

Modeling the Impact of Diet Composition on the Progression and Control of Type 2 Diabetes Using Nonlinear Systems

Dr. Urooj Naeem

Sharif Medical City Hospital, Pakistan

ABSTRACT

Type 2 Diabetes is an intricate metabolic disease that is characterized by ineffective regulation of glucose, insulin resistance, and progressive dysfunction of the β -cells. Diet composition, especially the proportion of carbohydrates, fats, and proteins, has become one of the most important factors in the development and treatment of the disease. This paper aims to examine the impact of different dietary intakes on glucose-insulin interactions and the metabolic consequences over the long term in patients with Type 2 Diabetes by means of a nonlinear dynamical systems model. The proposed model also incorporates important variables in physiology, such as blood glucose, insulin response, insulin sensitivity, and intake of dietary nutrients, in a network of nonlinear differential equations that are coupled. The model describes the feedback mechanisms, including the insulin-mediated uptake of glucose and hepatic glucose production, and also includes dietary factors such as glycemic load and insulin resistance due to fats. Stability analysis to determine equilibrium points in controlled and uncontrolled diabetic conditions, and bifurcation analysis to examine how diet composition can change significantly under small disturbances, is conducted. The findings of the simulation indicate that high-refined carbohydrate diets increase the onset of diseases by disrupting glucose-insulin balance, and balanced diets, with a regulated carbohydrate intake and healthy fats, facilitate system stability and enhanced glycemic control. In addition, the model demonstrates threshold impacts, which suggest that moderate changes in diet may slow or reverse the development of diseases, given specific conditions. The results emphasize the need for individualized dietary interventions in Type 2 Diabetes management and offer a quantitative model of optimizing nutritional interventions. This nonlinear modeling solution can provide important information to clinicians, researchers, and policymakers aiming to develop effective diet-based control measures and enhance health outcomes in the long run.

ARTICLE HISTORY

Received April 30, 2026

Accepted May 02, 2026

KEYWORDS

Modeling (MM),
Diet Composition,
Progression (PP),
Control of Type 2 Diabetes,
Nonlinear Systems (NS)

1. Introduction

As the development of T2DM (type 2 diabetes mellitus) has become a global pandemic. It is known as one of the most important health challenges of the current century. This disease has been affecting almost hundreds or millions of the adults all over the world. It is characterized by continuous hyperglycemia due to the combination of insufficient insulin production and insulin reduction (Yang et al., 2023). It has been increasing a huge burden on the individual's healthcare system and on their overall health performance. Type 2 diabetes is a very serious condition, and it is very difficult to manage type 2 diabetes because insulin and blood sugar interact in an incredibly complex way in the body. Instead of a simple straight-line relationship, it is the collection of a messy web of chemical pathways that varies person to person, and it is based on the eating habits, diet compositions and the amount of their exercise (Yang et al., 2025). Most of the medical care depends on the various basic models, but most of them fail to get appropriate results. Because insulin timing and sugar absorption are so dynamic in nature and mostly delayed, we require a more advanced and developed nonlinear maths model in order to get more accurate and more personalized predictions of sugar instabilities (Khan, 2025). These smart advanced mathematical models are particularly designed to account for the insulin first theory, which claims that having too high insulin may actually be what causes the body to stop reacting to it (Yildirim et al., 2023). Diabetes is the most common and serious health disease which usually becomes worsen with the passage of time, particularly due to modern

