

The GH-Method

Viscoelastic Medicine Theory (VMT #314): Two Engineering-Based Prediction Equations of Postprandial Plasma Glucose versus Fasting Plasma Glucose, Carbohydrates & Sugar Amount, Post-Meal Walking Steps Using 10-Years Collected Data with Linear Elasticity and Viscoplasticity of GH-Method: Math-Physical Medicine (No. 914)

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Abstract

As a former engineer who understands the importance of predicting structural responses to external forces to prevent machine damages or structural failures, the author, now a medical research scientist, seeks a way to predict postprandial glucose (PPG) levels using pancreatic beta cell health (assessed through fasting glucose levels in early morning), carbohydrate and sugar intake, and exercise level. The concepts of "prediction and prevention" hold significance in both engineering and medicine. In 2015, the author developed a PPG prediction equation using the physics concept of linear elasticity (LEGT): Predicted PPG = FPG * GH.F + Carbs * GH.P - Ksteps * GH.W. In above equation, three modulus values were applied: GH.F = 0.96; GH.P = 2.0; GH.W = 4.0. Under the guidance of his academic advisor at MIT, Professor Norman Jones, the author also incorporated one of the engineering models, the space-domain viscoplastic energy model (SD-VMT), into his 313 medical research projects over the past two years. Since January 2021, he has focused on identifying energy levels associated with influential causes and their relationship with medical symptoms. Additionally, he has been exploring ways to expand this VMT research methodology to incorporate a "prediction and prevention" capability using energy ratios identified by the SD-VMT energy ratios. As a result, another VMT-based prediction equation for

PPG has also been derived: Predicted Symptom = ((Normalized Input * Respective Input's VMT Energy Ratio) / Average Input Stress) * Average Measured Symptom. In summary, there are three observations: (1) Comparison of PPG prediction accuracy and waveform correlation between measured PPG and predicted PPG: The LEGT model achieves an R value of 92% and an accuracy of 99.8%, whereas the VMT model shows an R value of 76% and an accuracy of 100%. (2) Analysis of SD-VMT energy ratios: FPG accounts for 42%, Carbs account for 35%, and Ksteps account for 23%. The contributions of LEGT components are: FPG accounts for 90%, Carbs account for 24%, and Ksteps account for -14%. These findings indicate that FPG, which reflects the health state of pancreatic beta cells, is the most influential factor. Additionally, the ratio between diet and exercise is calculated as 1.54 based on SD-VMT, and 1.76 based on LEGT. These two ratios highlight a greater importance of diet in PPG formation compared to exercise. (3) Evaluation of time-zone energy distribution: 82% of the energy is allocated to the Y14-Y18 period, while only 18% is allocated to the Y19-Y23 period. This suggests that the earlier five-year period was worse in terms of PPG levels and the three influential factors compared to the more recent five-year period. In conclusion, both the LEGT and VMT prediction models have proven their effectiveness in managing diabetes through PPG prediction.

Keywords: Viscoelastic; Viscoplastic; Postprandial plasma glucose; Fasting plasma glucose; Lifestyle; Glucose; Diabetes

Abbreviations: MI: metabolism index; CVD: cardiovascular disease; CKD: chronic kidney disease; T2D: type 2 diabetes; PPG: postprandial plasma glucose; FPG: fasting plasma glucose; SD: space-domain

1. INTRODUCTION

As a former engineer who understands the importance of predicting structural responses to external forces to prevent machine damages or structural failures, the author, now a medical research scientist, seeks a way to predict postprandial glucose (PPG) levels using pancreatic beta cell health (assessed through fasting glucose levels in early morning), carbohydrate and sugar intake, and exercise level. The concepts of "prediction and prevention" hold significance in both engineering and medicine.

