ISSN: 2689-1204

Research Article

Journal of Applied Material Science & Engineering Research

Relationship between predicted morning body weight with body weight changes at night versus bowel movement, sleep hours, water drinking, food portion using viscoplastic energy model of GH-Method: Math-Physical Medicine (No. 1014, VMT #412

Gerald C. Hsu

EclaireMD Foundation, USA

***Corresponding Author**
Gerald C. Hsu, EclaireMD Foundation, USA

Submitted: 2024, Feb 26; **Accepted:** 2024, Mar 14; **Published:** 2024, Mar 18

Citation: Hsu, G. C. (2024). Relationship between Predicted Morning Body Weight with Body Weight Changes At Night Versus Bowel Movement, Sleep Hours, Water Drinking, Food Portion Using Viscoplastic Energy Model of Gh-Method: Math-Physical Medicine (No. 1014, VMT #412). *J App Mat Sci & Engg Res, 8*(1),01-07.

Abstract

Obesity is a primary factor contributing to a range of metabolic disorders, such as type 2 diabetes, hypertension, and dyslipidemia, among others. Unfortunately, these three metabolic disorders are closely linked to many serious health conditions, including mortalities. However, managing and reducing body weight is an extremely challenging endeavor that demands in-depth knowledge, strong determination, and perseverance. Because of these reasons, as of today, approximately 70% of the American adults grapple with either overweight or obesity.

In 2010, the author weighed 220 lbs (BMI 32) and successfully reduced his weight to 166 lbs (BMI 24.5) by the end of 2023. Throughout this journey, the author has utilized his extensive personal data collection, comprising approximately 3 million data points, to drive various medical research endeavors.

On April 23, 2023, the author modified his body weight prediction equation as follows:

Predicted Bw In The Early Morning
= Yesterday's BW in early morning
+ Yesterday's food quantity (m9a)
+ Yesterday's H2O drinking (m6)
- Yesterday's bowel movement / 4
- Last night's sleeping hours / 6

The author has implemented this equation in his developed chronic software on his iPhone, replacing the previous version of his body weight prediction algorithm. Using data collected from 1/1/2014 to 12/31/2023, this newly updated equation has achieved a 99.9% prediction accuracy for his annual morning body weight and a 99.3% correlation between his annual measured and predicted body weight curves of past 10 years.

These two analyses applied the same space-domain viscoplastic medicine theory (SD-VMT) energy method for his quantitative analysis.

In summary, the four correlations from two cases: (1) predicted body weight and (2) body weight changes at night time, are found to have directly opposite phase to each other, with sleep hours showing distinct differences.
Bowel = +83% for 1; -94% for 2
SleepH = -87% for 1; +84% for 2
H2O = +79% for 1; -93% for 2
FoodQ = +95% for 1; -87% for 2

For predicted BW case, the energy contribution ratios are:
Bowel = 18%; SleepH = 27%; H2O = 20%; FoodQ = 35%
For BW changes at night time case, the energy contribution ratios are:
Bowel = 16%; SleepH = 27%; H2O = 19%; FoodQ = 39%

For predicted BW case, the time-zone energy ratios are:

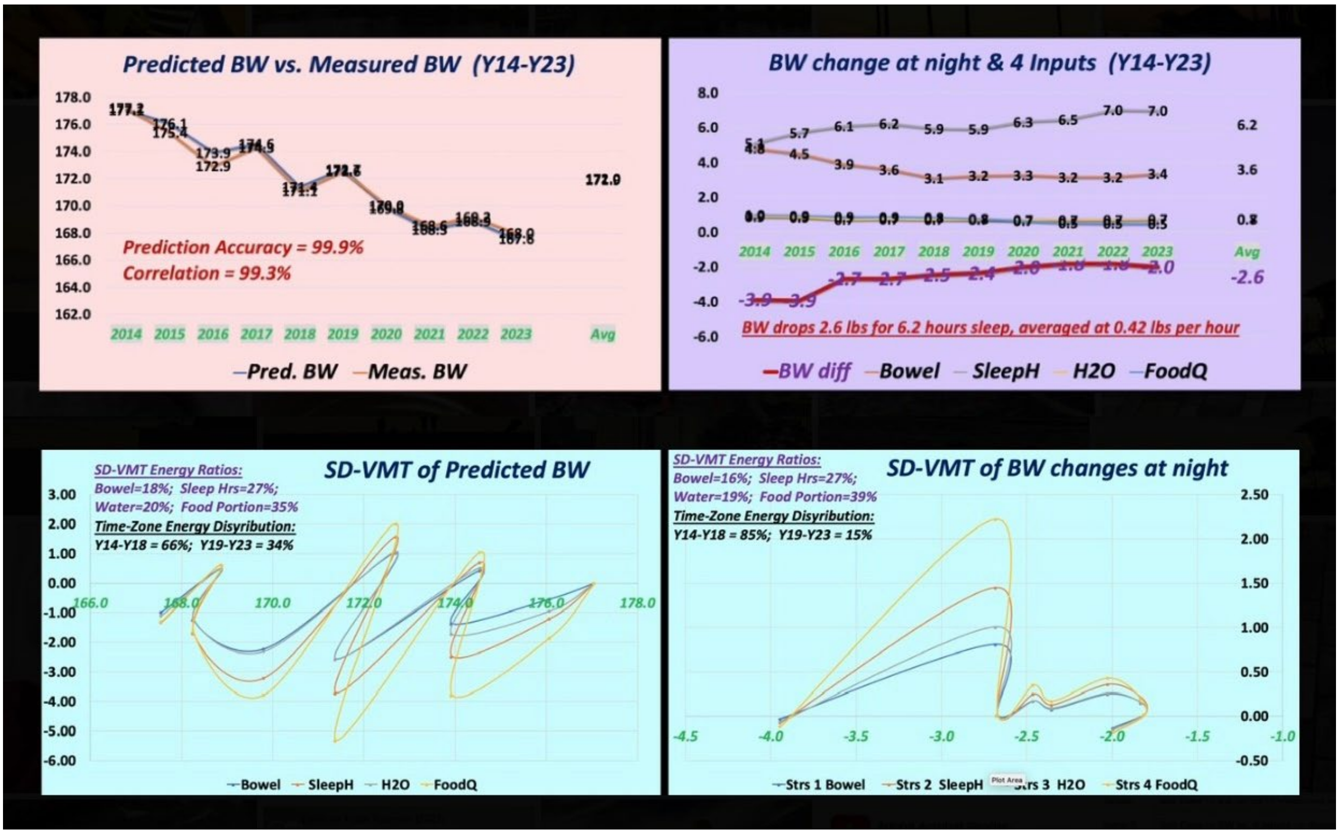
Y2014-Y2023 = 66%;
Y2019-Y2023 = 34%

For BW changes at night case, the time-zone energy ratios are:

Y2014-Y2023 = 85%;
Y2019-Y2023 = 15%

Key Message

For both predicted body weight and nighttime changes in body weight, the primary influencing factor is the size of food portions, contributing 35% and 39% respectively. This is followed by the duration of sleep (27% for both cases), water intake (20% and 19%), and the volume of bowel movements (18% and 16%). These quantitative findings offer a clear indication of effective strategies for reducing and managing body weight.



Introduction

Obesity is a primary factor contributing to a range of metabolic disorders, such as type 2 diabetes, hypertension, and dyslipidemia, among others. Unfortunately, these three metabolic disorders are closely linked to many serious health conditions, including mortalities. However, managing and reducing body weight is an extremely challenging endeavor that demands in-depth knowledge, strong determination, and perseverance. Because of these reasons, as of today, approximately 70% of the American adults grapple with either overweight or obesity.

In 2010, the author weighed 220 lbs (BMI 32) and successfully reduced his weight to 166 lbs (BMI 24.5) by the end of 2023. Throughout this journey, the author has utilized his extensive personal data collection, comprising approximately 3 million data points, to drive various medical research endeavors.

