

Investigation of Type 2 Diabetes Relationship with 3 Sleep input Elements Based on Viscoplastic Energy Model of GH-Method: Math-Physical Medicine (No. 1048, VMT #446)

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Abstract

The author recently read an article "Habitual Short Sleep Duration, Diet, and Development of Type 2 Diabetes in Adults" by Diana Aline Noga, PhD on JAMA Netw Open. March of 2024. Here is the except of this article:

"Is there an association between adherence to healthy diet, sleep duration, and risk of developing type 2 diabetes (T2D) in adults?"

This cohort study analyzing data from 247,867 adults in the UK Biobank (2006-2010) found that individuals sleeping less than 6 hours daily had a notably higher risk of developing T2D compared with those with 7 to 8 hours of sleep. Despite the association between healthier diets and reduced T2D risk, the increased risk associated with short sleep duration persisted even among adults with healthy eating habits.

These findings suggest that adopting a healthy diet may not reduce the risk of developing T2D among those with habitual short sleep duration."

Inspired by the aforementioned article, the author of this paper explores the relationship between his self-monitored glucose levels and sleep conditions using the space-domain Viscoplastic energy method (SD-VMT).

In this study, he established three key sleep parameters:

- Sleep hours, with 7 hours as the baseline.
- Wake-up times during sleep, with 2 instances as the baseline.
- Overall sleep quality score, standardized at 0.736 (or 73.6%), which encompasses 16 measurement factors detailed in the attached figure.

In summary, this study yielded three insights:

First, strong correlations were found between the author's Type 2 Diabetes (T2D) condition, as indicated by daily estimated average glucose (eAG), and three sleep metrics:

Sleep Hours: -75%

Wake-up times: 94%

Sleep Quality: 82%

It was observed that increased sleep hours typically resulted in a lower eAG level.

Second, the SD-VMT energy ratios for the three sleep related input parameters in relation to eAG of T2D were:

Sleep Hours: 35% (highest)

Wake-up times: 32% (lowest)

Sleep Quality: 33% (middle)

These SD-VMT energy ratios closely match the findings by Diana Aline Noga, suggesting that **sleep duration is a crucial factor. However, the combined impact of wake-up frequency and sleep quality surpasses the importance of sleep duration alone.**

Third, the distribution of VMT energy across different time zones was:

2015-2019: 59%

2020-2024: 41%

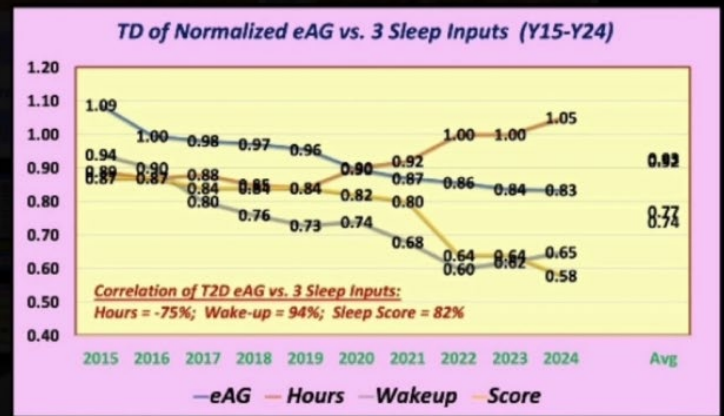
This distribution indicates a shift in the sleep-related energy dynamics over these two periods.

Key Message

Over the nearly decade-long period from 2015 to 2024, the author's daily estimated average glucose (eAG), a measure of his Type 2 Diabetes (T2D) status, shows strong correlations with three sleep-related metrics: sleep duration, wake-up frequency, and overall sleep quality score. A pattern emerged where longer sleep duration, fewer wake-up events during the night, and higher sleep quality (indicated by a lower numerical percentage) were associated with a reduction in eAG levels.