In 2015, the author developed a PPG prediction equation using the physics concept of linear elasticity (LEGT):

$$\text{Predicted PPG} = \text{FPG} * \text{GH.F} + \text{Carbs} * \text{GH.P} - \text{Ksteps} * \text{GH.W}$$

In above equation, three modulus values were applied:

$$\begin{aligned} \text{GH.F} &= 0.96; \\ \text{GH.P} &= 2.0; \\ \text{GH.W} &= 4.0 \end{aligned}$$

Under the guidance of his academic advisor at MIT, Professor Norman Jones, the author also incorporated one of the engineering models, the space-domain viscoplastic energy model (SD-VMT), into his 313 medical research projects over the past two years. Since January 2021, he has focused on identifying energy levels associated with influential causes and their relationship with medical symptoms. Additionally, he has been exploring ways to expand this VMT research methodology to incorporate a "prediction and prevention" capability using energy ratios identified by the SD-VMT energy ratios. As a result, another VMT-based prediction equation for PPG has also been derived:

$$\begin{aligned} \text{Predicted Symptom} \\ &= ((\text{Normalized Input} * \text{Respective Input's} \\ &\text{VMT Energy Ratio}) / \text{Average Input Stress}) * \\ &\text{Average Measured Symptom} \end{aligned}$$

1.1 Biomedical information

The following sections contain condensed information sourced from various published

medical articles that the author has reviewed. It is important to acknowledge that these sections are not the original work or creation of the author of this specific article. They have been included for the purpose of later review by the author and to provide useful information to other readers interested in this topic.

Health range of FPG:

FPG (Fasting Plasma Glucose) is a blood test used to measure the concentration of glucose in the blood after an overnight fast. It is an important indicator of a person's blood sugar level and is often used to diagnose diabetes and monitor its treatment.

The normal range for FPG is typically considered to be between 70-100 mg/dL (3.9-5.6 mmol/L). However, it is important to note that normal ranges can vary slightly depending on the specific laboratory and testing method used.

Here is a general breakdown of the FPG levels and what they indicate:

-Normal: FPG levels below 100 mg/dL (5.6 mmol/L)

-Prediabetes: FPG levels between 100-125 mg/dL (5.6-6.9 mmol/L)

-Diabetes: FPG levels of 126 mg/dL (7.0 mmol/L) or higher on two separate occasions

It is important to note that these ranges may differ for pregnant women, individuals with certain medical conditions, or based on specific guidelines set by healthcare professionals or organizations.

Pathophysiological explanations of using FPG value as an indicator of pancreatic beta cells health status regarding insulin resistance:

FPG (Fasting Plasma Glucose) is often used as an indicator of pancreatic beta cell health status and insulin resistance. Insulin resistance refers to the reduced ability of cells to respond to the action of insulin, resulting in elevated blood glucose levels. Here are some pathophysiological explanations for using FPG as an indicator of beta cell health and insulin resistance:

1. Insulin secretion

Pancreatic beta cells play a crucial role in secreting insulin, the hormone responsible for regulating blood glucose levels. In individuals with insulin resistance, the beta cells compensate by producing and secreting more insulin to overcome the decreased sensitivity of cells to insulin. Over time, this increased demand on the beta cells can lead to their dysfunction or failure, resulting in decreased insulin secretion. This dysfunction in beta cells can contribute to elevated FPG levels.

2. Glucose production

In addition to insulin secretion, beta cells also help regulate glucose production in the liver. In individuals with insulin resistance, the liver may produce excess glucose even when insulin levels are high. This abnormal glucose production contributes to elevated FPG levels.

3. Glucotoxicity and lipotoxicity

Prolonged exposure to high blood glucose levels, known as glucotoxicity, can lead to beta cell damage and dysfunction. Similarly, increased levels of free fatty acids, known as lipotoxicity, can also impair beta cell function. Both glucotoxicity and lipotoxicity can contribute to decreased insulin secretion and exacerbate insulin resistance.

4. Inflammation

Insulin resistance is often associated with chronic low-grade inflammation. Inflammatory cytokines, such as tumor necrosis factor-alpha (TNF-alpha), can impair insulin signaling pathways and contribute to beta cell dysfunction and insulin resistance. Inflammation within the pancreatic islets, where beta cells are located, can further contribute to their dysfunction and impact FPG levels.

It's important to note that FPG is just one of the many measures used to assess beta cell health and insulin resistance. Other tests, such as oral glucose tolerance test (OGTT) and measures of insulin secretion and insulin resistance, may provide additional information for a more comprehensive evaluation. Consulting with a healthcare professional can help in evaluating these parameters and developing an appropriate management plan.