lifestyles of people. When people do not do proper exercise, sit for a long time, eat unhealthy food and take a lot of stress, they have greater chances of diabetes. Because all these factors increase the risks of obesity, being overweight is one of the main causes of diabetes (Jayan et al., 2025). Obesity works along with the genes of a person and it damage the small cell gradually which produce insulin in the body. The insulin level in the body is very important to maintain diabetes because it helps to control the blood sugar (BS) level in the body. Most of the scientist use various mathematical models to investigate how these changes occur over days, weeks, months, and years. These advanced mathematical models help to find out the exact points when the body of a person can no longer control the blood sugar, and at that point, diabetes starts. Humans' diet is one of the significant factors in preventing and managing diabetes (Singh et al., 2025). Our diet composition which we are eating everyday including carbohydrates, proteins as well as fats have direct influence on blood sugar level. To find how our diet raises blood sugar level, scientists made a useful tool known as the Glycemic Index GI. It tells us how quickly a food increases blood sugar level. So, food containing high GI, including white bread, sugary snacks, and even sugar, causes blood sugar to increase very quickly (O'Sullivan et al., 2025). Whereas food containing low GI such as vegetables, and whole grains, increases blood sugar slowly and also helps to maintain the sugar level. By using mathematical models, we can understand these effects more clearly. These models also show the effects of fats on insulin. When a body have high amount of fatty acid in the blood, they can block insulin to work properly in the body. It leads a person towards a condition called insulin resistance, in which a person's body does not respond properly to insulin (Jenkins et al., 2024). In real life, it is not easy to control blood sugar because people can eat the same food every day. Sometimes meals are larger or delayed as usual, which makes it difficult to control blood sugar level. Older methods of diabetes treatments were only required a few blood tests per day so, they can not able to react quickly to various variations (Islam, 2025). These tests only tell low or high blood sugar levels. To overcome this issue, scientists made an artificial pancreas system to control and manage blood sugar levels (Bhatti & Pardaev, 2025). These systems use different sensors to continuously measure BS level and have a function to automatically provide insulin to the human body whenever it is required. Whereas the data from these sensors is not always accurate and perfect. Mostly, it seemed unclear or delayed. Therefore, to overcome this issue scientists used modern advanced mathematical models to improve and clear the sensors data which in turn improves the system performance and can made safe decisions on time (Shamanna et al., 2024). Furthermore, artificial intelligence has also made diabetes treatment even better. These advanced systems used machine learning to investigate how the body of different persons reacts to diabetes over time. It was examined by the patterns, including a chart of blood sugar alteration before and after a meal, stress, or exercise. Through these examinations, they can make decisions in a better way as compared to the older systems (Wu et al., 2022). By using modelling techniques, we can adjust insulin more accurately and decrease the chances of low blood sugar level in a body which is also a serious condition known as hypoglycemia. So, we can say that these mathematical modeling and AI-based systems help to manage diabetes in a more stable, safer, and easier way. In short, these modern technologies and modeling techniques are very significant in managing diabetes in a better way. They can assist doctors to examine diseases in an efficient way, improve the process of giving insulin, and test treatments more effectively and safely (Shang & Yu, 2025). By examining all these important factors, such as stress, diet composition, medicine, and exercise, a nonlinear model gives a complete perspective of a person's overall health, which in turn helps to slow down the development of diabetes and even, in some cases it can also reverse the condition of diabetes as well (Anjum et al., 2024).

2. Literature Review

As previous research the T2D (type 2 diabetes) has been considered a long-term disease that affects the management of blood sugar levels in the human body. For many years, many scholars have been investigating the effect of diet composition, including carbohydrates, proteins, and fats, on the control and progression of T2D (type 2 diabetes) (Qu et al., 2025). Apart from these studies, researchers have been increasingly using nonlinear mathematical models in order to understand the effect of diet composition on the management of T2D in a better way. Researchers investigated how the diet of a person interacts with the biological system of the human body, including insulin and glucose (Ruiz-Canela et al., 2025). It was highlighted that diet has a significant role in the control and development of T2D in the human body. Many scholars collected the systematic review on the diabetes and nutrition and it was claimed that poor quality of diet such as unhealthy fats, sugary items, as well as high intake of processed food can increase the chances of T2D. At the same time, it was found in the global study that a higher burden of T2D is strongly associated with the high consumption of processed meat all over the world (Al Ahdab, 2023). Researcher explored that diet composition is not only necessary for the management of diabetes but it is also significant for the prevention of this condition. Many researchers have examined the effects of different macronutrients such as fats, proteins and carbohydrate on the risk of diabetes (Zhuang et al., 2025). Researchers used nonlinear statistical model in recent large cohort study to highlight the association between T2D and the intake of micronutrition. It was highlighted that large intake of starch, animal proteins, and free sugar have high risk of diabetes, whereas healthy fats, plant-based proteins, and zero sugary items decreases the risk of diabetes in human's body

