking k-steps +109.79									45%		No.543		
S.PPG: walking k-steps S.PPG: LEGT PPG			Daily			Predicted S. PPG = 2.0914*walking k-steps +109.79 Predicted S.PPG = 0.2031*LEGT PPG + 94.661											No.540		
S.PPG: LEGT PPG S.PPG: LEGT PPG			90-di			Pedicted S.PPG = 0.2031*LEGT PPG + 94.661 Pedicted S.PPG = 0.4760*LEGT PPG + 62.548										No.540			
			Dally											_			No.541		
S.PPG: K-line PPG			90-di		Pedicted S.PPG = 0.8862*K-line PPG + 15.198								98%		NO.541				
S.PPG: K-line PPG			*OH/			Pedicted S.PPG = 0.9486*K-line PPG + 7.8157 K-line PPG = (open PPG + max, PPG + min PPG + close PPG) / 4									98%		10.541		
K-line PPG			UNI	-				13 +0.53*									38%		No.544
F.PPG: carbs & steps			LEGT					(daily) = (_			_	38%		10.544
S.eAG			LEGT								4)"5.PPG	0/(16/24				_			
A1C: 5.ed			_			Predicted A1C = 0.0107*measured 5.eAG +4.2327								_			No.559		
CVD risk:		& LD)	-			Predicted CVD/Stroke Risk = 0.2696*MC (medical) +1.0285*LD (lifestyle) - 0.0939									92%		No.546		
CVD Risk:						Predicted CVD/Stroke Risk = 10.066 *A1C - 0.122									90%		No.557		
CVD Risk: medical conditions							D/Stroke Risk = 0.2716+0.3103*MC (medical conditions)												
											nedical c	ondition	1)			_			
Cancer R	isk: CVD		12 ye					Risk = 0.2 = 0.762*C			nedical c	ondition	1)				80%		No.551
Cancer R	isk: CVD										nedical c	ondition	3)			eAG/A1C			
11/25/21		Risk	12 ye	ears	Pred	icted Car	scer Risk		/D Risk -		urgt .			Measured	Measured		80% MI =	MC = sum	No.551
	Measure	Risk d Measured	12 ye	Regression	Pred	icted Car	scer Risk	= 0.762°C	GH.p 3.057	0.0086				Measured F.A1C		18.25	MI + MC + LD	MC = sum of m1 - m4	No.551
11/25/21		Risk d Measured	12 ye	Regression	Pred	Measured	Measured	0.762°C	GHLp 3.057 LEGT	0.0086 Measured	LEGT	Measured	Measured		Measured Aug. A1C	18.25 Predicted	MI = MC + LD MI-based	MC = sum of m1 - m4 Regression	No.551
11/25/21 Period	Measure BT (F)	Risk d Measured Weight (#)	12 ye	Regression FPG via W	Pred Regression	Measured S. FPG	Measured	Measured	GH.p 3.057 LEGT S.PPG	Measured S. PPG	LEGT S. eAG	Measured 5. eAG	Measured S.A1C	F.A1C	Avg. A1C	18.25 Predicted S.AIC	MI = MC + LD MI-based CVD Risk	MC = sum of m1 - m4 Regression CVD Risk: MC	Regressi Cancer R
11/25/21 Period Y2020M10	Measures BT (F) 97.8	Risk d Measured Weight (#) 266.5	Regression FPG via BT	Regression FPG via W	Regression Aug S. FPG 94	Measured 5. FPG 93	Measured Carbs	Measured K-Steps	GHLp 3.057 LEGT 5.PPG	Measured 5. PPG	LEGT S. eAG	Measured 5. eAG 107	Measured S.A1C 6.0	F.A1C 6.0	Aug. A1C 6.0	18.25 Predicted 5.A1C 5.8	MI = MC + LD MI-based CVD Risk 48%	MC = sum of m1 - m4 Regression CVD Risk: MC 52%	Regressi Cancer Ri 36%
11/25/21 Period Y2020M10 Y2020M11	Measured BT (F) 97.8 97.9	Risk Measured Weight (#) 166.5 165.9	Regression FPG via BT 99 105	Regression FPG via W 89 86	Regression Aug S. FPG 94	Measured S. FPG 93	Measured Carbs 11.9	Measured K-Steps 4.8 5.4 4.9	GHLp 3.057 LEGT 5.PPG 104 112	0.0086 Measured 5. PPG 111 108 120 125	LEGT 5. eAG 99 105	Measured 5. eAG 107 106	Measured S.A1C 6.0 5.9	F.A1C 6.0 5.9	Avg. A3C 6.0 5.9	18.25 Predicted S.AIC 5.8 5.8 6.3 6.5	MI = MC+LD MI-based CVD Risk 48%	MC = sum of m1 - m4 Regression CVD Risk: MC 52% 52% 51%	Regressi Cancer R 36% 35%
