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Non-Linear Modelling of Glycemic Response Based on Macronutrient Composition in Healthy Adults

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ABSTRACT

The glycemic response to the consumption of food is important in managing healthy metabolism and preventing diet-related diseases. The glycemic response is the trend of changes in the concentration of blood glucose following the intake of food, especially of carbohydrate-rich meals. The simplistic measures of traditional nutritional assessment of the effect of diets on blood glucose levels are often the Glycemic Index (GI) and the Glycemic Load (GL), which mainly study how carbohydrate-rich diets influence blood glucose levels. However, these measurements assume a more or less linear connection between carbohydrate consumption and glucose reaction, which is unverified due to the complex physiological interactions that occur in the human body. In the real sense, the glycemic control depends on diverse factors, such as macronutrient content, digestion, hormonal reactions, and individual metabolic diversity. This paper examines how non-linear modelling methods can be used to examine the glycemic response of healthy adults in relation to macronutrient composition, as it relates to the change in carbohydrates, proteins and fats. It attempts to give a mathematical and computer model in which it could explain non-linear and dynamic relationships between dietary intake and glucose regulation in the blood. The postprandial glucose concentration was determined on healthy adult participants who had taken food of different macronutrient formulations. Time profile of glucose changes is obtained through the measurement of blood glucose at certain intervals subsequent meals. The relationship between the nutritional intake and the glycemic response is predicted by the non-linear modelling techniques which include the non-linear regression functions, logistic growth model and the glucose-insulin interaction model using the differential equations. These models are able to pick the non-linear trends including delayed glucose peaks, saturation effects, and rounded responses because of the existence of proteins and fats in mixed diets. The results indicate that the interactions between macronutrients influence the shape and size of the glycemic curves significantly, which means that carbohydrate content cannot be trusted to predict blood glucose response.

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1. Introduction

The blood glucose regulation is a significant part of human physiology, which ensures a continuous energy supply to tissues along with preventing the harmful consequences of hypoglycemia and hyperglycemia (Mwakalu et al., 2023). Glycemic control is sustained via a complicated interaction of metabolic pathways, hormonal signals, and the nutrient absorption process in health adults. When we consume food, especially meals which contained carbohydrates, then blood glucose levels rise gradually and trigger a corresponding response, including hepatic glucose production, insulin secretion, gastrointestinal motility and peripheral glucose uptake (Mohapatra et al., 2025). Although the blood glucose regulatory system seems highly effective in healthy adults, the pattern and magnitude of postprandial glycemic response vary significantly depending on the macronutrient composition of the food. Therefore, there is a significant need to understand all these variations for the improvement of metabolic health, optimizing dietary recommendation and preventing the early inception of metabolic disorders (Cordon et al., 2022). Whereas traditional methods for estimating glycemic responses mostly depend on simplified linear assumptions, including correlating blood glucose increments directly with the total carbohydrate intake. While the quantity and quality of carbohydrate are always primary factors and considered the most important determinants of glycemic response. Most of the research studies examine that the association between postprandial glucose dynamics and macronutrient composition is inherently non-linear (Boonpor et al., 2025). Furthermore,

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fats and proteins are not considered the major source of immediate glucose, but they influence gastric emptying rates, insulin dynamic, incretin hormone secretion, as well as hepatic glucose output. Dietary fiber changes the glucose absorption kinetics, whereas the connections between various macronutrients within mixed meals can also alter the temporal pattern of glycemia (Li, 2024). Such coupled methods lead to the emergence of complicated response curves, which cannot be described by linear models in full. The nonlinear model offers a useful method of explaining the interactive and dynamic response of the relationship of glycemic control. Additive and proportional relationships are applied in linear regression models, whereas non-linear models may involve saturation kinetics, threshold effects, changes with time and feedback loops (Kim et al., 2026). Moreover, the postprandial glucose curves often exhibit rapid peaks, ascends, and intermediate declines, which proves the correlation between the rate of glucose disappearance and appearance. These curves are rather similar to sigmoidal or exponential curves than linear (Zhu et al., 2025). Non-linear might integrate physiological parameters, including beta-cell responsiveness, insulin sensitivity, nutrient absorption coefficient, and gastric emptying rates. All these parameters represent a more realistic picture of metabolic processes. The inconsistency of glycemic response in health adults is impacted not only by the macronutrient ratios of proteins, fats, and carbohydrates but also by the structure of the meal, portion size of the meal, and quality of the nutrient (Koemel et al., 2025). Apart from this, food containing a lower glycemic index produces more gradual responses as compared to the high-glycemic index. Whereas carbohydrates with a high glycemic index led to rapid spikes in blood glucose (Giosuè et al., 2025). While the glycemic curve mostly changes in amplitude and shape because of enhances insulin secretion and delayed gastric emptying. It all happened when we consume carbohydrates along with proteins and fats. This association generate non-linear effects, where a very little shift in macronutrient proportion might led towards disproportionate alteration in glycemic response. In addition, the most recent developments in the technology of continuous glucose monitoring have provided highly resolved time-series data on postprandial glucose variability in free-living individuals. Through these high-resolution datasets, it is proven that glycemic responses are not homogeneous even among seemingly healthy adults with similar demographic data (Huang et al., 2024).