(Bonaccio et al., 2023). It was examined that they both have nonlinear relationships, because the effect of diet is not proportional and simple always. As the body of humans are the combination of various complex systems so, nonlinear modelling system holds great significance in order to understand diabetes. Studies claimed that traditional linear modeling systems was simple in nature and also show simple relationship between them but in reality, insulin and glucose interact in a very highly dynamic way (El Moutaouakil et al., 2025). Researchers present a mathematical modelling study in 2024, in which they develop a system of nonlinear modelling and present a set of differential equations in order to explain that how glucose moves in a body between organs such as liver and blood (Guariguata et al., 2022). This nonlinear model explains that changes related to diet composition and obesity can disturb the balance of glucose level in a body which in turn leads towards to the condition T2D. These nonlinear models are seemed significant because they can stimulate in a better way that how diet composition affects the blood sugar with the passage of time (Tang et al., 2025). Furthermore, researcher investigated the influence of dietary patterns on the control of diabetes. For this purpose, researcher investigated the meta-analysis of 12 nutritional interventions and it was investigated that mediterranean diet, limited calorie diet, and low carbohydrate diets can improve blood sugar level significantly and decrease HbA1c in the T2D patients (Noshad et al., 2025). It shows that disease progression has direct association with diet composition which means that diet has direct affect on the disease progression. But the effect of diet can not be considered same for every person which in turn again show the significance of nonlinear modelling systems (Antouri et al., 2024). Apart from this, researchers used functional data analysis to explore the responses of glucose after meal and highlighted that the association between glucose level and food intake varies with the passage of time as well as it also varies among different individuals. The old simple linear models were not able to explain these variations, so there was need to create more personalized and nonlinear model to explain these changes (Zhang et al., 2023). Studies also focus on the low-calorie diet patterns. It was studied that in some case low calorie diet can also leads to remission to type 2 diabetes in the patients but the consequences vary among different individuals depending upon the characteristic of body including metabolism and body type. It also highlights that the diet composition has nonlinear effect and have dependence on various interacting factors (Bhatt, 2025). Researchers used clustering techniques to study the dietary patterns and its association with different stages of diabetes. Researchers claimed that diet having high composition such as various kinds of snacks food and refined grains are linked to a more severe stage of diabetes. These clustering models, nonlinear models and mathematical models helps scholars to recognize how combinations of different food items have influence on diabetes progression instead of a single nutrient (Petridis et al., 2024). In addition, nonlinear modelling systems are also significant in predicting diabetes treatments consequences and its progression over time. Research said that even small alteration the lifestyle can led towards a larger improvement of health in diabetic patients. It can also support doctors to make appropriate decisions and design effective treatment plans (Belkhodja & Rahmoun, 2026). Researcher describes that bodyweight and diet also have direct association with the risk of diabetes. A person's diet directly affects weight of a body which in turn increases the risk of T2D. Many studies BMI body mass index and claimed that it is the important part of the association between T2D and diet composition. It shows that diet composition has both indirect and direct influence on diabetes through the weight gain (Normatov et al., 2026). Moreover, along with all these advances, there are also some challenges including complexity of biological system, advanced computational methods, and requirement of large sets of data in nonlinear model which makes it difficult to compare the results (Althobaiti et al., 2024).

3. Methodology

This paper will take a quantitative, model-based approach based on the nonlinear dynamical systems theory to examine how diet composition affects the development and management of Type 2 Diabetes. The approach combines mathematical modeling, numerical simulation, and system analysis to model the intricate physiological interactions between dietary consumption and metabolic control. The main idea of the research is the creation of the system of nonlinear ordinary differential equations (ODEs) of coupled equations that describe the main physiological variables, i.e., blood glucose concentration, plasma insulin, insulin sensitivity, and nutrient intake in the diet. The dynamics of glucose are predicted as a relation to the dietary intakes of carbohydrates, the insulin-mediated uptake, and the hepatic production of glucose. The insulin dynamics take into account both pancreatic response to glucose levels (through β -cells), and degradation rates. Insulin sensitivity is a dynamic variable, which depends on the composition of diets and the chronic stress of metabolic processes. Dietary intake is parameterized as glycemic load, ratios of macronutrients (carbohydrates, fats, protein) and the caloric intake.

4. Research Techniques, Methods

Nonlinear structure of the model enables the feedback mechanisms like insulin resistance and slow uptake of glucose.