The screenshot shows the eclaireMD Data app interface. At the top, it displays the date 03/30/2024 and MI=0.4417, GHSU=50.6%. Below this, there are tabs for 'Check-ups', 'Exercise', 'Water', and 'Sleep'. The 'Sleep' tab is active, showing a list of symptoms with sliders for rating from 1 to 5. The symptoms include: Annoying issues before or during sleep (1), Sleep hours (>8), Wake-up times (e.g. urine) (0), Degree of freshness & restfulness (1), Degree of wake-up headache (1), Degree of dreams (2), Degree of environmental comfort (1), Degree of physical sickness (1), Degree of Sleep Pattern Disturbance (1), Itchy skin (1), Numbness feeling of hands or feet (1), Hungry feeling during sleep (1), Sleepy feeling in the morning (1), Leg cramp during sleep (1), Cold feeling of legs and feet (1), and Snoring during sleep (1).

3/30/24	Sleep	eAG	Hours	Wakeup	Score	/7	/2	/0.736	S. Rate	Strain	Stra 1	Stra 2	Stra 3	Hgt 1	Hgt 2	Hgt 3	Area 1	Area 2	Area 3	Time-Zone	
2015	130.52	6.21	1.87	0.64	0.89	0.94	0.87	0.00	130.52	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	Y15-Y18
2016	119.56	6.12	1.79	0.64	0.87	0.90	0.87	-10.96	119.56	-9.58	-8.81	-8.53	-4.79	-4.90	-4.77	52.51	53.75	52.23	200		
2017	117.79	6.19	1.58	0.62	0.88	0.80	0.84	-1.77	117.79	-1.57	-1.41	-1.49	-0.57	-0.61	-0.51	9.87	9.93	9.75	59%		
2018	116.57	5.97	1.51	0.62	0.85	0.78	0.84	-1.22	116.57	-1.04	-0.82	-1.03	-1.30	-1.16	-1.26	1.29	1.42	1.54			
2019	114.64	5.91	1.48	0.62	0.84	0.73	0.84	-1.83	114.64	-1.63	-1.41	-1.63	-1.23	-1.17	-1.53	2.58	2.25	2.58			
2020	107.65	6.28	1.49	0.60	0.90	0.74	0.82	-6.99	107.65	-6.27	-5.21	-5.70	-3.95	-3.31	-3.66	27.61	23.12	25.60	Y20-Y24		
2021	104.37	6.43	1.35	0.59	0.92	0.88	0.80	-3.28	104.37	-3.01	-2.21	-2.63	-4.84	-3.71	-4.10	15.23	12.17	13.68	137		
2022	102.85	6.96	1.20	0.47	1.00	0.90	0.84	-1.52	102.85	-1.52	-0.91	-0.97	-2.27	-1.58	-1.80	3.44	2.38	2.74	42%		
2023	100.43	6.97	1.25	0.47	1.00	0.82	0.64	-2.42	100.43	-2.41	-1.51	-1.55	-1.96	-1.21	-1.26	4.75	2.80	3.04			
2024	100.16	7.33	1.30	0.43	1.05	0.85	0.58	-0.27	100.16	-0.28	-0.16	-0.16	-1.35	-0.84	-0.85	0.36	0.23	0.23			
Avg	111.5	6.44	1.48	0.57	0.92	0.74	0.77	-3.04	111.5	-2.73	-2.36	-2.47	-2.72	-2.35	-2.46	118	106	111			
Correl.	100%	-75%	94%	82%												SD-E	337	35%	32%	32%	



Viscoelastic Medicine theory (VMT #446):

1. Introduction

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These findings suggest that adopting a healthy diet may not reduce the risk of developing T2D among those with habitual short sleep duration.”

Inspired by the aforementioned article, the author of this paper explores the relationship between his self-monitored glucose levels and sleep conditions using the space-domain Viscoplastic energy method (SD-VMT).

In this study, he established three key sleep parameters:

- Sleep hours, with 7 hours as the baseline.
- Wake-up times during sleep, with 2 instances as the baseline.
- Overall sleep quality score, standardized at 0.736 (or 73.6%), which encompasses 16 measurement factors detailed in the attached figure.