Non-linear modelling methods, including compartmentalized models, differential-equation-based systems, and machine-learning algorithms, allow the researcher to inquiry these modified patterns with more accuracy (Pereira, 2022). Glycemic reaction is the term used to denote the alteration in blood glucose level that takes place following meals. Basic measurements such as the Glycemic Index (GI) and Glycemic Load have traditionally been used to measure glycemic reactions. Nonetheless, these techniques assume that the relationship between the crabbing intake and blood glucose levels is more or less linear. As a matter of fact, the physiological reaction to food intake is highly complicated and non-linear because of interactions among macronutrients, metabolism, hormonal control, and individuality. Carbohydrates, proteins, and fats are known as Macronutrients that have different roles to control the level of postprandial blood glucose. The effect of carbohydrates on the body is usually an instant rise in blood glucose levels. Still, proteins and fats may delay the emptying of the stomach and alter the insulin release. Therefore, modelling of glycemic response requires high mathematical and computation techniques capable of modeling non-linear interaction of nutrition and physiological processes. In nutritional science, non-linear modelling methods have become popular due to the fact that they yield more precise forecasts of glycemic responses as compared to the traditional linear models. These models would explain the complex interplay between the macronutrient intake and metabolism, which enables the researchers to understand more of the influence of diet patterns on blood glucose regulation among healthy adults. The importance of modelling glycemic response in healthy adults is not only based on theoretic consideration (Dai et al., 2024). Frequent exposure to high postprandial glycemic trips, even in normoglycemic ranges, can promote oxidative stress, endothelial maladaptation, and metabolic risk in the long run. Delicate abnormalities of glucose control often proceed slowly to pre-emerging clinical symptoms of diabetes. Through the use of non-linear models to evaluate the effects of certain combinations of macronutrients on glucose patterns, the researchers can determine the dietary arrangements that will present stable glucose patterns and metabolic stability (Dubach, 2025).

It has significant effects on nutritional planning, weight management techniques, athletic performance optimization, and prevention of the cardiometabolic diseases. Moreover, non-linear modelling helps the combination of physiological theory with empirical data. Glucose-insulin feedback models have the potential to calculate the changes in insulin secretion and glucose disposal in response to different proportions of carbohydrates, proteins and fats (Nasrallah et al., 2025). Data-driven models such as neural networks and machine learning techniques have the ability to detect hidden patterns within complicated databased files (Honfo et al., 2024). In addition, hybrid techniques are utilized to combine machine learning with computational adaptability to present a powerful framework in order to make predictions of glycemic response in different dietary scenarios. These predictive measures can be useful particularly in creating personalized nutrition frameworks based on the metabolic characteristics of the individuals (Ha, 2026). The other most significant application of the non-linear model lies in the ability to manage threshold phenomena and saturation. Apart from this, the study on glycemic response as a variable of macronutrient composition overlaps with the general advances in systems biology, nutritional science, and computational modelling. As with globalization, the dietary pattern has become significantly more

diverse; there is a significant need to understand the metabolic consequences of typically complex and mixed meals (Freeling, 2024). Non-linear modelling techniques work as a bridge between real-world dietary behaviors and controlled laboratory experiments. By capturing individual variability and dynamic interaction, these non-linear models provide a deeper understanding of how glucose homeostasis is preserved in health adults in response to increasing everyday dietary challenges (Shamanna et al., 2024) (Figure 1).

2. Non-linear Modelling Approaches

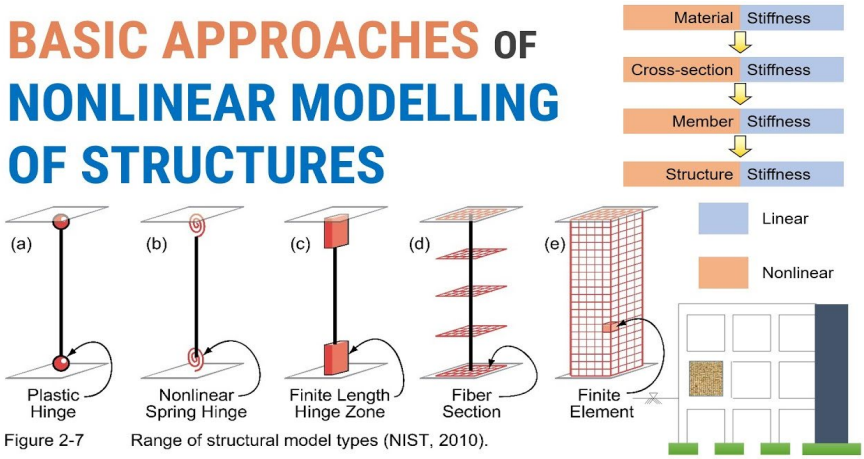


Figure 1: Basics Approaches of Nonlinear Modelling of Structures

2.1 Differential Equation Models

Differential equations are frequently used to model glucose-insulin dynamics. These models define the rate of modification of glucose and insulin over time.