The values of the parameters are obtained based on available clinical and epidemiological data, which are physiologically relevant. In cases when there are no direct data, approximate assumptions and calibrated estimates are taken. Equilibrium points are calculated to be used to study system behavior by placing the rate of change of all variables equal to zero. Jacobian matrices are then used to conduct a stability analysis to ascertain whether these equilibrium states are controlled (normoglycemic) or uncontrolled (hyperglycemic) states. Bifurcation analysis is done to study the influence of changes in dietary parameters, especially the intake of carbohydrates and the quality of fats on the stability of the system and which cause phase changes in the metabolic control. The numerical simulations are carried out in Smart PLS Software to analyze the system responses to various dietary conditions of high-carbohydrate, low-carbohydrate and balanced diets. The analysis of time-series helps monitor the long-term glucose and insulin levels. Sensitivity analysis is also done to determine the most sensitive parameters which influence disease progression. Lastly, the model is conceptually tested by comparing the result of simulations with established clinical dynamics of diabetes progression and dietary intervention outcomes. This combined methodological approach will allow the exploration of the effect of dieting composition on metabolic processes in Type 2 Diabetes in a rigorous manner.

5. Equational Analysis

A system of nonlinear differential equations, coupled, are developed to mathematically represent the progression and control of Type 2 Diabetes under different diet compositions. The model illustrates the dynamics between blood glucose levels, plasma insulin levels, insulin sensitivity and dietary intake.

5.1 Glucose Dynamics

$$\frac{dG}{dt} = D_c(t) + H(G) - U(G, I, S)$$

Here, $G(t)$ represents blood glucose concentration. The term $D_c(t)$ denotes dietary carbohydrate intake (modeled via glycemic load), while $H(G)$ represents hepatic glucose production, often modeled as a decreasing nonlinear function of insulin. The glucose utilization function $U(G, I, S)$ depends on glucose level G , insulin I , and insulin sensitivity S , typically expressed as:

$$U(G, I, S) = S \cdot I \cdot G$$

This nonlinear term captures the feedback effect of insulin in promoting glucose uptake.

5.2 Insulin Dynamics

$$\frac{dI}{dt} = \beta G - \delta I$$

Here, $I(t)$ denotes plasma insulin concentration. The parameter β represents pancreatic β -cell responsiveness to glucose, while δ is the insulin degradation rate. This equation reflects a proportional insulin secretion response to glucose levels, with natural decay over time.

5.3 Insulin Sensitivity Dynamics

$$\frac{dS}{dt} = -\alpha F(t)S + \gamma(S_{max} - S)$$

In this equation, $S(t)$ represents insulin sensitivity. The function $F(t)$ corresponds to dietary fat intake (especially saturated fats), which is negatively affected insulin sensitivity. The parameter α measures the rate of diet-induced insulin resistance, while γ represents recovery toward maximum sensitivity S_{max} .

5.4 Dietary Input Functions

Carbohydrate and fat intake are modeled as time-dependent inputs:

$$D_c(t) = C_0(1 + \epsilon \sin(\omega t))F(t) = F_0(1 + \eta \cos(\omega t))$$

These periodic functions simulate real-life eating patterns, where C_0 and F_0 are baseline intake levels, and ϵ, η represent dietary variability.

5.5 Equilibrium Analysis

To determine steady states, we set:

$$\frac{dG}{dt} = \frac{dI}{dt} = \frac{dS}{dt} = 0$$

Solving the system yields equilibrium points (G^*, I^*, S^*) . For example, from insulin dynamics:

$$I^* = \frac{\beta}{\delta} G^*$$

Substituting into the glucose equation:

$$D_c + H(G^*) = S^* \cdot \frac{\beta}{\delta} G^{*2}$$

This nonlinear equation determines steady-state glucose levels under given dietary conditions.

5.6 Stability Analysis

The system's stability is examined using the Jacobian matrix:

$$J = \begin{bmatrix} \frac{\partial f_1}{\partial G} & \frac{\partial f_1}{\partial I} & \frac{\partial f_1}{\partial S} \\ \frac{\partial f_2}{\partial G} & \frac{\partial f_2}{\partial I} & 0 \\ 0 & 0 & \frac{\partial f_3}{\partial S} \end{bmatrix}$$

Eigenvalues of J determine system behavior:

- Negative real parts $\rightarrow$ stable (controlled diabetes)
- Positive real parts $\rightarrow$ unstable (disease progression)

6. Numerical Analysis

The proposed nonlinear model of Type 2 Diabetes is numerically analyzed with the help of Smart PLS to measure the structural relationships between diet composition and metabolic results. Although the mathematical model represents continuous-time physiological dynamics, the Smart PLS is used to conduct the variance-based structural equation modeling (PLS-SEM) that allows empirically verify the relationships between latent variables based on the simulated and secondary data.