11/25/21 Period Y2020M10 Y2020M11 Y2020M12 Y2021M01 Y2021M02	Measures BT (F) 97.8 97.9 97.8 98.0	Measured Weight (8) 165.9 165.5 167.5 168.3	8egression FPG via 87 99 305 302 110	Regression FPG via W 89 86 89 93 97	Pred Regression Aug 5. FPG 96 96 95 102	Measured 5. FPG 93 93 103 106	Measured Carbs 11.9 15.1 25.1 19.5	Measured K-Steps 5.4 4.9 4.4 5.2	GH.p 3.057 LEGT 5.89G 104 112 144 136	0.0086 Measured 5.99G 111 108 120 125 127	LEGT S. eAG 99 105 123 121	Measured 5. eAG 107 106 116 119	Measured S.AIC 6.0 5.9 6.0 6.1	5.9 5.9 6.0 6.0	5.9 5.9 6.1 6.3	18.25 Predkted S.A1C 5.8 5.8 6.3 6.5 6.6	MI = MC+LD MI-based CVD Risk 48% 48% 50% 52%	MC = sum of m1 - m4 Regression CVD Risk: MC 52% 52% 52% 52% 51%	Regressi Cancer Ri 36N 35N 37N 38N 36N
11/25/21 Period Y2020M10 Y2020M12 Y2020M12 Y2021M02 Y2021M02 Y2021M02	Measures 8T (F) 97.8 97.9 97.8 98.0 98.0	d Measured Weight (F) 166.5 166.5 167.5 168.3 168.3	Regression FPG via 8T 9 105 100 113 207	Regression FPG via W 89 86 89 93 97	Regression Aug S. FPG 96 95 102 105	Measured 5. FPG 93 93 103 106 111	Measured Carbs 11.9 15.1 25.1 19.5 9.0	Measured K-Steps 5-4 4-9 4-4 5-2 4-8	GH.p 3.057 LEGT 5.99G 104 112 144 136 103	0.0086 Measured 5. PPG 131 108 120 125 127 123	LEGT S. eAG 99 105 123 121 104	Measured 5. eAG 107 106 116 119 121	Measured S.AIC 6.0 5.9 6.0 6.1 6.4 6.5	5.9 5.9 6.0 6.3 6.1	Avg. A1C 6.0 5.9 5.9 6.1 6.3	18.25 Predicted S.AIC 5.8 5.8 6.3 6.5 6.6	MI = MC + LD MI-based CVD Risk 48% 50% 52% 49%	MC = sum of m1 - m4 Regression CVD Risk: MC 52% 52% 52% 51% 51%	Regressi Cancer R 35% 35% 38% 36% 37%
11/25/21 Period Y2020M10 Y2020M12 Y2020M12 Y2021M01 Y2021M02 Y2021M03 Y2021M04	Measures 8T (9) 97.8 97.9 97.9 98.0 98.0 97.9	Measured Weight (F) 166.5 165.9 166.5 167.3 168.3 168.0 169.1	12 ye Regression FPG via 81 99 105 102 110 113 107 100	Regression FPG via W 89 84 89 93 97 94	Pred Regression Aug S. FPG 94 96 95 102 105 100	Measured 5. FPG 93 93 103 106 111 111	Measured Carbs 11.9 15.1 25.1 29.0 14.3	Measured K-Steps 4.8 5.4 4.9 4.5 4.9 4.8 5.2	GH.p 3.057 LEGT 5.PPG 104 112 144 103 118	0.0086 Measured 5.PPG 111 108 120 125 127 123 116	LEGT S. eAG 99 105 123 121 104 110	Measured 5. eAG 107 106 116 119 121 120	Measured S.AIC 6.0 5.9 6.0 6.1 6.4 6.5	F.A1C 6.0 5.9 5.9 6.0 6.3 6.1 6.2	Aug. A1C 6.0 5.9 5.9 6.1 6.3 6.3	18.25 Predicted S.AIC 5.8 5.8 6.3 6.5 6.6 6.6 6.6	80% MI = MC + LD MI-based CVD Risk 48% 50% 52% 49% 50%	MC = sum of m1 - m4 Regression CVD Risks MC 52% 52% 52% 52% 52% 52% 51% 52% 51% 52%	Regressi Cancer R 35% 35% 37% 36% 37% 38% 36% 37%
11/25/21 Period Y2020M10 Y2020M11 Y2020M12 Y2021M01 Y2021M02 Y2021M04 Y2021M04 Y2021M05	Measures 8T (9) 97.8 97.9 97.9 98.0 98.0 97.9 97.4	Measured Weight (F) 166.5 167.5 167.5 168.3 169.1 169.1	12 ye Regression FPG via 8T 99 105 102 113 107 100 91	Regression FPG via W 85 89 93 97 96 100	Pred Regression Aug S. FPG 94 96 95 102 105 100 95	Measured 5. FPG 93 93 103 106 111 111 108	Measured Carbs 11.9 15.1 25.1 19.5 9.0 14.3 13.4	Measured K-Steps 4.8 5.4 4.9 4.4 5.2 4.8 4.3	GH.p 3.057 LEGT 5.PPG 104 112 144 103 118 117	0.0086 Measured 5. PPG 111 108 120 127 123 116 113	LEGT S. eAG 99 105 123 121 104 110 109	Measured 5. eAG 107 106 116 119 121 120 114	Measured S.AIC 6.0 5.9 6.0 6.1 6.4 6.5 6.5	FAIC 6.0 5.9 5.9 6.0 6.3 6.1 6.2	Aug. A1C 6.0 5.9 5.9 6.1 6.3 6.3 6.3	18.25 Predicted S.AIC 5.8 5.8 6.3 6.5 6.6 6.6 6.6	80% MI = MC + LD MI-based CVD Risk 48N 50% 52% 49% 50%	MC = sum of m1 - m4 Regression CVD Risk: MC 52% 52% 52% 52% 51% 51% 51% 52% 52% 52%	Regressi Cancer R 36% 35% 37% 38% 38% 37% 38% 37%