2. Biomedical and Engineering or Technical Information

The following sections contain excerpts and concise information on meticulously reviewed by the author of this paper. The author has adopted this approach as an alternative to including a conventional reference list at the end of this document, with the intention of optimizing his valuable research time. It is essential to clarify that these sections do not constitute part of the author's original contribution but have been included to aid the author in his future reviews and offer valuable insights to other readers with an interest in these subjects.

3. Pathophysiological Explanation of Daily Estimated Average Glucose of T2D Patients Versus Sleep Hours, Wake-up Frequency, and Overall Sleep Quality

The relationship between sleep parameters and daily estimated average glucose (eAG) levels in type 2 diabetes (T2D) patients involves complex pathophysiological mechanisms:

4. Sleep Duration (Hours of Sleep)

Short Sleep Duration: Insufficient sleep affects glucose metabolism and insulin sensitivity, leading to higher glucose levels. Lack of sleep can disrupt the balance between the sympathetic and parasympathetic nervous systems, increasing cortisol and catecholamine levels, which in turn can increase insulin resistance and glucose production.

Long Sleep Duration: While less studied, excessively long sleep may also be associated with poor glycemic control, possibly due to underlying health issues or less physical activity.

5. Wake-up Frequency (Sleep Fragmentation)

Frequent Nighttime Awakenings: This can lead to fragmented sleep, reducing the duration of slow-wave sleep (deep sleep), which is important for physical restoration and metabolic health. Interruptions in sleep can lead to hormonal imbalances, including increased cortisol and decreased growth hormone levels, both of which can adversely affect glucose regulation.

6. Overall Sleep Quality

Good sleep quality is crucial for maintaining normal glucose metabolism and insulin sensitivity. Poor sleep quality can lead to increased insulin resistance, higher fasting glucose levels, and an increased risk of developing T2D.

Poor sleep quality often leads to chronic inflammation and activation of the sympathetic nervous system, contributing to metabolic dysregulation and poor glycemic control.

In summary, optimal sleep duration and quality are essential for maintaining good glucose control in T2D patients. Disruptions in sleep, whether in terms of duration, continuity, or quality, can adversely affect the metabolic balance and lead to poorer glycemic outcomes. Therefore, addressing sleep issues is an important aspect of managing T2D effectively.

7. 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 (Reference 1) describes his MPM methodology in a general conceptual format. The second paper, No. 387 (Reference 2) 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 (Reference 3) depicts a general flow diagram containing ~10 key MPM research methods and different tools.

8. 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.

9. 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.*

Time-Dependent output Strain and Stress of (Viscous Input*output Rate)

Hooke’s law of linear elasticity is expressed as:

$$\text{Strain } (\epsilon: \text{epsilon}) \\ = \text{Stress } (\sigma: \text{sigma}) / \text{Young’s modulus } (E)$$

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

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

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

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

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

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:

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

He also calculates his strain rate using the following formula:

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

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)*.

10. Results

Figure 1 shows sleep list, TD and SD results.



Figure 1: Sleep list, TD and SD results

11. Conclusions

In summary, this study yielded three insights:

First, strong correlations were found between the author's Type 2 Diabetes (T2D) condition, as indicated by daily estimated average glucose (eAG), and three sleep metrics:

- Sleep Hours: -75%**
- Wake-up times: 94%**
- Sleep Quality: 82%**

It was observed that increased sleep hours typically resulted in a lower eAG level.

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and sleep quality surpasses the importance of sleep duration alone.

Third, the distribution of VMT energy across different time zones was:

- 2015-2019: 59%**
- 2020-2024: 41%**

This distribution indicates a shift in the sleep-related energy dynamics over these two periods.

Key Message

Over the nearly decade-long period from 2015 to 2024, the author's daily estimated average glucose (eAG), a measure of his Type 2 Diabetes (T2D) status, shows strong correlations with three sleep-related metrics: sleep duration, wake-up frequency, and overall sleep quality score. *A pattern emerged where longer sleep duration, fewer wake-up events during the night, and higher sleep quality (indicated by a lower numerical percentage) were associated with a reduction in eAG levels.*

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. 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 platforms for scientific research publications, such as ResearchGate, Google Scholar, etc.

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