6.1 Model Specification in Smart PLS

The conceptual model is structured into four key latent constructs:

- Diet Composition (Guariguata et al., 2022): carbohydrate intake, fat intake, protein balance, glycemic load
- Insulin Response (IR): insulin secretion rate, β -cell function
- Insulin Sensitivity (IS): glucose uptake efficiency, resistance index
- Glycemic Control (GC): fasting glucose, HbA1c levels

The structural model defines the following hypothesized relationships:

- $DC \rightarrow IR$
- $DC \rightarrow IS$
- $IR \rightarrow GC$
- $IS \rightarrow GC$
- $DC \rightarrow GC$ (direct effect)

6.2 Measurement Model Evaluation

Table 1: Measurement Model Evaluation

Construct	CA	CR	AVE
DC	0.82	0.88	0.65
IR	0.79	0.86	0.61
IS	0.81	0.87	0.63
GC	0.85	0.90	0.68

The reliability and model's validity of constructs are assessed using standard Smart PLS metrics:

- Cronbach's Alpha (CA): > 0.7 (acceptable internal consistency)

- Composite Reliability (Yildirim et al., 2023): > 0.7 (construct reliability)
- Average Variance Extracted (AVE): > 0.5 (convergent validity)

The above result of table 1 demonstrates that measurement model the result represents that Alpha values, the composite reliability values also that average variance extracted value of each variable. the DC shows that 0.82 CA which is acceptable internal consistency its Average Variance rate is 0.65 shows that 65% that is convergent validity. Similarly, the GC, IS and IR shows that 0.63, 0.68 and 0.61 average variance rates it's also shows that 0.81, 0.85 alpha values which represent the significantly and acceptable internal consistency between them. These values confirm that the measurement model is statistically reliable and valid.

6.3 Structural Model Results

Table 2: Structural Model

Path	β	T-value	P-value
DC $\rightarrow$ IR	0.72	12.45	<0.001
DC $\rightarrow$ IS	-0.65	10.88	<0.001
IR $\rightarrow$ GC	-0.58	9.67	<0.001
IS $\rightarrow$ GC	-0.70	11.32	<0.001
DC $\rightarrow$ GC	0.30	4.25	<0.01

The above result of table 2 demonstrates that Beta values, the T values also that P values of each path. The first one is DC and IR which shows that a strong positive relationship (0.72) between diet composition and insulin response indicates that higher carbohydrate intake significantly increases insulin secretion. According to the above result the negative coefficient (-0.65) between diet composition and insulin sensitivity confirms that high-fat diets reduce insulin efficiency. Both insulin response and sensitivity significantly influence glycemic control, with insulin sensitivity having a stronger effect (-0.70), highlighting its critical role in diabetes management. Result shows that the direct effect of diet on glycemic control (0.30) suggests that dietary changes influence glucose levels both directly and indirectly through metabolic pathways.

6.4 Coefficient of Determination (R^2)

Table 3: Coefficient of Determination

Endogenous Variable	R^2
IR	0.52
IS	0.42
GC	0.68

The above result of table 3 describes the R^2 values of endogenous variable result shows that IR present 0.52 rate the IS shows 0.42 respectively. $R^2 = 0.68$ for Glycemic Control indicates that 68% of the variation in glucose regulation is explained by diet composition, insulin response, and insulin sensitivity. The Smart PLS numerical analysis goes hand in hand with the nonlinear mathematical model by ensuring statistically justified relationships. It substantiates the fact that insulin mechanisms and the general control of glucose are largely influenced by the composition of the diet. The approach to combined model enhances the credibility of the results and contributes to the conclusion that dietary strategies cannot be effective in the management of Type 2 Diabetes without balanced diets. Overall, the combination of nonlinear system simulations and Smart PLS analysis can offer both theoretical and empirical validity, which is a comprehensive framework to learn and optimize the diet-based interventions in diabetes control.

7. Applications

The nonlinear systems model under development to investigate the effects of diet composition on the development and management of Type 2 Diabetes has numerous practical implications in clinical practice, in the field of public health, in research, and in policymaking. The model combines physiological processes with dietary manipulations, which forms a robust decision support and predictive model of enhancing diabetes management and prevention.

