

# The GH-Method

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## **Viscoelastic or Viscoplastic Glucose Theory (VGT #143): A Neural Communication Model Between the Cerebral Cortex of the Brain and Gastrointestinal Organs Including the Stomach and Small Intestine, Plus the Liver and Pancreas via the Central Nervous System which is Proven via a Study of Postprandial Plasma Glucose Waveforms and Levels Resulting from a Total of 483 Egg Meals versus 280 Liquid Egg Meals and 203 Solid Egg Meals by Applying 3 Energy Tools of Time Domain, Space Domain, and Frequency Domain of the GH-Method: Math-Physical Medicine (No. 735)**

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**Keywords:** Viscoelastic; Viscoplastic; Brain; Gastrointestinal organs; Stomach; Small intestine; Liver; Pancreas; Central nervous system; Postprandial plasma glucose; Fasting plasma glucose; Type 2 diabetes; Fast Fourier transform

**Abbreviations:** GI: gastrointestinal; CNS: central nervous system; FFT: fast Fourier transform; T2D: type 2 diabetes; PPG: postprandial plasma glucose; FPG: fasting plasma glucose; FD: frequency domain; SD: space domain; TD: time domain; MPM: math-physical medicine

### 1. INTRODUCTION

The author recently read an article, “Central Neurocircuits Regulating Food Intake in Response to Gut Inputs—Preclinical Evidence,” by Kirsteen N. Browning and Kaitlin E. Carson on March 11, 2021. He has selected its abstract section as one of his excerpts at below:

“Abstract:

The regulation of energy balance requires the complex integration of homeostatic and hedonic pathways, but sensory inputs from the gastrointestinal (GI) tract are increasingly recognized as playing critical roles. The stomach and small intestine relay sensory information to the central nervous system (CNS) via the sensory afferent vagus nerve. This vast volume of complex sensory information is received by neurons of the nucleus of the tractus solitarius (NTS) and is

integrated with responses to circulating factors as well as descending inputs from the brainstem, midbrain, and forebrain nuclei involved in autonomic regulation. The integrated signal is relayed to the adjacent dorsal motor nucleus of the vagus (DMV), which supplies the motor output response via the efferent vagus nerve to regulate and modulate gastric motility, tone, secretion, and emptying, as well as intestinal motility and transit; the precise coordination of these responses is essential for the control of meal size, meal termination, and nutrient absorption. The interconnectivity of the NTS implies that many other CNS areas are capable of modulating vagal efferent output, emphasized by the many CNS disorders associated with dysregulated GI functions including feeding. This review will summarize the role of major CNS centers to gut-related inputs in the regulation of gastric

function with specific reference to the regulation of food intake.”

Furthermore, another published article: “Pitt study shows brain and stomach connections are a two-way street” by David Templeton of Pittsburgh Post-Gazette on May 27, 2020 has also revealed similar neuroscience findings:

“Published May 18th, 2020 in the Proceedings of the National Academy of Sciences, an important world first, a study co-authored by Dr. Levinthal and Dr. Peter Strick, both from the Pitt School of Medicine, has explained what parts of the brain’s cerebral cortex influence stomach function and how it can impact health. Dr. Peter Strick is a world leader in establishing evidence that internal organs are strongly modulated at the highest levels by the cerebral cortex. It’s been traditional in biology and medicine that the internal organs are self-regulatory through the autonomic nervous system, largely independent of higher brain regions. Dr. Strick’s previous research, for instance, also showed that similar areas of the cerebral cortex also control kidney and adrenal function. That course of research now could extend to “the heart, liver and pancreas to discover more about how the brain coordinates control of internal organs,” said Mr. Sterling who holds a Ph.D. in neuroscience. When it comes to trusting your gut, it already is well-established that the stomach and gut send “ascending” signals to the brain in a way that influences brain function. But the study has found that the “central nervous system both influences and is influenced by the gastrointestinal system.” What people haven’t understood to date, Dr. Strick said, is that the brain also has “descending influences on the stomach” with various parts of the brain involved in that signaling, including those areas that control movement and emotions. Those areas control the stomach “as directly as cortical control of movement. These are not trivial influences.”