What are other indicators of pancreatic beta cells health state other than FPG in early morning?

Along with FPG, there are several other indicators that can be used to assess beta cell health status:

1. Postprandial glucose levels

Postprandial glucose refers to blood glucose levels after consuming a meal. Elevated postprandial glucose levels may indicate impaired beta cell function and insulin secretion, as the beta cells may be unable to respond adequately to the glucose load.

2. Glucose tolerance test (GTT)

This test measures blood glucose levels before and after consuming a standardized amount of glucose. It helps assess the body's ability to handle a glucose load and provides information about beta cell function and insulin secretion.

3. Insulin levels

Along with glucose levels, measuring insulin levels can provide insights into beta cell function. In response to elevated blood glucose levels, beta cells should secrete insulin to help regulate glucose levels. However, if insulin levels are low despite high glucose levels, it may indicate impaired beta cell function.

4. C-peptide levels

C-peptide is a byproduct of insulin production. Measuring C-peptide levels can provide information about the amount of insulin being produced by the beta cells. Lower C-peptide levels may indicate beta cell dysfunction or inadequate insulin secretion.

5. Proinsulin levels

Proinsulin is a precursor molecule to insulin that is converted into insulin and C-peptide. Increased levels of proinsulin may be a sign of reduced beta cell function or impaired insulin processing.

6. HOMA-B (Homeostatic Model Assessment of Beta cell function)

HOMA-B is a calculation that estimates beta cell function based on fasting glucose and fasting insulin levels. It provides an assessment of beta cell health and insulin secretion.

7. Islet autoantibodies

In certain cases, measuring the presence of autoantibodies against beta cells, such as antibodies against glutamic acid decarboxylase (GAD) or islet antigen-2 (IA-2), can help diagnose autoimmune conditions that can affect beta cell health, such as type 1 diabetes and latent autoimmune diabetes in adults (LADA).

These indicators, along with FPG, provide a comprehensive picture of beta cell health and insulin secretion. Healthcare professionals may use one or multiple indicators based on the specific clinical scenario and individual patient characteristics to evaluate beta cell health status accurately. Unfortunately, most of these mentioned tests can not be performed by an individual diabetes patient at home without proper background knowledge, specific training and testing facility.

Pathophysiological explanations of PPG versus FPG level in early morning, carbohydrates and sugar intake amount, and post-meal exercise level:

1. Pathophysiological explanations of PPG (Postprandial plasma glucose) versus FPG (Fasting plasma glucose) levels

-PPG levels: After consuming a meal, blood glucose levels increase due to the breakdown and absorption of carbohydrates. This triggers the release of insulin from beta cells, which helps transport glucose from the bloodstream into cells for energy utilization or storage. In individuals with impaired beta cell function or insulin resistance, the insulin response may be delayed or insufficient, leading to elevated PPG levels.

-FPG levels: Fasting plasma glucose refers to the glucose levels in the blood after an overnight fast. It primarily reflects hepatic glucose production, as the liver produces glucose to maintain blood glucose levels during fasting. In individuals with impaired insulin secretion or insulin resistance, the liver may overproduce glucose during fasting, leading to elevated FPG levels.

2. Carbohydrates and sugar consumption amount

-Carbohydrates are the main source of dietary glucose. When consumed, carbohydrates are broken down into glucose, leading to an increase in blood glucose levels.

Foods with high carbohydrate content, such as rice, bread, pasta, and sugary treats, can cause a rapid spike in blood glucose levels. Consuming excessive amounts of carbohydrates or foods high in refined sugars can contribute to persistent high blood glucose levels, especially if there is underlying beta cell dysfunction or insulin resistance.

3. Post-meal exercise level

-Engaging in physical activity after a meal can have beneficial effects on blood glucose levels. Exercise enhances glucose uptake by muscles, independent of insulin, thereby reducing postprandial glucose levels. This is because exercise stimulates the translocation of glucose transporters (GLUT4) to the cell surface, allowing glucose to enter the muscle cells and be utilized for energy. Regular exercise can also improve insulin sensitivity, reducing insulin resistance and improving beta cell function over time.