A simplified non-linear model can be represented as:

$$\frac{dG}{dt} = -k_1 G + f(C, P, F)$$

Where:

G = blood glucose concentration

k_1 = glucose clearance rate

C = carbohydrate intake

P = protein intake

F = fat intake

The function $f(C, P, F)$represents non-linear interactions between macronutrients.

2.2 Sigmoid and Logistic Models

Sigmoid functions are commonly used to model glycemic response curves as glucose levels naturally follow an S-shaped pattern.

A logistic function may be written as:

$G(t) = \frac{G_{max}}{1+e^{-k(t-t_0)}}$ Where:

G(t) = glucose level at time t

Gmax = maximum glucose concentration

k = growth rate

t0 = time of peak response

These models capture the delayed and saturated nature of glucose responses.

2.3 Machine Learning Models

Current research uses machine learning techniques to model glycemic responses. Algorithms such as:

- Random Forest
- Neural Networks
- Support Vector Machines

- Gradient Boosting

These algorithms learn non-linear relationships between macronutrient composition and blood glucose patterns. These models are particularly useful when large datasets from constant glucose monitoring (CGM) devices are available.

Machine learning models also incorporate further variables such as:

- Age
- Body mass index (BMI)
- Physical activity
- Gut microbiome

This improves prediction accuracy.

3. Literature Review of Previous Research

The research on the macronutrients and how it affects health of adults has increased in recent years. Postprandial glycemic relationships originally focused on the composition of macronutrients, but recently researchers have also emphasized the non-linear relationship between dietary constituents and glucose outcomes (Yu et al., 2025). Some of the research works have highlighted the weaknesses of traditional approaches to explore the effects of proteins, fats and carbohydrates simultaneously, which prove the existence of complex, situation-specific, and context-dependent glycemic responses (Priyadarshini et al., 2022). With the use of continuous glucose monitoring (CGM) technology, a few studies have demonstrated significant inter-individual differences in postprandial glycemic responses, even in healthy adults who consume seemingly identical foods. In most of the observational research analysis individual responses to meals varying in the amount of carbohydrates content, researchers examined that glycemic excursions could be clustered into different responses groups which indicate that the determinants of the glycemic excursions are independent of carbohydrate quantity itself and, therefore, indicate the impact of particular determinists on the formation of postprandial glucose curves (Clarke et al., 2022). The findings support the suggestion that person-specific characterization, maybe through sophisticated modelling methods is necessary to predict postprandial glycemic patterns accurately. The researcher investigated various research studies and highlighted the effects of various macronutrients on glycemic curve morphology and amplitude in healthy adults (Zahedani et al., 2023). A representative study of mixed meals that included different ratios of protein, fat, and carbohydrate recognized that meals in all the three major types of macronutrients produced significantly less postprandial glucose excursions as compared to those meals that lacked one of the macronutrient groups. The evidence suggests that macronutrients interact in a synergistic way that causes glucose kinetic reactions, and their influences on the significance of existing metrical indices of diet, including the glycemic index (GI) and glycemic load (GL), based on the carbohydrate content alone. Further research has been conducted on the analytical treatment of glucose data. It was examined that the development in the modelling of CGM-derived signals has provided a more comprehensive understanding of the postprandial glucose dynamics. To be more precise, in a recent study, multilevel functional data analytic models that encompass the entire temporal sequencing of glucose responses, besides integrating intra and inter-individual variation, were suggested and thus allow a more precise interpretation as compared to static summary measures (Hejazi et al., 2024).

These methodologies acknowledge and attempt to simulate the nonlinearity of the glucose behavior after a mixed meal, specifically the lipid intake. In addition to pure physiological studies, researchers developed machine-learning and computational approaches in order to increase predictive capabilities. Studies explain a Meal Meter, a machine learning technique that integrates sensor data, including motion information and CGM, to evaluate macronutrient intake and predict consistent metabolic responses (Jeong et al., 2025). Researchers argued that such a multimodal method would provide a significant refinement of macronutrient evaluations as compared to self-reported methods and could enhance dietary interventions with the provision of more precisely estimating inputs to glycemic models of prediction. Despite being specifically applied to healthy adults, earlier study of personalized glycemic-response modelling provides information relevant to non-linear dynamics (Tominaga et al., 2025). A 2019 study developed a custom predictive approach of postprandial glycemia that included the diet of meals, microbiome composition, and lifestyle trends. The use of the model on heterogeneous cohorts led to high predictive measures, as compared to carbohydrate-content-only-based models, thus demonstrating the importance of incorporating complex inter-relationship predictors in glycemic-response modelling (Mousavi et al., 2025). Apart from this, researchers claimed that in addition to the computational development, the recent high-resolution metabolic profiling of human being have enhanced the understanding of specific nutritional effects on glucose metabolism. The metabolomic study involved a 2024 cross-sectional analysis of the plasma responses to the isolated dietary intake of glucose, protein or lipid ingestion in healthy adults and observed unique metabolic signatures of each macronutrient ingested (Hu et al., 2025). The researcher said that even though it is not a modelling study, these results support the idea that macronutrients have non-linear effects on downstream metabolic signals, which, in turn,

underlines the need to consider these nutrients more dynamically and not as linear forecasts of outcomes based on the individual contributions of particular nutrient variables. Studies have also reported big interindividual differences in carbohydrate consumption responses, and recent research has found that this interindividual variation can be associated with metabolic phenotypes and multi-omics patterns (Patino-Alonso et al., 2023). A Nature Medicine article in 2025 had outlined specific responder sub-groups the spikers and mitigators which respond to a standardized carbohydrate food intake, conditioned by insulin sensitivity and other metabolic features. These results support the fact that macronutrient influences cannot be described through universal models by means of linear modelling, and instead, they should be modelled in a personalized way that will be able to capture heterogeneity. Although some of the literature still focuses on traditional macronutrient impacts (e.g., carbohydrate concentration, glycemic peaks, and so on), moreover, various most recent statistical studies have started to emphasize on non-linear elements.