These two excerpts have summarized the interconnectivity of the brain and the gastrointestinal organs regarding meals, using a biological research method. These two papers have provided additional backup information and better biological descriptions to the author for his similar neuroscience research using a math-physical research method.

The author started his neuroscience study on inter-connectivity among brain and other internal organs since 11/8/2019 with his published paper No.136. Since then, he has written 29 medical papers regarding this neuroscience subject. As early as 2019, the author observed his postprandial plasma glucose (PPG) levels and waveforms are different with identical food materials and ingredients (i.e. 1 egg or 2 eggs) but with different cooking methods (egg drop liquid egg meals versus pan-fried or hard-boiled solid egg meals). This biophysical observation did not make any sense to him using his learned knowledge of both food nutrition and internal medicine. By that time, he has already identified 19 influential factors of PPG. After conducting various research tasks, he had eliminated the possibility of all of these 19 factors being the cause of this strange outcome, but with only one remaining factor which he named as the “unknown reason”. By going through a process of “decision making through elimination” which he learned from his MBA courses around 40 years ago. He allowed his brain and thoughts to wonder around many “wild and crazy” directions or ideas in order to identify a final answer of the cause for this strange outcome. He hoped that he could interpret his observed strange biophysical phenomenon and also could justify his bold hypothesis of brain’s involvement. His final bold and crazy hypothesis in 2019 was that “the brain makes decisions and controls the glucose produced by liver as well as the insulin produced by pancreatic beta cells based on inputs sending from stomach and intestine, i.e. guts, through central nerve system to the brain for its decision-making”.

After consuming 483 experimental meals that include both soup-based meals (liquid egg) and solid food meals (pan-fried egg or hard-boiled egg), the author has noticed that there are noticeable differences in the peak PPG and average PPG values by eating two different prepared egg meals. For example, there are 17 mg/dL of peak PPG difference and 13 mg/dL of average PPG difference between 280 liquid egg meals and 203 solid egg meals. These observed glucose differences resulting from consuming different egg meal cook methods (both are using ~4 grams of carbohydrates/sugar amount and >4k post-meal walking exercise) have pushed his comprehension beyond his existing knowledge learned from his past 13

years of self-study of diabetes and food nutrition. In other words, he could not understand why and also could not interpret the different PPG differences given the same food ingredient (almost equal amount of carbs/sugar consumption) and the same level of post-meal walking exercises (around 4k steps).

This article has combined his 280 PPG results from his meals with a liquid state of food, i.e. egg drop soup, known as “liquid egg” meals. These liquid meals have a carbs/sugar intake amount of 4.3 grams and post-meal walking exercise of 4,062 steps. In addition, he also cooked 203 egg meals in a solid state. These solid egg meals consisted of both pan-fried eggs and hard-boiled eggs known as “solid egg” meals. These solid meals have a carbs/sugar intake of 4.8 grams and post-meal walking exercise of 4,321 steps. A food nutrition scientist and an internal medicine scientist cannot explain this strange observed biophysical phenomenon.

Other than the observation and research on the PPG amplitude difference, he has also wondered what are the differences from the viewpoint of associated energies with those different egg meals PPG, particularly utilizing 3 different energy models. The discovery in this article has further presented some probable but reasonable proof for him to spend additional time and effort to delve deeper into the subject of neural communication.

From the practical viewpoint of diabetes control, he can now apply what he has learned from his egg meals experimental findings, to reduce his average PPG, daily estimated average glucose (eAG), and hemoglobin A1C (HbA1C) level which assists in the continuous daily fighting efforts of his type 2 diabetes (T2D) control. More importantly, by knowing the PPG-associated energy quantitatively, he would know what degrees of damage are done to his various internal organs resulting from the situation of hyperglycemia, e.g. High PPG. Also, using a time-zone study, he can offer an estimated timeframe regarding the time when he would face severe medical complications resulting from his T2D.

It should be noted that in this article, he has utilized two cases, including the meals number percentages and excluding the meals

number percentages. This inclusion or exclusion of “data quantity” would result in vastly different energy results with proper interpretations.