Overall, the pathophysiological explanations of PPG and FPG levels, carbohydrate and sugar consumption, and post-meal exercise are interconnected. Any imbalance in insulin secretion, insulin resistance, or glucose uptake can influence postprandial and fasting glucose levels. Understanding these interactions helps in managing diabetes or identifying potential risk factors for developing metabolic disorders. It is important to note that individual responses may vary, and healthcare professionals can provide personalized guidance based on specific conditions and needs.

2. METHODS

2.1 MPM background

To learn more about his developed GH-Method: math-physical medicine (MPM) methodology, readers can read the following three papers selected from his published 760+ 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.

2.2 The author's diabetes history

The author was a severe T2D patient since 1995. He weighed 220 lb. (100 kg) at that time. By 2010, he still weighed 198 lb. with an average daily glucose of 250 mg/dL (HbA1C at 10%). During that year, his triglycerides reached 1161 (high risk for CVD and stroke) and his albumin-creatinine ratio (ACR) at 116 (high risk for chronic kidney disease). He also suffered from five cardiac episodes within a decade. In 2010, three independent physicians warned him regarding the need for kidney dialysis treatment and the future high risk of dying from his severe diabetic complications.

In 2010, he decided to self-study endocrinology with an emphasis on diabetes and food nutrition. He spent the entire year of 2014 to develop a metabolism index (MI) mathematical model. During 2015 and 2016, he developed four mathematical prediction models related to diabetes conditions: weight, PPG, fasting plasma glucose (FPG), and HbA1C (A1C). Through using his developed mathematical metabolism index (MI) model and the other four glucose prediction tools, by the end of 2016, his weight was reduced from 220 lbs. (100 kg) to 176 lbs. (89 kg), waistline from 44 inches (112 cm) to 33 inches (84 cm), average finger-piercing glucose from 250 mg/dL to 120 mg/dL, and A1C from 10% to ~6.5%. One of his major accomplishments is that he no longer takes any diabetes-related medications since 12/8/2015.

In 2017, he achieved excellent results on all fronts, especially his glucose control. However, during the pre-COVID period, including both 2018 and 2019, he traveled to ~50 international cities to attend 65+ medical conferences and made ~120 oral presentations. This hectic schedule inflicted damage to his diabetes control caused by stress, dining out frequently, post-meal exercise disruption, and jet lag, along with the overall negative metabolic impact from the irregular life patterns; therefore, his glucose control was somewhat affected during the two-year traveling period of 2018-2019.

He started his COVID-19 self-quarantined life on 1/19/2020. By 10/16/2022, his weight

was further reduced to ~164 lbs. (BMI 24.22) and his A1C was at 6.0% without any medication intervention or insulin injection. In fact, with the special COVID-19 quarantine lifestyle since early 2020, not only has he written and published ~500 new research articles in various medical and engineering journals, but he has also achieved his best health conditions for the past 27 years. These achievements have resulted from his non-traveling, low-stress, and regular daily life routines. Of course, his in-depth knowledge of chronic diseases, sufficient practical lifestyle management experiences, and his own developed high-tech tools have also contributed to his excellent health improvements.

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. Furthermore, he extracted the 5-minute intervals from every 15-minute interval for a total of 96 glucose data each day stored in his computer software.

Through the author's medical research work over 40,000 hours and read over 4,000 published medical papers online in the past 13 years, he discovered and became convinced that good life habits of not smoking, moderate or no alcohol intake, avoiding illicit drugs; along with eating the right food with well-balanced nutrition, persistent exercise, having a sufficient and good quality of sleep, reducing all kinds of unnecessary stress, maintaining a regular daily life routine contribute to the risk reduction of having many diseases, including CVD, stroke, kidney problems, micro blood vessels issues, peripheral nervous system problems, and even cancers and dementia. In addition, a long-term healthy lifestyle can even "repair" some damaged internal organs, with different required time-length depending on the particular organ's cell lifespan. For example, he has "self-repaired" about 35% of his damaged pancreatic beta cells during the past 10 years.