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11/25/21 Period Y2020M10 Y2020M11 Y2020M12 Y2021M02 Y2021M03 Y2021M04 Y2021M06 Y2021M06 Y2021M06 Y2021M06 Y2021M06	Measures BT (P) 97.8 97.9 97.8 98.0 98.0 97.9 97.8 97.4 97.4 97.7 97.7	Weight (#) 166.5 165.9 166.5 167.5 168.9 168.9 168.9 169.1 168.9 169.3	Regression FPG via 81 99 105 102 110 113 207 200 91 94 96	Regression FPG via W 89 86 89 91 100 99 100 101 95	Pred Regression Aug S. FPG 94 96 95 102 105 100 95 99 98	Measured 5. FPG 93 93 103 106 111 111 108 97 101 87	Measured Carbs 11.9 15.1 25.1 19.5 9.0 14.3 13.4 10.1 11.1 11.6	Measured K-Steps 48 5.4 4.9 4.4 5.2 4.8 1.9 1.8 1.8	GH.p 3.057 LEGT 5.99G 104 112 144 136 103 118 117 103 111 104	0.0086 Measured 5. PPG 111 108 120 125 127 123 116 113 116 112 108	105 105 105 107 108 109 100 100 105 101	Measured 5. eAG 107 106 116 119 121 120 114 109 113 107	Measured 6.0 5.9 6.0 6.1 6.4 6.5 6.3 6.1 6.1 5.9	5.9 5.9 6.0 6.3 6.1 6.2 6.2 6.2 6.2	Avg. A1C 5.9 5.9 6.1 6.3 6.3 6.3 6.2 6.2 6.2	18.25 Predicted S.AIC 5.8 6.3 6.5 6.6 6.6 6.3 6.0 6.2 5.8	80% MI = MC + LD MI-based CVD Risk 48% 50% 52% 49% 50% 52% 53% 53% 53%	MC = sum of m1 - m4 Regression CVD Risk: MC 52% 52% 52% 52% 51% 53% 52% 52% 52% 52% 52% 52% 52% 52% 52% 52	Regressi Cancer R 36% 35% 35% 35% 36% 35% 36% 36% 36% 36% 36% 36% 40%
11/25/21 Period Y2020M10 Y2020M12 Y2021M01 Y2021M02 Y2021M04 Y2021M06 Y2021M06 Y2021M06 Y2021M06 Y2021M07	Measures BT (9) 97.8 97.9 97.8 98.0 97.9 97.4 97.4 97.7 97.7 97.7	Risk Measured Weight (F) 166.5 165.9 166.5 167.5 166.3 166.0 166.9 169.1 164.9 169.3	12 years Regression FPG via BT 99 105 110 113 120 91 98 94 95 95 95 95 95 95 95	Regression FPG via W 89 86 89 93 97 96 100 99 101 101 95	Pred Regression Aug S. FPG 94 96 95 102 105 101 100 95 99 98 96	Measured 5. FPG 93 93 103 106 111 108 97 101 97	Measured Carbs 11.9 15.1 25.1 29.5 9.0 14.3 10.1 11.1 11.6 10.6	Measured K-Steps 4.8 5.4 4.9 4.4 5.2 4.3 3.9 3.8 3.8 3.8	GH.p 3.057 LEGT 5.PPG 104 112 144 136 103 118 117 103 111 111 106 108	0.0086 Measured 5.PPG 131 108 120 125 123 116 113 116 116 1108 111	LEGT S. eAG 99 105 123 121 104 110 109 100 106 101 101	Measured 5. eAG 107 106 116 119 120 114 109 113 101 107	Measured 5.40 5.9 6.0 6.1 6.5 6.5 6.3 6.1 5.9 5.7	5.9 5.9 5.9 6.0 6.3 6.1 6.2 6.2 6.2 6.2 6.2	Avg. A3C 5.9 5.9 6.1 6.3 6.3 6.3 6.2 6.2 6.2 6.1	18.25 Predkted S.AIC 5.8 6.3 6.5 6.6 6.6 6.6 6.0 6.2 5.8 5.8	80% MI = MC + LD MI-based CVD Risk 48% 50% 52% 49% 52% 53% 53% 53% 53% 53%	MC = sum of m1 · m4 Regression CVD Risk: MC 52% 52% 52% 52% 51% 52% 52% 52% 52% 52% 52% 52% 52% 52% 52	Regressi Cancer R 36% 35% 37% 38% 38% 39% 40% 39% 40% 40%
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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.