Furthermore, his developed equation for the predicted egg PPG without meals number percentages is listed as:

Predicted PPG based on SD hysteresis loop areas (fire case of without meal #)  
= (Liquid egg PPG component value\* SD Liquid egg PPG energy ratio of 45% + Solid egg PPG component value\* SD Solid egg PPG energy ratio of 55%)

However, his developed equation for the predicted egg PPG with meals number percentages is listed as:

Predicted PPG based on SD hysteresis loop areas (for the case of with meal #)  
= (Liquid egg PPG component value\* SD Liquid egg PPG energy ratio of 56% + Solid egg PPG component value\* SD Solid egg PPG energy ratio of 44%)

Finally, he calculates the prediction accuracy and correlation between measured PPG versus predicted PPG.

Prediction Accuracy  
= (predicted PPG - measured PPG) / measured PPG

## 2. METHODS

### 2.1 The author’s case of diabetes and complications

The author has been a severe T2D patient since 1996. He weighed 220 lb. (100 kg, BMI 32.5) at that time with a one-time glucose reading of 380 mg/dL. By 2010, he still weighed 198 lb. (BMI 29.2) with average daily glucose of 250 mg/dL (HbA1C of 10%). During that year, his triglycerides reached 1161b (hyperlipidemia) and albumin-creatinine ratio (ACR) at 116 (kidney issues). He also suffered from five cardiac episodes within a decade from 1993 through 2003 caused by work stress and diabetes. In 2010, three independent physicians warned him about his urgent need for kidney dialysis treatment and the risk of his life-threatening health situation such as dying from his severe diabetic complications. Other than the

cerebrovascular disease (stroke), he has suffered most of the known diabetic complications, including both macro-vascular & micro-vascular complications, nerve damage as in retinopathy and foot ulcer, as well as a hormonal disturbance, e.g. hypothyroidism.

In 2010, he decided to launch his self-study on endocrinology, diabetes, and food nutrition to save his own life. After developing the metabolism model in 2024, 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 those 4 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 as of 12/8/2015.

Around that time (2014-2017), he started to focus on preventive medicine instead of blindly trusting and depending on medication treatments only. He also gambled on his belief that most human organs have strong inherent abilities to self-repair themselves through lifestyle improvements by taking good care of them - even though it can only accomplish a certain degree of repairing or healing dependent on certain organ cells and their status of damage, such as pancreatic beta cells.

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 dining out frequently, post-meal exercise disruption, jet lag, and along with the overall metabolic 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 traveling period.

Since 1/19/2020, living in a COVID-19 quarantined lifestyle, not only has he written and published ~500 medical papers in 100+ journals, but he has also reached his best health conditions in the past 26 years. By the beginning of 2022, his weight was further reduced to 168 lbs. (BMI 24.8) along with a 5.8% A1C value (beginning level of pre-diabetes), without having any medication interventions or insulin injections. During the period from 1/1/2022 to 8/20/2022, his average FPG is 93 mg/dL, PPG is 113 mg/dL, and daily glucose is 106 mg/dL. These good results are due to his non-traveling, low-stress, and regular daily life routines. Of course, the accumulated knowledge of chronic diseases, various complications, practical lifestyle management experiences, and development of many high-tech tools along with his medical research academic findings have contributed to his excellent health status since 1/19/2020, the beginning date of his self-quarantined life.

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 the present day. In his research work, he uses his CGM sensor glucose at a time interval of 15 minutes (96 data per day). Incidentally, the average sensor glucoses between 5-minute intervals and 15-minute intervals has only a 0.6% difference (average glucose of 111.86 mg/dL for 5 minutes and average glucose of 111.18 mg/dL for 15 minutes with a correlation of 94% between these two sensor glucose curves) during the period from 2/19/20 to 7/22/22.

Therefore, over the past 13 years, he could study and analyze his 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 research work has a goal of achieving both “high precision” and “quantitative proof” in the medical findings for the ultimate objectives of “preventive medicine”.

The following timetable provides a rough sketch of the emphasis in 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 (CKD), bladder, foot, and eye issues (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, 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 from quantum mechanics on medical research subjects, such as chronic diseases and their complications, cancer, and dementia.

2022: Applications of viscoelastic/viscoplastic glucose theory (LEGT) on 142 biomedical research cases and 5 economics research cases.