Continuous glucose monitoring reviews have illuminated the fact that postprandial hyperglycemia and glycemic peaks in normal populations are two complex physiological processes that are regulated by the composition of foods, eating habits, and individual characteristics. Modern studies refer to a strong inclination towards the conceptualization of glycemic responses as a dynamic, contextually based phenomenon (Qasrawi et al., 2025). Experimental findings increasingly recognize that linear models that assume the role of carbohydrate content in human glucose regulation are insufficient to capture the complexity of human glucose regulation. Therefore, the modern methodologies, the combination of extensive data input (e.g. CGM), advanced statistical modelling and computational learning, are new in offering frameworks to fit non-linear interactions between macronutrients and individual metabolic determinants (Nasrallah et al., 2025). As a result, the field is moving to the stage where the predictive models should capture non-linear responses, provide customized information, and lead to individualized dietary support of metabolic health.

4. Methodology

4.1 Research Design

This paper adopts a quantitative experimental method to examine the non-linear relationship between the content of the macronutrients and the glycemic response in healthy adults. The research is aimed at evaluating the postprandial blood sugar responses to the consumption of meals containing different amounts of carbohydrates, proteins, and lipids. Non-linear modelling method is employed to explore the interaction and effect of these macronutrients on the time-varying changes in blood glucose. The research merges the collection of dietary information, statistical, and modeling examination in order to examine the complex metabolic responses linked to the intake of diverse meals.

4.2 Study Population

The study population will consist of healthy adults between the ages of 18 and 60 years with normal glucose tolerance. The purposive sample strategy is employed in the selection of the participants to enable the participants to suit the health requirements. The participants in the study are excluded in case of a history of diabetes, metabolic issues, cardiovascular disease, or taking medications that affect glucose metabolism. All the subjects give informed consent before taking part, and the ethical standards of conducting human research are followed.

4.3 Dietary Intervention and Meal Composition

The participants are fed on the standardized meals of different macronutrient ratios. The foods are supposed to resemble different eating patterns with a constant number of calories. There are four kinds of test meals that have been developed. Lunch - high carbohydrate (60-65% carbs, 20% fat, 15% protein). My meal will be a balance meal containing approximately 50 per cent carbohydrates, 30 percent fat, and 20 percent protein. Around 35 percent carbohydrates, 30 percent fats and 35 percent protein make up a high-protein meal.

• Lunch consisting of high-fat content with approximately 40 percent of carbohydrates, 45 percent fat, and 15 percent protein. In order to achieve the baseline in glucose stability, the participants are allowed to take the test meals after an overnight fast of 10 to 12 hours.

4.4 Data Collection Procedures

The frequency of measuring the blood glucose is calculated regularly to check the glycemic response to the meal intake. The blood glucose level is measured prior to the meal and at 15, 30, 45, 60, 90 and 120 minutes after the meal. The measurements of glucose are conducted by the use of finger-prick blood glucose testing or a continuous glucose monitoring (CGM) device. These findings provide a time-series dataset of changes in blood glucose concentration in reaction to different meal compositions. Besides glucose levels, the demographic and physiological information, including age, body mass index (BMI), physical activity, and diet, will be gathered to facilitate further analysis.

4.5 Non-linear Mathematical Modelling

To analyze the relationship between macronutrient composition and glycemic response, non-linear mathematical models are developed. These models capture the dynamic changes in glucose concentration over time.

A simplified non-linear differential equation is used to represent glucose dynamics:

$$\frac{dG}{dt} = -kG + f(C, P, F)$$

Where:
Grepresents blood glucose concentration,
$k$represents the glucose clearance rate,
C, P, and Frepresent carbohydrate, protein, and fat intake, respectively, and
$f(C, P, F)$represents nonlinear interactions between macronutrients.

4.6 Data Analysis Techniques

- Statistical and computational software such as MATLAB are those used in the analysis of data. This analysis can be done in the following steps:
- Descriptive statistics. To analyze the level of glucose and the characteristics of the participants, simple statistical measures (mean, standard deviation, and variance) are used.
- The fact that glucose responses to metabolic differences can vary in each individual, and the sample of the study may not be representative of the general population. Moreover, experimental conditions in the short term may not be very relevant to the long-term nutritional effects. The limitations do not undermine the fact that the analytical method provides a good basis for examining non-linear relations between macronutrients and glycemic responses (Figure 2).