2. Biomedical Information

The following sections contain excerpts and concise information drawn from multiple medical articles, which have been 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 Explanations of Morning Body Weight and Overall Sleep Conditions, Including Sleep Hours and Wake-Up Times At Night

The relationship between sleep and body weight is complex and influenced by various pathophysiological factors. Here are some key considerations:

3.1 Hormonal Fluctuations
Sleep affects the balance of hormones that control appetite. Ghrelin, the hormone that stimulates appetite, and leptin, which signals satiety, are influenced by sleep. Poor sleep can lead to increased ghrelin and decreased leptin, leading to increased hunger and appetite.

3.2 Metabolic Changes
Lack of sleep can affect the body's ability to regulate glucose and can lead to insulin resistance, a risk factor for obesity and diabetes. The metabolic rate may also be altered by disrupted sleep patterns.

3.3 Energy Expenditure
Sleep deprivation may lead to reduced physical activity due to fatigue, contributing to weight gain. Conversely, more energy might be expended if wakefulness is prolonged into the night.

3.4 Eating Patterns
Disrupted sleep can lead to changes in eating habits, such as increased late-night snacking or preference for high-calorie foods, which can contribute to weight gain.

3.5 Cortisol Levels
Stress and sleep deprivation can increase cortisol levels, a hormone associated with fat storage, particularly in the abdominal area.

3.6 Sleep Timing and Duration
Both the amount and the timing of sleep can affect body weight. Irregular sleep patterns, like going to bed and waking up at different times, can disrupt the body's internal clock and affect eating patterns and metabolism.

3.7 Water Retention
Fluctuations in body weight can also be due to variations in hydration status. The body may retain more water after a night of poor sleep.

3.8 Muscle Recovery and Growth
Sleep is crucial for muscle recovery and growth. Reduced sleep can impair muscle recovery and growth, which can affect metabolism since muscle tissue burns more calories than fat tissue.

In summary, the quality and quantity of sleep can significantly impact various physiological processes that influence body weight. Disruptions in sleep patterns can lead to hormonal imbalances, metabolic changes, altered eating patterns, and increased stress, all of which can contribute to weight gain.

4. Pathophysiological Explanations of Body Weight Variation Versus Food Portion Intake, Sleep Hours, Water Drinking and Bowel Movement Volume
Understanding body weight variation involves considering several physiological factors, including food portion intake, sleep hours, water drinking, and bowel movement volume. Each of these elements plays a distinct role in weight management:

4.1 Food Portion Intake
The size of food portions directly impacts caloric intake. Consuming more calories than the body expends leads to weight gain, while consuming fewer calories results in weight loss. Over time, consistent overeating or undereating can significantly affect body weight.

4.2 Sleep Hours
Sleep affects weight in multiple ways. Lack of sleep can disrupt hormonal balances, specifically those regulating hunger (ghrelin) and fullness (leptin). This disruption often leads to increased appetite and cravings for high-calorie, carbohydrate-rich foods. Additionally, poor sleep can decrease energy levels, reducing physical activity and thus calorie expenditure.

4.3 Water Drinking
Adequate hydration can influence body weight, though its effects are more subtle compared to diet and sleep. Drinking water can promote a feeling of fullness, potentially reducing overall calorie intake. Moreover, water is essential for efficient metabolic processes, including the breakdown of fats.

4.4 Bowel Movement Volume
Regular bowel movements are a sign of a healthy digestive system. While the direct impact on body weight is not as significant as diet or sleep, irregular bowel movements or constipation can lead to temporary weight gain due to retained waste. Additionally, a healthy digestive system aids in proper nutrient absorption and metabolism, indirectly influencing weight.

These factors are interconnected, and their combined effects on weight are complex. For example, lack of sleep can lead to poor dietary choices, and inadequate hydration might affect physical activity levels. Understanding and balancing these factors are key to effective weight management.

5. 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.

6. 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.