Again, to date, he has spent ~40,000 hours self-studying and researching medicine and he has read 4,000+ published medical papers online. He has collected and calculated more than 3+ million pieces of data regarding his own medical conditions and lifestyle details. In addition, he has written and published 700+ medical research papers in 100+ various medicine, physics, mathematics, and engineering journals. Moreover, he has also given 120+ presentations at 70+

international medical conferences. He has continuously dedicated his time (11-12 hours per day and work each day of a year, without rest during the past 13 years) and efforts to his medical research work and shared his findings and learnings with other patients worldwide. In addition, he has also spent the past 12 years developing and maintaining a medicine and health software APP on his iPhone which functions as his private numerical laboratory to process the various experimental datasets of his medical conditions and lifestyle details.

## **2.2 Brief introduction of math-physical medicine (MPM) research**

The author has collected 3+ million pieces of data regarding his health condition and lifestyle details over the past 13 years. He spent the entire year of 2014 developing a metabolism index (MI) model using a topology concept, nonlinear algebra, algebraic geometry, and finite element method. This MI model contains various measured biomarkers and recorded lifestyle details along with their induced new biomedical variables for an additional ~1.5 million data. Detailed data of his body weight, glucose, blood pressure, heart rate, blood lipids, body temperature, and blood oxygen level, along with important lifestyle details, including diet, exercise, sleep, stress, water intake, and daily life routines are included in the MI database. In addition, these lifestyle details also include some lifetime bad habits and certain environmental exposures. Fortunately, the author has none of these lifetime bad habits and an extremely low degree of exposure to environmental factors. The developed MI model has a total of 10 categories covering approximately 500 detailed elements that constitute his defined “metabolism index model” which are the building blocks or root causes for diabetes and other chronic disease-induced complications, including but not limited to CVD, CHD, stroke, CKD, DR, neuropathy, foot ulcer, hypothyroidism, dementia, and various cancers. The end result of the MI development work is a combined MI value within any selected period with 73.5% as its dividing line between a healthy and unhealthy state. The MI serves as the foundation for many of his follow-up medical research work.

During the period from 2015 to 2017, he focused his research on T2D, especially glucose, including fasting plasma glucose (FPG), PPG, estimated average glucose (eAG), and hemoglobin A1C (HbA1C). During the following period from 2018 to 2022, he concentrated on researching medical complications resulting from diabetes, chronic diseases, and metabolic disorders which include heart problems, stroke, kidney problems, retinopathy, neuropathy, foot ulcer, diabetic skin fungal infection, hypothyroidism, diabetic constipation, dementia, and various cancers. He also developed a few mathematical risk models to calculate the probability percentages of developing various diabetic complications based on this MI model. From his previous medical research work with 700+ published papers, he has identified and learned that the associated energy of hyperglycemic conditions is the primary source of causing many diabetic complications which lead to death. Therefore, a thorough knowledge of these energies is important for achieving a better understanding of the dangerous complications.

### 2.3 TD, SD, and FD analysis tools

This section has brief descriptions of TD correlation analysis with other observational results, SD VGT analysis with hysteresis loop area's energy results, and FD analysis with frequency curve area's energy results.

First of all, by using a TD analysis tool, we can examine the curves' moving trend and pattern visually along with their correlation numerically. We can also study the extremely high or low data values in the dataset. The visual observation or calculation-derived interpretations are a part of statistical analysis results which can indeed provide some useful hints or even derive some accurate conclusions. However, we must be aware of the limitations of the selected data-size and time-window and also be cautious of the appropriate statistics tool we choose.

The author would like to describe the essence of his developed "hybrid model" that combines both the SD viscoelastic/plastic VGT analysis method and FD fast Fourier transform (FFT) analysis method together with a comparison against the traditional time-domain statistical correlation analysis.

It is described in 10 steps in the English language instead of using mathematical equations to explain it. In this article, he has applied both the SD-VGT operations (steps 1-7) and the FD-FFT operations (steps 8-10). As a result, it is aimed at readers who do not have an extensive background in those academic subjects of engineering, physics & mathematics.