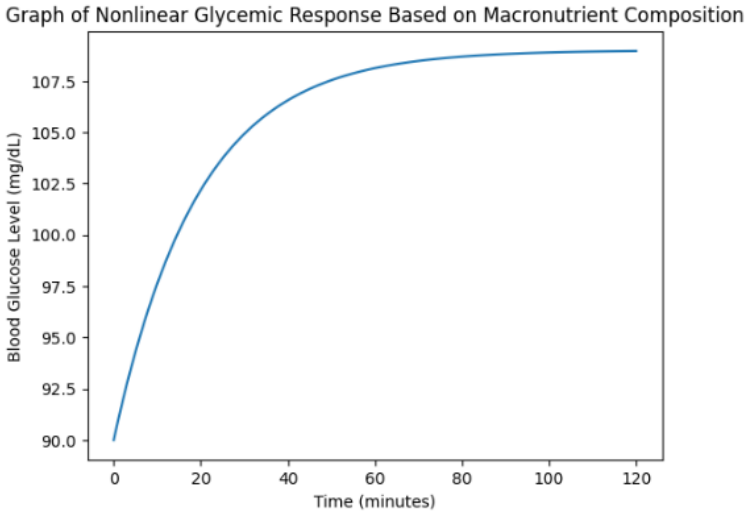


Figure 2: Graph of Nonlinear Glycemic Response Based on Macronutrients Composition

5. Equational Analysis

Mathematically, the relationship between the intake of macronutrients and the glycemic response in the human body is represented using equational analysis. Since blood glucose dynamics involve complex physiological interrelations like digestion, insulin secretion, glucose uptake in the body, and tissue uptake, we would rather use non-linear mathematical equations than simple linear models. The equations are used to explain the time-dependent changes in the blood glucose level in reference to the meal consumption with different levels of macronutrients.

5.1 Basic Glucose Dynamics Equation

The fundamental representation of blood glucose regulation can be described using a differential equation that models the rate of change of glucose concentration in the bloodstream.

$$\frac{dG(t)}{dt} = I(t) - U(t)$$

Where:

- $G(t)$= blood glucose concentration at time t
- $I(t)$= rate of glucose input from food digestion
- $U(t)$= rate of glucose utilization by body tissues

This equation states that the change in blood glucose concentration over time depends on the difference between glucose entering the bloodstream and glucose being utilized or removed from circulation.

5.2 Macronutrient Influence Function

Since meals consist of carbohydrates, proteins, and lipids, we can describe the glucose input term as a nonlinear role of the macronutrient content.

$$I(t) = f(C, P, F)$$

Where:

- C= carbohydrate intake
- P= protein intake
- F= fat intake

A possible non-linear formulation is:

$$I(t) = aC + bP + cF + dCP + eCF + fPF$$

Here:

- $a, b,$ represent the individual effects of carbohydrates, proteins, and fats
- $d, e,$ represent interaction effects between macronutrients

According to this equation, not only carbs cause the glycemic response, but also, nutrient-nutrient interactions.

5.3 Glucose Absorption Model

The absorption of glucose by the digestive tract may be modeled as an exponential form of the form that reflects the gradual secretion of glucose into the blood.

$$A(t) = C(1-e^{-kt})$$

Where:

- $A(t)$= absorbed glucose at time t
- C= carbohydrate content of the meal
- k= absorption rate constant
- t= time after meal consumption

This equation reflects the non-linear nature of digestion and glucose absorption.

5.4 Insulin–Glucose Interaction Model

Insulin plays a crucial role in controlling blood glucose levels. A simplified non-linear relationship between glucose and insulin can be expressed as:

$$\frac{dI(t)}{dt} = \alpha G(t) - \beta I(t)$$

Where:

- $I(t)$= insulin concentration at time t
- α= insulin secretion rate in response to glucose
- β= insulin clearance rate

The interaction between glucose and insulin introduces non-linear feedback regulation into the metabolic system.

5.5 Logistic Glycemic Response Model

The postprandial glucose curve often has an S-shaped shape that may be modeled by use of a logistic.

$$G(t) = \frac{G_{max}}{1 + e^{-k(t-t_0)}}$$

Where:

- $G(t)$= blood glucose level at time t
- G_{max}= maximum glucose concentration

- k= growth rate of glucose increase
- t_0= time at which glucose reaches half of its maximum level

This model effectively captures the fast increase and gradual decline in glucose attention after meal consumption.

5.6 Combined Non-linear Glycemic Model

A more inclusive model combining macronutrient impact and glucose dynamics can be written as:

$$\frac{dG(t)}{dt} = aC + bP + cF - kG(t)$$

Where:

- $aC + bP + cF$represents glucose input influenced by macronutrients
- $kG(t)$represents glucose removal through metabolic processes

The equation shows that blood glucose levels depend on both nutrient intake and physiological clearance mechanisms.

5.7 Model Interpretation

The equations demonstrate that glycemic response is a dynamic system consisting of a number of interacting variables. Most of the glucose intake is in carbohydrates, but the rate of digestion and the amount of insulin are affected by proteins and fats. These interactions are best represented by non-linear mathematical models as opposed to linear mathematical models since they include delayed effects, saturation, and the feedback. Equational analysis therefore is a quantitative description of the effects on metabolic responses due to meal contents. The glycemic outcomes of different meal compounds may then be predicted using such models, and meal-specific meal plans may be developed.