7. 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:

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 (dε/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 = (body weight at certain specific time instant)

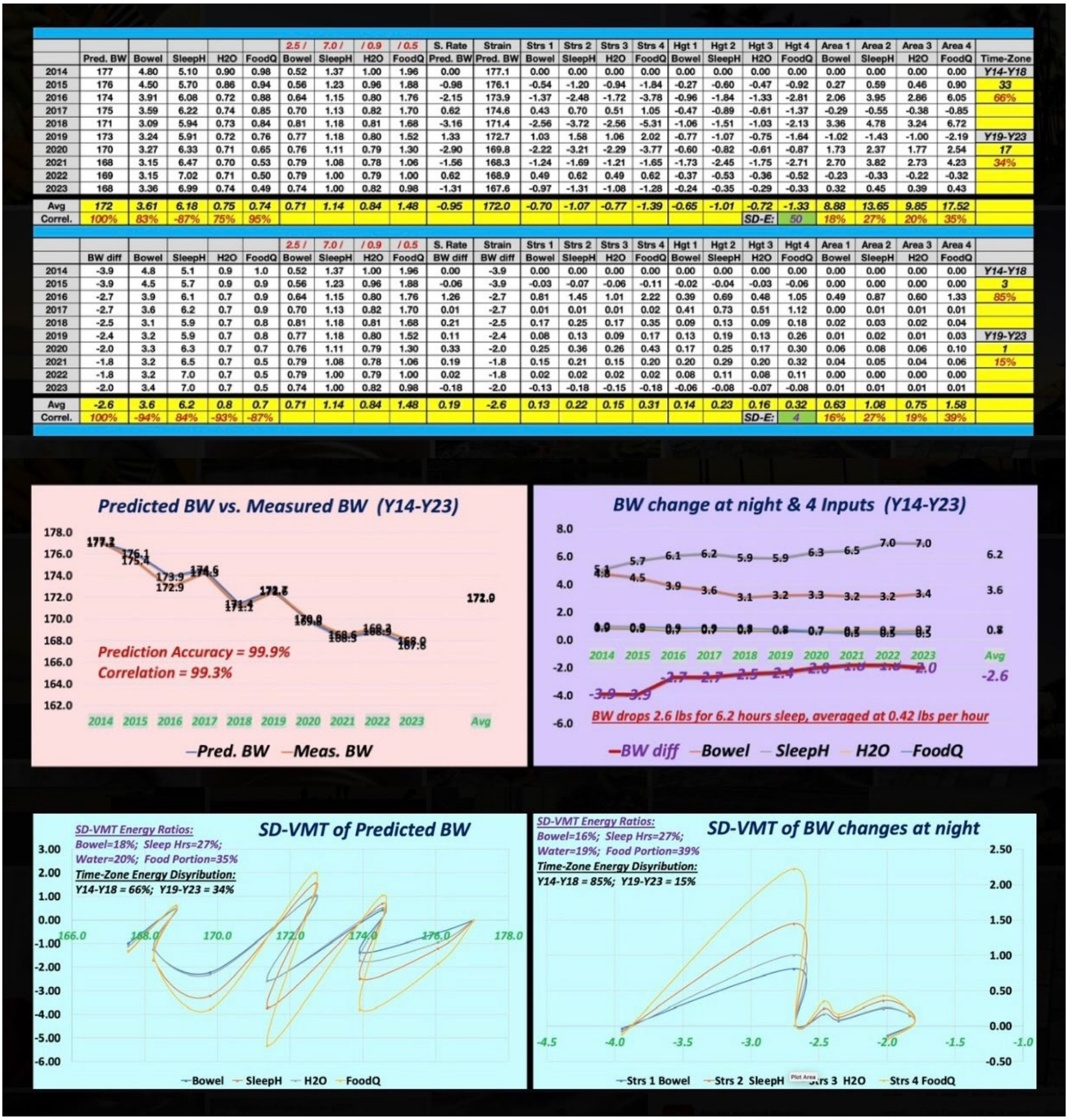
He also calculates his strain rate using the following formula:

Strain rate = (body weight at next time instant) - (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).*

8. Results



	Pred. BW	Bowel	SleepH	H2O	FoodQ	2.5 / Bowel	7.0 / SleepH	/ 0.9 H2O	/ 0.5 FoodQ	S. Rate Pred. BW	Strain Pred. BW	Strs 1 Bowel	Strs 2 SleepH	Strs 3 H2O	Strs 4 FoodQ	Hgt 1 Bowel	Hgt 2 SleepH	Hgt 3 H2O	Hgt 4 FoodQ	Area 1 Bowel	Area 2 SleepH	Area 3 H2O	Area 4 FoodQ	Time-Zone
2014	177	4.80	5.10	0.90	0.98	0.52	1.37	1.00	1.96	0.00	177.1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	Y14-Y18
2015	176	4.50	5.70	0.86	0.94	0.56	1.23	0.96	1.88	-0.98	176.1	-0.54	-1.20	-0.94	-1.84	-0.27	-0.60	-0.47	-0.92	0.27	0.59	0.46	0.90	33
2016	174	3.91	6.08	0.72	0.88	0.64	1.15	0.80	1.76	-2.15	173.9	-1.37	-2.48	-1.72	-3.78	-0.96	-1.84	-1.33	-2.81	2.06	3.95	2.86	6.05	66%
2017	175	3.59	6.22	0.74	0.85	0.70	1.13	0.82	1.70	0.62	174.6	0.43	0.70	0.51	1.05	-0.47	-0.89	-0.61	-1.37	-0.29	-0.55	-0.38	-0.85	
2018	171	3.09	5.94	0.73	0.84	0.81	1.18	0.81	1.68	-3.16	171.4	-2.56	-3.72	-2.56	-5.31	-1.06	-1.51	-1.03	-2.13	3.36	4.78	3.24	6.72	
2019	173	3.24	5.91	0.72	0.76	0.77	1.18	0.80	1.52	1.33	172.7	1.03	1.58	1.06	2.02	-0.77	-1.07	-0.75	-1.64	-1.02	-1.43	-1.00	-2.19	Y19-Y23
2020	170	3.27	6.33	0.71	0.65	0.76	1.11	0.79	1.30	-2.90	169.8	-2.22	-3.21	-2.29	-3.77	-0.60	-0.82	-0.61	-0.87	1.73	2.37	1.77	2.54	17
2021	168	3.15	6.47	0.70	0.53	0.79	1.08	0.78	1.06	-1.56	168.3	-1.24	-1.69	-1.21	-1.65	-1.73	-2.45	-1.75	-2.71	2.70	3.82	2.73	4.23	34%
2022	169	3.15	7.02	0.71	0.50	0.79	1.00	0.79	1.00	0.62	168.9	0.49	0.62	0.49	0.62	-0.37	-0.53	-0.36	-0.52	-0.23	-0.33	-0.22	-0.32	
2023	168	3.36	6.99	0.74	0.49	0.74	1.00	0.82	0.98	-1.31	167.6	-0.97	-1.31	-1.08	-1.28	-0.24	-0.35	-0.29	-0.33	0.32	0.45	0.39	0.43	
Avg	172	3.61	6.18	0.75	0.74	0.71	1.14	0.84	1.48	-0.95	172.0	-0.70	-1.07	-0.77	-1.39	-0.65	-1.01	-0.72	-1.33	8.88	13.65	9.85	17.52	
Correl.	100%	83%	-87%	75%	95%													SD-E:	50	18%	27%	20%	35%	