The first step is to collect the output data or symptom (strain or  $\epsilon$ ) on a time scale. The second step is to calculate the output change rate with time ( $d\epsilon/dt$ ), i.e. the change rate of strain or symptom over each period. The third step is to gather the input data or cause (viscosity or  $\eta$ ) on a time scale. The fourth step is to calculate the time-dependent input or cause (time-dependent stress or  $\sigma$ ) by multiplying  $d\epsilon/dt$  and  $\eta$  together. The "time-dependent input or cause equation" of "stress  $\sigma = \text{strain change rate of } d\epsilon/dt * \text{viscosity } \eta$ " is the essential part of this "time dependency". The fifth step is to plot the input-output (i.e. stress-strain or cause-symptom) curve in a two-dimensional space-domain or SD (x-axis versus y-axis) with strain (output or symptom) on the x-axis and stresses (time-dependent inputs, causes, or stresses) on the y-axis.

The sixth step is to calculate the total enclosed area within these stress-strain curves or input-output curves (i.e. the hysteresis loops), which is also an indicator of associated energies (either created energy or dissipated energy) of this input and output dataset. These energy values can also be considered as the degrees of influence on output by inputs. The seventh step is the assembly of the area values of the selected periods to compare the "historical progression and contribution of medical condition" over certain periods. For the frequency domain, the eighth step is to define a "hybrid input variable" by using "strain\*stress" which yields another accurate estimation of energy ratio similar to the SD-VGT energy ratio associated with the hysteresis loop. The ninth step is to present these hybrid models' results of (strain\*stress) in TD and then perform the FFT operation to convert them into FD. The enclosed area of the frequency curve (where the x-axis is the frequency and the y-axis is the amplitude of energy) can be used to estimate the total FD-FFT energy. The tenth step is to compare

these FD energy results against the SD-VGT energy results, or even TD energy results.

After providing the above 10-step description, the author would still like to use the following set of VGT stress-strain mathematical equations in a two-dimensional SD to address the selected medical variables:

**Strain**

=  $\epsilon$  (time-dependency characteristics of individual strain value at the present time duration)

**Stress**

=  $\sigma$  (based on the change rate of strain multiplying with a chosen viscosity factor  $\eta$ )  
 =  $\eta * (d\epsilon/dt)$   
 =  $\eta * (d\text{-strain}/d\text{-time})$   
 = (viscosity factor  $\eta$  using individual viscosity factor at present time duration) \* (strain at present quarter - strain at previous time duration)

Some of these inputs (causes or viscosity factors) are further normalized by dividing them or being divided by a normalization factor using certain established health standards or medical pieces of knowledge. Some examples of normalization factors are 6.0 for HbA1C, 120 mg/dL for glucose, 25 for body mass index (BMI), 4,000 steps after each meal, 10,000 or 12,000 steps for daily walking exercise depending on time-period selection, 13 grams to 20 grams of carbs/sugar intake amount per meal depends on time-period selection. If using the originally collected data, i.e. the non-normalized data, it would distort the numerical comparison of the hysteresis loop areas. Using this “normalization process”, we can remove the dependency of the individual unit or certain unique characteristics associated with each viscosity factor. This process allows us to convert the originally collected variables into a set of “dimensionless variables” for easier numerical comparison and result interpretation.

The normalization factor for the “without meals number” is divided the egg meal PPG by 120 mg/dL; and the normalization factor for the “with meals number” is divided the egg meal PPG by (120\*egg meal number percentages”.

**Note:** For a more detailed description, please refer to the “consolidated method” section

which is given at the beginning of the special issue.

**3. RESULTS**

Figure 1 shows two data tables and the background information regarding meals numbers, carbs/sugar grams, and post-meal walking steps for each type of egg meals.



Figure 1: Data table of meals background information.

Figure 2 depicts both 1 TD-squared PPG analysis results and 2 FD-FFT analysis results.

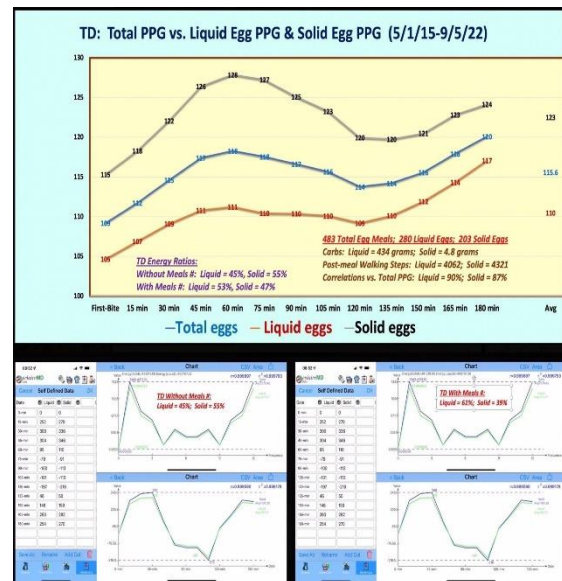


Figure 2: 1 time-domain and 2 frequency-domain results.