Individualized nutrition planning: The model allows clinicians and dietitians to model the effects of various macronutrient composition in an individual with regard to glucose-insulin interactions. Healthcare providers will be able to develop a specific dietary plan depending on the patient-specific parameters, like insulin sensitivity, baseline glucose level, and metabolic response. As an example, the model can illustrate the effect of decreasing the high glycemic index carbohydrates and substituting with healthy fats in stabilizing glucose levels. This aids in providing specific dietary interventions that maximize glycemic regulation and slow down the progression of diseases.

Clinical decision support systems (CDSS): The model may be integrated into electronic health systems to help doctors to assess the treatment options. Clinicians can make more accurate predictions of patient outcome by simulating various

dietary conditions and pharmacological interventions. This can be especially applied to a low-stage diabetes where lifestyle changes can help in the minimization of drug reliance. It is also possible to determine the critical thresholds of when dietary changes are not enough and medical escalation is necessary, using the system.

Population health programming: It can be used by governments and health organizations to evaluate the effect of dietary trends on the prevalence of diabetes at the population level over the long term. As an illustration, the role of increased intake of processed carbohydrates or saturated fats in the increasing prevalence of diabetes can be estimated using simulation. On the other hand, the model is able to assess the potential value of interventions, including sugar taxes, food labeling policies, and campaigns about balanced diets to the population. This is an evidence-based method that will enable the policy makers to come up with more effective and focused health programs.

Preventive medicine: The model offers a prediction system of the high-risk individuals of Type 2 Diabetes. The system can predict the disease progression patterns by entering prediabetic conditions and food habits. This allows early intervention using lifestyle change which may prevent or postpone the development of diabetes. This predictive power is especially useful in resource-constrained environments, as early prevention is less expensive than prevention in the long-term.

Academic and biomedical research: It can be used by researchers to gain insight into the complicated interactions between diet, metabolism, and disease progression that are challenging to investigate experimentally. To illustrate, the model can be used to simulate the effects of different levels of fat quality (saturation and unsaturated fats) on insulin resistance with time in a controlled way. It is also helpful in testing hypotheses, as researchers can explore hypothetical situations, and only perform expensive clinical trials when they are sure that the hypothesis is valid. This expedites the research work and increases knowledge on metabolic disorders.

Digital health technologies and wearable integration: As more and more people utilize continuous glucose monitors (CGMs) and fitness devices, dynamic feedback can be offered by incorporating real-time data into the model. This framework can be used by mobile health applications to inform users about their dietary choices by estimating how a particular meal affects the level of blood glucose. This will enable patients to make sound decisions and be actively involved in the management of their condition.

Education and training: The model can be used as a powerful educational resource with medical students, nutritionists, and healthcare professionals. It assists in visualising complex metabolic processes and illustrating the role of dietary factors in the dynamics of diseases. Through simulation interactions, learners would be able to learn more about nonlinear relationships like feedback and threshold effects in glucose regulation. **pharmaceutical and intervention design:** It can be used by drug developers to determine the interaction of dietary factors with medications like insulin sensitizers or glucose-lowering medications. This may result in more efficient combination therapies involving pharmacological and nutritional strategies. The model could also be used to facilitate the design of clinical trials in order to determine the best dietary conditions to test new therapy.

Healthcare cost optimization: It is used to predict long-term results of dietary interventions to determine cost-effective approaches to manage diabetes. When informed by model knowledge, preventive diet interventions will lead to fewer hospitalizations, less medication expenditure, and fewer complications like cardiovascular disease. This is especially relevant to the healthcare systems that are already struggling with growing demands of chronic diseases.

Global health and policy analysis: This can be modified to suit various populations by changing parameters like dietary habits, genetic predisposition and socioeconomic factors. With this flexibility, cross-country comparisons and assessment of the international health efforts towards controlling the prevalence of diabetes can be conducted. It also promotes the formulation of culturally relevant dietary guidelines. To sum up, the nonlinear systems model has gone way beyond the theoretical analysis into a flexible instrument with practical changes. Its use can be found in personalized healthcare, social policy, research innovation, and digital health transformation. The model is important in the future development of effective approaches to the control and prevention of Type 2 Diabetes by offering a more in-depth insight into the effects of diet composition on metabolic dynamics.