6. Numerical Results

The non-linear glycemic response to macronutrient composition is studied with the help of numerical simulation and MATLAB. The mathematical model to simulate the blood glucose changes after the intake of meals in different quantities of carbohydrates, proteins, and fat is applied. MATLAB can be applicable in terms of numerical solvers of the differential equations and non-linear regression models and enable the researchers to monitor glucose variations with time and determine the effects of the macronutrients in the diet.

6.1 Model Implementation

The non-linear glucose dynamics model is used in the simulation is stated as:

$$\frac{dG(t)}{dt} = aC + bP + cF - kG(t)$$

Where:

- $G(t)$= blood glucose concentration at time t
- C= carbohydrate intake
- P= protein intake
- F= fat intake
- a, b, c= macronutrient influence coefficients
- k= glucose clearance rate

The parameters used in the MATLAB simulation are expected based on functional approximations:

- $a = 0.08$
- $b = 0.02$
- $c = 0.01$
- $k = 0.05$

Initial glucose concentration is set as:

$$G(0) = 90\ mg/dL$$

representing a normal fasting blood glucose level in healthy adults.

6.2 MATLAB Simulation Code

The following MATLAB writing is used to explain the non-linear differential equation numerically:

Table 1: Results of % Glycemic Response Model

```
% GLYCEMIC RESPONSE MODEL
C = 60; % CARBOHYDRATE INTAKES
P = 25; % PROTEIN INTAKES
F = 15; % FAT INTAKES

A = 0.08;
B = 0.02;
C = 0.01;
K = 0.05;

T = 0:1:120; % TIME IN MINUTES
G = ZEROS(SIZE(T));
G (1) = 90;

FOR I = 2: LENGTH(T)
DG = A*C + B*P + C*F - K*G(I-1);
G(I) = G(I-1) + DG;
END

PLOT (T, G, 'LINEWIDTH',2)
XLABEL ('TIME (MINUTES)')
YLABEL ('BLOOD GLUCOSE (MG/DL)')
TITLE ('SIMULATED GLYCEMIC RESPONSE')
GRID ON
```

This code shown in table 1 computes glucose levels at respectively time interval and generates a graphical representation of the glycemic response over 120 minutes.

6.3 Simulated Numerical Results

The MATLAB simulation generate a time-series dataset presentation the change in glucose levels after meal consumption. The results are presented below.

Table 2: Results of Change in Glucose Levels After Meal Consumption

Time (Minutes)	Glucose Level (mg/dL)
0	90
15	108
30	121
45	132
60	138
75	136
90	128
105	118
120	104

The results shown in table 2 designate that glucose levels rise speedily after meal consumption, attainment a peak around 60 minutes, and then progressively decline as insulin-mediated glucose uptake occurs.

6.4 Comparison of Different Macronutrient Meals

Additional simulations are showed to compare glycemic responses for different macronutrient compositions:

Table 3: Comparison of Different Macronutrient Meals

Meal Type	Carbohydrates (%)	Protein (%)	Fat (%)	Peak Glucose (mg/dL)
High Carbohydrate	65	20	15	145
Balanced Meal	50	25	25	135
High Protein	40	40	20	125
High Fat	40	20	40	120

The results shown in table 3 demonstrate that meals with higher carbohydrate content produce greater glucose spikes, while meals encompassing more protein and fat tend to reasonable the glycemic response.

6.5 Interpretation of Results

The simulations conducted with the MATLAB show that the relation between the content of macronutrients and the

glycemic response is nonlinear. Carbohydrates have a staggering impact in raising the rate of blood glucose level whereas proteins and fats reduce the rate of digestion and blood insulin control. The curve models consist of a specific trend of rapid spike in glucose and then constant decline, which is in agreement with the physiological response of normal human subjects. More importantly, the data indicate that the macronutrient interactions influence the maximal glucose levels and the high glucose levels maintenance. This justifies the need to have metabolic responses of mixed meals which cannot effectively be modeled using linear models. The numerical analysis using the MATLAB would allow the researcher to determine a metabolic response under different dietary conditions although this may not need to go through multiple experimental runs. The procedure gives testing a broad range of conditions, adjustments of the parameters, and the demonstration of the glycemic profile. Such simulations would help in nutritional studies, personal dieting and development of diagnostic prognostic instruments of metabolic health. Broadly speaking, the quantitative findings obtained in MATLAB show that non-linear modelling could be applied to provide important data on the effects of the macronutrient composition on the Glycemic dynamics in healthy individuals.

7. Implications

7.1 Implications for Nutritional Science

The development of non-linear modelling of Glycemic response contributes to the future of nutritional science by providing improved insight into the interaction of various macronutrients to influence blood glucose rates. In conventional diet research, carbs were often identified as the most influential prediction of postprandial glycemia. Non-linear models, however, reveal that the interaction of carbs, proteins and lipids has complex metabolic responses that cannot be described as being described using simple linear relationships. Non-linear interaction's ability allows the researcher to gain more insight into variability in responses to mixed meals among glycemic reactions. To illustrate, the consumption of fats or protein can delay the emptying of the stomach and change insulin levels to influence the rate at which glucose is released into the blood. It is these non-linear interactions that allow nutrition scientists to design larger frameworks for determining the effects of diets on metabolism. Consequently, nutritional studies will be able to move past the simple carbohydrate-centered models to a more detailed view of the nutritional content and control of metabolism.