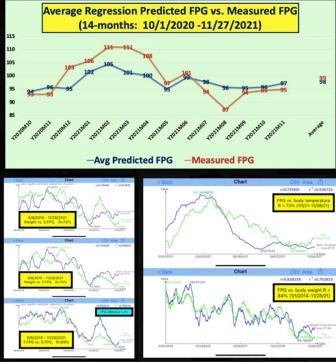


Figure 2: FPG prediction results over 14-month period from 10/1/2020 to 11/24/2021

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:

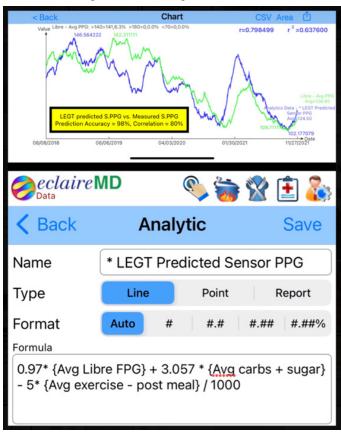


Figure 3: LEGT PPG equation and results (8/8/2018 - 11/27/2021)

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.

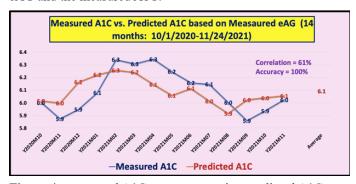


Figure 4: measured A1C versus regression predicted A1C over 14 months from 10/1/20 to 11/24/21

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.

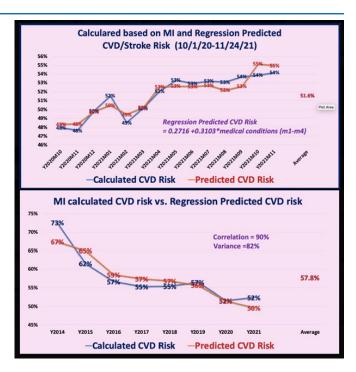


Figure 5: CVD risk (14 months and 8 years)

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.

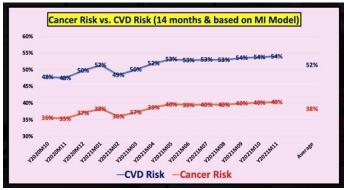


Figure 6: Cancer risk (14 months)

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)]						
LEGT Predicted S.PPG (daily) = 0.97*	1							
LEGT Predicted S.eAG (daily) = ((7/2	1							
Regreesion Predicted A	1C (daily) = 0	1							
						•			
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 W	eight			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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