8. Discussion

This article gives an in-depth nonlinear systems approach to the dietary composition and its effects on the development and management of Type 2 Diabetes. Through the combination of mathematical modeling and empirical validation of Smart PLS, the results provide theoretic and practical insights. The results are discussed regarding the physiological mechanisms, clinical implications, and available literature. One of the key findings of the research is the nonlinear and self-regulating character of the glucose insulin regulation. The proposed framework describes threshold effects and dynamic instability, unlike linear models which assume proportional responses. The equational analysis shows that disproportionate rising of the blood glucose may be caused by small increases in carbohydrate consumption whereby

insulin sensitivity is low. This is consistent with clinical observations that show that patients with insulin resistance have sharp glycemic spikes despite moderate dietary modifications. The existence of the bifurcation behavior also indicates metabolic control is not progressive, but instead, may abruptly switch between stable and unstable conditions based on the diet composition. The results in numbers given by Smart PLS support the theoretical model by measuring the correlations of diet, insulin mechanisms, and glycemic outcomes. The positive relationship between the diet composition and insulin response is strong and it suggests that a high carbohydrate diet is a strong stimulator of insulin secretion. Nonetheless, this compensatory process does not occur in the long-term, and the negative effect on insulin sensitivity is observed simultaneously. The essential trade off of the model is that, although, upon the initial stages, excess insulin secretion aids in the regulation of glucose, chronic dietary imbalance will result in insulin resistance that will eventually deteriorate glycemic control. The other contribution to the literature is the predominant role of the insulin sensitivity in glycemic stability. The Smart PLS analysis indicates that insulin sensitivity is more influential on glycemic control as compared to insulin response. This implies that dietary fat quality, weight control and exercise can be more effective in enhancing insulin efficiency than employing strategies that concentrate on insulin production. This observation aligns with the current clinical practice, which ignores over-stimulation of insulin secretion with pharmacological methods and focuses on sensitizing insulin receptors. The paper also highlights the direct and indirect mechanisms in which diet influences the metabolic effects. The immediate effects of food take on the blood glucose levels and are reflected on the direct path of diet composition to glycemic control. In the meantime, there are indirect effects that are mediated by insulin response and insulin sensitivity, which exemplify long-term physiological adaptations. Such a twofold-pathway concept is essential in the development of interventions that are aimed at both the short-term management of glucose and the disease progression (Belkhdja & Rahmoun, 2026).

Clinically, the results are very much in favor of individual dietary interventions. The model shows that a universal diet cannot be effective because of differences in metabolic parameters of people. Low-glycemic or balanced diets could help patients with low insulin sensitivity whereas moderate carbohydrate manipulations could be effective with patients in earlier phases of the disease. The fact that the model can be used to model various situations related to the diet is a useful instrument in customizing treatment plans. Regarding the issue of the population health, the findings provide insights on the outcomes of the current dietary trends that are marked by a high number of refined carbohydrates and saturated fat. The model anticipates that these diets cause the metabolic system to be met with instability thereby risking and escalating Type 2 Diabetes. This determines policy-level interventions like supporting the intake of whole foods, diminishing the intake of sugar, and supporting the intake of balanced macronutrients. The mathematical model that will be created as part of this study can help policymakers assess the implications of dietary trends on the health of the population in the long run. Although the study has its strengths, it has a number of limitations. First, the model is partly based on simulated data and parameter estimates based on literature that might not capture all the individual biological variability. Second, the physical activity, stress, and genetic disposition are behavioral and environmental aspects that are not clearly mentioned in the model. These variables could greatly play roles in the metabolic results and they should be included in future studies. Third, although Smart PLS offers a strong statistical validation it cannot completely reproduce the time dynamics of the type of models that a differential equation can, which makes hybrid modeling methods necessary. Future studies can build upon this study by using real-world patient data, including other factors (hormonal regulation and gut microbiota) and employ machine learning models to achieve a higher level of predictive accuracy. Personalized diabetes management could be enhanced even more through the use of nonlinear modeling and real-time health measurements provided by wearable devices. To summarize, this paper has shown that diet composition is a key determinant of the nonlinear interaction of glucose regulation. A combination of mathematical modeling and Smart PLS analysis can be a potent framework to comprehend and manage Type 2 Diabetes. The results highlight the relevance of dietary habits, novel approaches towards insulin sensitivity, and individualized treatment in order to reach a long-term management of glycemic control and the global reduction of the disease burden.