Figure 3 reflects 2 SD graphic diagrams and their analysis results.

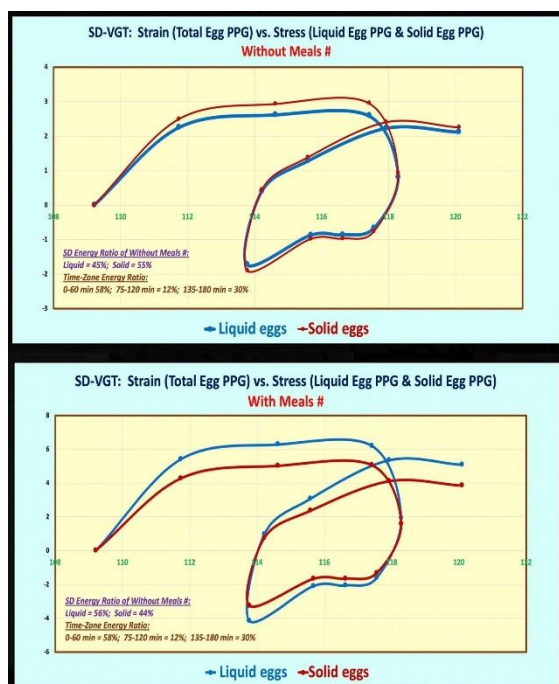


Figure 3: 2 space domain VGT analysis results.

Figure 4 illustrates the comparison of the measured total egg PPG curve against 2 predicted egg PPG curves (without and with meals number %).

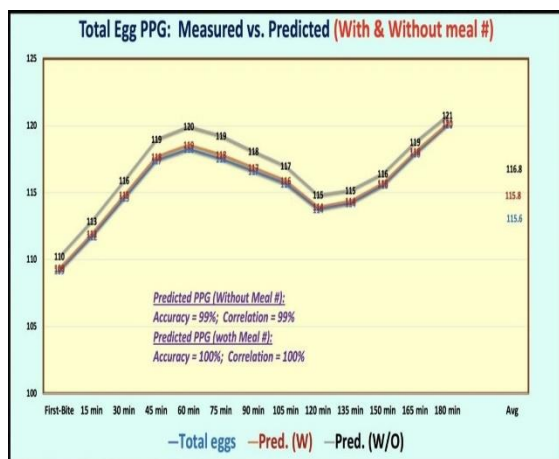


Figure 4: Comparison of measured total egg PPG curve versus 2 predicted total egg PPG curves.

#### 4. CONCLUSION

In summary, there are 5 observations listed below regarding total egg PPG versus both liquid egg PPG and solid egg PPG.

(1) From the three PPG waveforms in TD, the 3-hour solid egg PPG waveform shows a mountain shape curve, while the 3-hour liquid egg PPG waveform reflects a rather

“flat” curve. This solid egg meal PPG waveform has an average PPG of 123 mg/dL and peak PPG at 60-minutes of 128 mg/dL. On the other hand, the liquid egg PPG waveform has a “pseudo-flatline” shape or more of a “low rolling-hill” shape, but with an upward-titled tail between the second and third hour after the first bite of his meal. This liquid egg meal PPG waveform has an average PPG of 110 mg/dL and peak PPG at 60-minutes of 111 mg/dL. Actually, from a research viewpoint, he should focus on the segment of 0-min to 120-min only while ignoring the segment of 120-min to 180-min since his post-meal exercise usually ends around 120-minutes. In summary, between 203 solid egg meals and 280 liquid egg meals, the difference in average PPG is 13 mg/dL and peak PPG is 17 mg/dL. More importantly, his squared PPG energy ratio for the case without meal number is 45% for liquid eggs versus 55% for solid eggs, with a 10% TD energy difference. This is due to the average solid PPG being higher than the average liquid PPG. However, his squared PPG energy ratio for the case with meal number is 53% for liquid eggs versus 47% for solid eggs, with a 6% TD energy difference. This is due to the meals number of liquid egg PPG being higher (38% more of data quantity) than the meal number of solid egg PPG.