2.3 Energy theory

The human body and organs have around 37 trillion live cells which are composed of different organic cells that require energy infusion from glucose carried by red blood

cells; and energy consumption from labor-work or exercise. When the residual energy (resulting from the plastic glucose scenario) is stored inside our bodies, it will cause different degrees of damage or influence to many of our internal organs.

According to physics, energies associated with the glucose waves are proportional to the square of the glucose amplitude. The residual energies from elevated glucoses are circulating inside the body via blood vessels which then impact all of the internal organs to cause different degrees of damage or influence, e.g. diabetic complications. Elevated glucose (hyperglycemia) causes damage to the structural integrity of blood vessels. When it combines with both hypertension (rupture of arteries) and hyperlipidemia (blockage of arteries), CVD or Stroke happens. Similarly, many other deadly diseases could result from these excessive energies which would finally shorten our lifespan. For an example, the combination of hyperglycemia and hypertension would cause micro-blood vessel's leakage in kidney systems which is one of the major cause of CKD.

The author then applied Fast Fourier Transform (FFT) operations to convert the input wave from a time domain into a frequency domain. The y-axis amplitude values in the frequency domain indicate the proportional energy levels associated with each different frequency component of input occurrence. Both output symptom value (i.e. strain amplitude in the time domain) and output symptom fluctuation rate (i.e. the strain rate and strain frequency) are influencing the energy level (i.e. the Y-amplitude in the frequency domain).

Currently, many people live a sedentary lifestyle and lack sufficient exercise to burn off the energy influx which causes them to become overweight or obese. Being overweight and having obesity leads to a variety of chronic diseases, particularly diabetes. In addition, many types of processed food add unnecessary ingredients and harmful chemicals that are toxic to the bodies, which lead to the development of many other deadly diseases, such as cancers. For example, ~85% of worldwide diabetes patients are overweight, and ~75% of patients with cardiac illnesses or surgeries have diabetes conditions.

In engineering analysis, when the load is applied to the structure, it bends or twists, i.e. deform; however, when the load is removed, it will either be restored to its original shape (i.e. elastic case) or remain in a deformed shape (i.e. plastic case). In a biomedical system, the glucose level will increase after eating carbohydrates or sugar from food; therefore, the carbohydrates and sugar function as the energy supply. After having labor work or exercise, the glucose level will decrease. As a result, the exercise burns off the energy, which is similar to load removal in the engineering case. In the biomedical case, both processes of energy influx and energy dissipation take some time which is not as simple and quick as the structural load removal in the engineering case. Therefore, the age difference and 3 input behaviors are "dynamic" in nature, i.e. time-dependent. This time-dependent nature leads to a "viscoelastic or viscoplastic" situation. For the author's case, it is "viscoplastic" since most of his biomarkers are continuously improved during the past 13-year time window.

2.4 Time-dependent output strain and stress of (viscous input*output rate)

Hooke's law of linear elasticity is expressed as:

Strain (ϵ : epsilon)
= Stress (σ : sigma) / Young's modulus (E)

For biomedical glucose application, his developed linear elastic glucose theory (LEGT) is expressed as:

PPG (strain)
= carbs/sugar (stress) * GH.p-Modulus (a positive number) + post-meal walking k-steps * GH.w-Modulus (a negative number)

Where GH.p-Modulus is reciprocal of Young's modulus E.

However, in viscoelasticity or viscoplasticity theory, the stress is expressed as:

Stress
= viscosity factor (η : eta) * strain rate ($d\epsilon/dt$)

Where strain is expressed as Greek epsilon or ϵ .