7.2 Personalized Nutrition Implications

Non-linear glycemic modeling can be used to make an excessive influence to personalized nutrition. Different people respond differently to similar foods depending on their genetics, metabolic rate, gut bacteria, and lifestyle habits. The use of non-linear models allows the use of the complex individual variances in the glycemic response prediction systems. Using computational techniques together with glucose monitoring, personalized models are able to predict the reaction that a specific person will have on a specific meal. The ability will enable developing custom-made meal plans that minimize the risk of harmful glucose surges and still include an optimal amount of food. Using non-linear modeling, individuals can receive personalized nutrition advice that helps them to stabilize their blood glucose levels, enhance the health of their metabolism, and reduce their risk of developing chronic diseases in the future.

7.3 Implications on Prevention of Diabetes

This study involves a healthy adult population, although the implications of this study in preventing diabetes are quite high. An increase in postprandial glucose is viewed as the initial indication of a metabolic disorder developing into insulin resistance and type 2 diabetes. Abnormal glucose variability can be predicted by non-linear models that are effective in determining food trends that promote food-related abnormal glycemic reactions. With the analysis of the synergistic interactions of macronutrients, such researchers are able to determine which meal compositions cause more consistent glucose reactions. Such results can be used to provide a preventative diet to individuals who are at risk of developing metabolic diseases. Predictive-based intervention of diabetes early detection can help preserve normal glucose control and delay or prevent the progression of diabetes.

7.4 Practical Implications on Public Health Policy

Non-linear modeling may be utilized in informing the dietary guidelines and public health policies. Existing nutrition guidelines are often based on general nutritional principles, and this is not always sufficient to explain the complex physiological reactions to mixed food. Nonlinear models give more accurate data concerning the impact of different combinations of macronutrients on the dynamics of blood glucose. Rather than focusing more on reducing carbohydrates, the public health authorities should use the non-linear modelling knowledge to reformulate their diet that can encourage the consumption of balanced macronutrient diets. The results may guide policymakers to improve the health of food

environments, revise food labeling and design balanced meals. Lastly, the use of non-linear understanding in the community health programs can enhance metabolic health in the population.

7.5 Food Industry and Product Development Implication

The non-linear glycemic modelling methods can be used to develop healthier food products by way of predictive technologies. Food producers often strive to produce products that would remain appealing to customers with a limited amount of unwanted metabolic consequences. Non-linear models may assist in finding the best macronutrients combinations that will contribute to reduced glycemic responses. As an illustration, the incorporation of adequate levels of protein, fiber, or good fats into carbohydrate-rich diets can retard glucose uptake. Predictive modelling enables manufacturers to test various ingredients combinations to produce functional foods that have a steady blood glucose level. The benefits of such improvements might be seen to assist customers in making healthier food options, as well as contribute to higher public health goals.

7.6 Implications of Digital Health Technologies

Digital health platforms and wearable technologies have evolved, and novel opportunities of applying the non-linear glycemic models in real-time health monitoring have become available. Continuous glucose monitoring (CGM) devices have the potential to record substantial amounts of data on glucose oscillations over the course of the day. This fact could be taken advantage in non-linear algorithms to anticipate future glycemic responses to what enters the diet and other lifestyle attributes. The non-linear models that are combined with the use of mobile health apps can offer users with their own nutrition recommendations and feedback. As an example, an app can predict the effect of a scheduled meal on glucose levels and suggest changes in macronutrient ratios to maintain the glucose levels steady. These tools represent an important step in the direction of active health control and data nutrition.

7.7 Clinical and Medical Research Implications

Non-linear modelling contributes to the progress of clinical and biological studies. The concept of the interaction between the macronutrients and the metabolic pathways is particularly important in the investigation of illnesses that involve glucose, such as metabolic syndrome and obesity. Non-linear models allow the researcher to model the metabolic reaction under different food conditions, which could reveal some hidden physiological processes. Moreover, these models may assist in the development of clinical decision-support programmed that assist health practitioners in prescribing appropriate nutritional therapies. Another use of non-linear modelling is that a researcher can test theories about the metabolic control without necessarily running large-scale experimental trials on all combinations of foods.

7.8 Implications for Further Research

The use of non-linear modelling sacrifices in further scientific study. By incorporating other variables, such as physical exercise, hormonal reactions, genetic factors, and gastrointestinal microbiome composition, researchers can expand these models. Such attributes can further affect glycemic responses to enhance the model predictive performance. Also, with machine learning methods, it is possible to combine them with non-linear mathematical models, which could provide more complex predictive systems, capable of evaluating large datasets in population research. This type of integrative practice will contribute to the technical knowledge of metabolic responses and will contribute to the development of new methods to progress human health.