	BW diff	Bowel	SleepH	H2O	FoodQ	2.5 / Bowel	7.0 / SleepH	/ 0.9 H2O	/ 0.5 FoodQ	S. Rate BW diff	Strain BW diff	Strs 1 Bowel	Strs 2 SleepH	Strs 3 H2O	Strs 4 FoodQ	Hgt 1 Bowel	Hgt 2 SleepH	Hgt 3 H2O	Hgt 4 FoodQ	Area 1 Bowel	Area 2 SleepH	Area 3 H2O	Area 4 FoodQ	
2014	-3.9	4.8	5.1	0.9	1.0	0.52	1.37	1.00	1.96	0.00	-3.9	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	Y14-Y18
2015	-3.9	4.5	5.7	0.9	0.9	0.56	1.23	0.96	1.88	-0.06	-3.9	-0.03	-0.07	-0.06	-0.11	-0.02	-0.04	-0.03	-0.06	0.00	0.00	0.00	0.00	3
2016	-2.7	3.9	6.1	0.7	0.9	0.64	1.15	0.80	1.76	1.26	-2.7	0.81	1.45	1.01	2.22	0.39	0.69	0.48	1.05	0.49	0.87	0.60	1.33	85%
2017	-2.7	3.6	6.2	0.7	0.9	0.70	1.13	0.82	1.70	0.01	-2.7	0.01	0.01	0.01	0.02	0.41	0.73	0.51	1.12	0.00	0.01	0.01	0.01	
2018	-2.5	3.1	5.9	0.7	0.8	0.81	1.18	0.81	1.68	0.21	-2.5	0.17	0.25	0.17	0.35	0.09	0.13	0.09	0.18	0.02	0.03	0.02	0.04	
2019	-2.4	3.2	5.9	0.7	0.8	0.77	1.18	0.80	1.52	0.11	-2.4	0.08	0.13	0.09	0.17	0.13	0.19	0.13	0.26	0.01	0.02	0.01	0.03	Y19-Y23
2020	-2.0	3.3	6.3	0.7	0.7	0.76	1.11	0.79	1.30	0.33	-2.0	0.25	0.36	0.26	0.43	0.17	0.25	0.17	0.30	0.06	0.08	0.06	0.10	1
2021	-1.8	3.2	6.5	0.7	0.5	0.79	1.08	0.78	1.06	0.19	-1.8	0.15	0.21	0.15	0.20	0.20	0.29	0.20	0.32	0.04	0.05	0.04	0.06	15%
2022	-1.8	3.2	7.0	0.7	0.5	0.79	1.00	0.79	1.00	0.02	-1.8	0.02	0.02	0.02	0.02	0.08	0.11	0.08	0.11	0.00	0.00	0.00	0.00	
2023	-2.0	3.4	7.0	0.7	0.5	0.74	1.00	0.82	0.98	-0.18	-2.0	-0.13	-0.18	-0.15	-0.18	-0.06	-0.08	-0.07	-0.08	0.01	0.01	0.01	0.01	
Avg	-2.6	3.6	6.2	0.8	0.7	0.71	1.14	0.84	1.48	0.19	-2.6	0.13	0.22	0.15	0.31	0.14	0.23	0.16	0.32	0.63	1.08	0.75	1.58	
Correl.	100%	-94%	84%	-93%	-87%													SD-E:	4	16%	27%	19%	39%	