In this article, in order to construct an “ellipse-like” diagram in a stress-strain space domain (e.g. “hysteresis loop”) covering both the positive side and negative side of space, he has modified the definition of strain as follows:

Strain

$$= (\text{body weight at certain specific time instant})$$

He also calculates his strain rate using the following formula:

Strain rate

$$= (\text{body weight at next time instant}) - (\text{body weight at present time instant})$$

The risk probability % of developing into CVD, CKD, Cancer is calculated based on his developed metabolism index model (MI) in 2014. His MI value is calculated using inputs of 4 chronic conditions, i.e. weight, glucose, blood pressure, and lipids; and 6 lifestyle details, i.e. diet, drinking water, exercise, sleep, stress, and daily routines. These 10 metabolism categories further contain ~500 elements with millions of input data collected and processed since 2010. For individual deadly disease risk probability %, his mathematical model contains certain specific weighting factors for simulating certain risk percentages associated with different deadly diseases, such as metabolic disorder-induced CVD, stroke, kidney failure, cancers, dementia; artery damage in heart and brain, micro-vessel damage in kidney, and immunity-related infectious diseases, such as COVID death.

Some of explored deadly diseases and longevity characteristics using the viscoplastic medicine theory (VMT) include stress relaxation, creep, hysteresis loop, and material stiffness, damping effect based on time-dependent stress and strain which are different from his previous research findings using linear elastic glucose theory (LEGT) and nonlinear plastic glucose theory (NPGT).

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 data tables, VMT analysis results, and TD predicted PPG versus measured PPG.

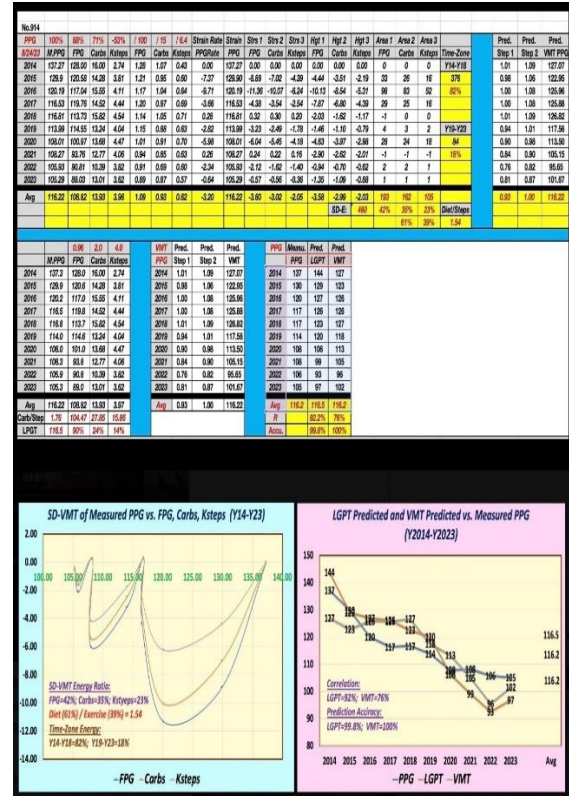


Figure 1: Data tables, VMT analysis results, and TD predicted PPG versus measured PPG.

4. CONCLUSION

In summary, there are three observations:

- (1) Comparison of PPG prediction accuracy and waveform correlation between measured PPG and predicted PPG: The LEGT model achieves an R value of 92% and an accuracy of 99.8%, whereas the VMT model shows an R value of 76% and an accuracy of 100%.
- (2) Analysis of SD-VMT energy ratios: FPG accounts for 42%, Carbs account for 35%, and Ksteps account for 23%. The contributions of LEGT components are: FPG accounts for 90%, Carbs account for 24%, and Ksteps account for -14%. These findings indicate that FPG, which reflects the health state of pancreatic beta cells, is the most influential factor. Additionally, the ratio between diet and exercise is calculated as 1.54 based on SD-VMT, and 1.76 based on LEGT. These two ratios highlight a greater importance of diet in PPG formation compared to exercise.

(3) Evaluation of time-zone energy distribution: 82% of the energy is allocated to the Y14-Y18 period, while only 18% is allocated to the Y19-Y23 period. This suggests that the earlier five-year period was worse in terms of PPG levels and the three influential factors compared to the more recent five-year period.

In conclusion, both the LEGT and VMT prediction models have proven their effectiveness in managing diabetes through PPG prediction.

5. 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.eclaircmd.com.

Readers may use this article as long as the work is properly cited, and their use is educational and not for profit, and the author's original work is not altered.

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: Sony Hazi).

Viscoelastic and Viscoplastic Glucose Theory Application in Medicine

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