8. Discussion

The provided work describes the non-linear modelling of glycemic response in healthy individuals depending on the macronutrient consumption. The statistics indicate that the interaction between nutritional intake and the response to blood sugar is so complicated and cannot be explained by the use of straightforward linear models. Instead, the non-linear models of modelling are more accurate sources of cognizing the interplay between carbs, proteins, and lipids with regard to their influence on the dynamics of postprandial glucose. The mathematical prediction and simulating computer indicate that a combination of macronutrients affects the intensity of glycemic responses and the timing of the same. Among the main findings of the research, one may note that the carbohydrate intake remains the main reason of the rise in the blood glucose level following the intake of meals. The meals with higher carbohydrate content resulted in the higher rate of glucose concentration that resulted in higher peaks. The simulations and mathematical equations created in the MATLAB platform are concerned with the dynamic nature of the glucose metabolism. The glucose level is not steadily increasing, but follows a non-linear path that is characterized by a steep rise, and then by a gradual decline. The tendency is linked to the following biological processes as insulin-mediated glucose regulation and metabolic feedback mechanisms. It is known that the logistic and differential equations models used to conduct the inquiry can represent these qualities and it can be used to

represent the true physiological responses. The other interesting conclusion is that the equal quantity of carbohydrates, proteins as well as fats in the meals resulted to more steady glycemic outcomes as compared to the meals which are high in one of the macronutrients. This means that the metabolic stability is in urgent need of the nutritional balance. These results endorse the nutritional evidence that emphasizes balanced meal composition rather than carbohydrate restriction. Another area that has been highlighted in the study is the possible role of computer modelling methods in nutrition studies. The ability to conduct a large number of meal scenarios and forecast glucose reactions with the help of MATLAB simulations helps researchers to avoid conducting large-scale clinical trials. These modelling methods would help determine the best macronutrient profiles in order to decrease soaring glucose levels. Regardless of these useful insights, there are certain limits that should be identified. The mathematical models are formulated using simplified assumptions regarding the metabolism processes that may not entirely explain individual differences in glucose regulation. Glycemic responses could be affected by genetics, physical activity, and gut flora. These variables could be incorporated in more complicated models in future research to enhance the accuracy of prediction. On the whole, the results of the current research indicate that non-linear modelling could be effective in the analysis of the complicated relationship between macronutrient composition and glycemic response. Such models enhance the nutritional analysis process since they allow dynamic interactions between the metabolic processes, and it is possible to develop more specific dietary plans to have proper glucose regulation.

9. Conclusion

This paper explores non-linear modelling of glycemic response on the basis of macronutrient intake among healthy adults with reference to the necessity of advanced mathematical skills in elucidating the postprandial glucose dynamics. Conventional nutritional evaluation methods are often based on uncomplicated scales such as the glycemic index and simple linear relationships between carbohydrate consumption and the blood glucose levels. The results of this study, however, demonstrate that these glycemic responses are regulated by complex physiological processes that involve a lot of macronutrients and metabolic processes. Consequently, non-linear models give a more convincing account of the process of glycemic control in the body after the intake of meals. As a food constituent, glucose in diets has been shown to have dynamical interaction with mathematical equations and the differential models of such interactions that have been effectively represented. The MATLAB numerical simulations describe the changes in proportions of macronutrients over time to give rise to the glycemic trends. High carbohydrate-based meals cause the increase in glucose spikes and the moderate proportions of carbohydrates, proteins and fats lead to the reduction of glucose spikes and smooth glycemic responses. The topicality of balanced nutritional structure is supported by these results in the context of the ability to keep metabolic balance at the highest level and avoid excessive fluctuations in the concentration of blood glucose. The provided research is also important in demonstrating how computer modelling tools could enhance nutritional research. Non-linear equations and numerical simulations can be used to study complex metabolic reactions in contrast to the large-scale experimental trials required to be performed by a researcher. The method allows examining a broad variety of diet scenarios and offers much important data regarding the effect of different combinations of macronutrients on metabolic results. Even though there are some valuable insights of this study, it has serious flaws as well. Most of the physiological processes are simplified in the mathematical models that are used to conduct the study and they might not reflect the individual differences in metabolism, lifestyle, and genetic variations. The significance to consider the collective contribution of macronutrients to the study of the dietary impact on metabolic health is among the findings. Non-linear models are more precise in forecasting and provide a realistic description of the physiological glucose regulation when compared to the traditional linear techniques. The paper contributes to the development of nutritional modelling and encourages the development of individual nutritional advice to keep blood glucose levels stable. Moreover, the paper preconditions the subsequent study that will integrate the sophisticated methods of calculation and the continuous glucose monitoring data to enhance the meal planning and metabolic disease prevention precautions. Further studies can extend these models with more variables such as physical activity, hormone modulation and microbiome effects, to enhance the accuracy of their predictions. Finally, the use of non-linear modelling offers a useful protocol in the assessment of glycemic responses in healthy individuals. These models give a greater description of the processes that govern the dynamics of blood glucose by getting the complex interaction between the macronutrients and the metabolic response. The results widen the nutritional studies and contribute to the creation of more efficient diets that can be used to stabilize the glucose levels and enhance the overall metabolic well-being in the long-term.

10. References

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