Figure 1: Data tables, inputs and SD-VMT energy output diagram

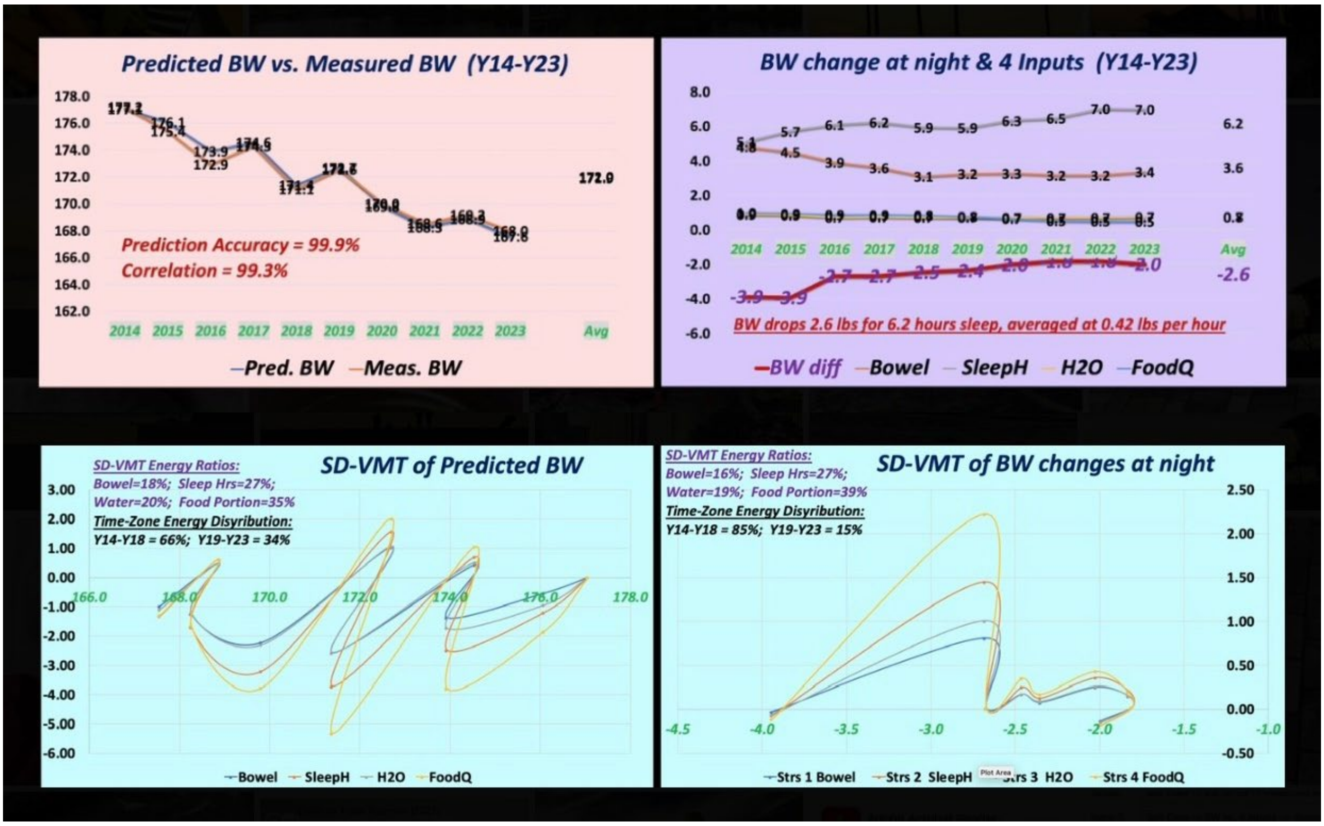


Figure 2: shows inputs and SD-VMT energy output diagram.

9. Conclusions

In summary, the four correlations from two cases: (1) predicted body weight and (2) body weight changes at night time, are found to have directly opposite phase to each other, with sleep hours showing distinct differences.

Bowel = +83% for 1; -94% for 2
SleepH = -87% for 1; +84% for 2
H2O = +79% for 1; -93% for 2
FoodQ = +95% for 1; -87% for 2

For predicted BW case, the energy contribution ratios are:
Bowel = 18%; SleepH = 27%; H2O = 20%; FoodQ = 35%

For BW changes at night time case, the energy contribution ratios are:
Bowel = 16%; SleepH = 27%; H2O = 19%; FoodQ = 39%

For predicted BW case, the time-zone energy ratios are:
Y2014-Y2023 = 66%;
Y2019-Y2023 = 34%

For BW changes at night case, the time-zone energy ratios are:
Y2014-Y2023 = 85%;
Y2019-Y2023 = 15%

Key Message

For both predicted body weight and nighttime changes in body weight, the primary influencing factor is the size of food portions, contributing 35% and 39% respectively. This is followed by the duration of sleep (27% for both cases), water intake (20% and 19%), and the volume of bowel movements (18% and 16%). These quantitative findings offer a clear indication of effective strategies for reducing and managing body weight.

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.