(2) Applying SD viscoelastic or viscoplastic glucose (SD-VGT) energy tool, both of his two hysteresis loops have presented a “viscoplastic” behavior and their moving paths and patterns look like a “bow-tie” shape. Furthermore, the energy ratio of two hysteresis loop areas for the case without meal number is liquid eggs 45% versus solid eggs 55% due to the higher viscosity and higher stress of solid egg meals. However, the energy ratio of two hysteresis loop areas for the case with meal number is liquid eggs 56% versus solid egg 44% due to the higher meal number of liquid egg meals (38% larger data quantity). In addition, his 3 time-period energy ratios for both without and with meal number cases are identical as: 0-min to 60-min at 58%, 60-min to 120-min at 12%, and 120-min to 180-min at 30%. This shows that from the viewpoint of energy generation and energy dissipation, the first hour’s generated energies are not totally dissipated during the second hour, therefore, the third hour’s left-over energies are still at 1/3 level (30%) which cannot be ignored.

(3) Applying the FD-FFT energy tool and using a new variable of (strain\*stress) from SD, his FD energy ratios of solid eggs versus liquid eggs are: for the case of without meal number, liquid = 45% versus solid = 55% is due to higher average solid PPG; while for the case of with meal number, liquid = 61% versus solid = 39% is due to higher meal number for liquid PPG.

(4) The above 3 energy ratio findings have the same pattern that for the case of without meal number influence, solid eggs being higher than liquid eggs due to average PPG of solid eggs is higher than liquid eggs, while for the case of with meal number influence, liquid eggs being higher than solid eggs due to high meal numbers of liquid eggs. However, in FD-FFT analysis, the absolute numerical values are higher for FD energy than both SD and TD energies which is resulted from the amplification effect of his FD's newly-defined variable of (strain\*stress). But the numerical values of SD energies and TD energies are quite comparable to each other.

(5) As a comparison of the measured total egg PPG waveform versus two predicted total egg PPG waveforms, the case with meal number influence has higher accuracy and correlation (both are at 100%) than the case without meal number influence (both are at 99%).

From a neuroscientific viewpoint, the author could utilize the developed GH-Method: math-physical medicine methodology (MPM) and learned biomedical knowledge from his medical research work to “trick” or “trigger” the cerebral cortex of the brain into producing or releasing a “lesser” amount of PPG from the liver which resulted from liquid egg drop soup meals, without worrying about the important food nutritional balance. In other words, changing the food cooking method or preparation way to transform meals from a solid physical phase into a liquid physical phase (fundamental concept of physics), it can help lowering peak PPG value, average PPG level, HbA1C, and their associated energy levels without altering the necessary nutritional balance. The author made another hypotheses that the brain actually

considers liquid food similar to drinking water or tea (not coffee).

This article offers some practical ideas and effective ways on how to control a T2D patient's daily glucose situation through the biophysical findings using energy analysis tools related to the food preparation method.

## 5. REFERENCES

For editing purposes, the 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.eclaircmd.com](http://www.eclaircmd.com)

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For reading more of the author's published VGT or FD analysis results on medical applications, please locate them through three published special editions from the following three specific journals:

- (1) Special Issue. The GH-Method. (<https://www.theghmethod.com>)
- (2) Journal of Applied Material Science & Engineering Research (contact: Catherine)
- (3) Advances in Bioengineering and Biomedical Science Research (contact: Sonny Hazi)

### External source of referenced paper

- 1) Templeton D. Pitt study shows brain and stomach connections are a two-way street. Pittsburgh Post-Gazette. 2020.
- 2) Browning KN, Carson KE. Central neurocircuits regulating food intake in response to gut inputs—preclinical evidence. *Nutrients*. 2021;13(3):908.

# Viscoelastic and Viscoplastic Glucose Theory Application in Medicine

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