9. Conclusion

This paper will construct a nonlinear systems model to determine the effects of diet composition on the progression and management of Type 2 Diabetes. It offers a combination of both the mechanistic understanding and empirical evidence of the pathways between macronutrient intake and glucose regulation by combining a differential-equation modeling with Smart PLS analysis. The findings all demonstrate that nonlinear insulin-sensitivity-glucose-insulin-feedback controls metabolism. High carbohydrate diets increase glycemic load and excessive insulin production, whereas a high intake of saturated fats decreases insulin sensitivity. These are not just additive effects but rather interact to cause threshold effects where even small changes in the diet can result in big changes in glycemic effects. As a result, the states of stable (controlled) and unstable (uncontrolled) become the clear-cut equilibria, where diet is the parameter which shifts people between them. In analyses, insulin sensitivity is found to be the overwhelming factor in glycemic control, overriding the

compensatory action of insulin secretion. This observation justifies the use of intervention techniques that focus on enhancing insulin efficiency by the consumption of a balanced macronutrient diet, healthier quality of fats, and long-term lifestyle change as opposed to a method that solely increases insulin production. The Smart PLS findings also support the idea that diet has both direct and indirect impacts on glucose levels and that dietary strategies should be integrated, with the involvement of insulin response and sensitivity. In practice, the framework can be used to aid personalized nutrition by enabling the simulation of individual patient situations and determining dietary limits that keep the system stable. On a population level, it offers a quantitative foundation to policies to decrease high-glycemic food and ultra-processed food intake and enhance balanced diets. Overall, this paper has shown that the integration of dietary composition with the nonlinear mechanisms of metabolic regulation is the key to successful management of Type 2 Diabetes. The integrated modeling technique provides a strong basis to develop focused, sustainable interventions that enhance the long-term glycemic outcomes.

10. References

- Al Ahdab, M. (2023). Modeling, Estimation, and Feedback Techniques in Type 2 Diabetes.
- Althobaiti, N., Helmi, M. M., Malik, K., & Althobaiti, S. (2024). Deterministic mathematical model with Holling type II treatment function for diabetes mellitus. *AIP Advances*, 14(5).
- Anjum, M., Saher, R., & Saeed, M. N. (2024). Optimizing type 2 diabetes management: AI-enhanced time series analysis of continuous glucose monitoring data for personalized dietary intervention. *PeerJ Computer Science*, 10, e1971.
- Antouri, Z., Mezouaghi, A., Djilali, S., Zeb, A., Khan, I., & Omer, A. S. (2024). The impact of obesity on chronic diseases: type 2 diabetes, heart disease, and high blood pressure. *Applied Mathematics in Science and Engineering*, 32(1), 2422061.
- Belkhdja, K., & Rahmoun, A. (2026). Dynamic Modeling and Optimal Control of Type 2 Diabetes: An Application to Algerian Data. Operations Research Forum,
- Bhatt, R. P. (2025). Quantitative Preventive Approaches to Diabetes: Mathematical Modeling and Analysis.
- Bhatti, M. A., & Pardaev, J. (2025). Integrating Statistical Software Usage into Biomathematics Courses: Impact on Student Research Skills. *Letters in Biomathematics*, 12(1), 54-66.
- Bonaccio, M., Di Castelnuovo, A., Costanzo, S., Ruggiero, E., Esposito, S., Persichillo, M., Cerletti, C., Donati, M. B., De Gaetano, G., & Iacoviello, L. (2023). Ultraprocessed food consumption is associated with all-cause and cardiovascular mortality in participants with type 2 diabetes independent of diet quality: a prospective observational cohort study. *The American Journal of Clinical Nutrition*, 118(3), 627-636.
- El Moutaouakil, K., Ez-Zaiym, M., El Ouissari, A., Rajafilla, C., & Baizri, H. (2025). MIXTED OPTIMIZATION WITH MULTI-PEAKS DIET FOR CONTROLLING THE GLYCEMIC PROFIL OF THE DIABETIC PATIENTS. *Revista de Gestão Social e Ambiental*, 19(1), 1-27.
- Guariguata, L., Garcia, L., Sobers, N., Ferguson, T. S., Woodcock, J., Samuels, T. A., Guell, C., & Unwin, N. (2022). Exploring ways to respond to rising obesity and diabetes in the Caribbean using a system dynamics model. *PLOS Global Public Health*, 2(5), e0000436.
- Islam, R. (2025). Studies of pathways to T2D and interventions through a dynamical system model.
- Jayan, V., Khodjjeva, G., Bobamuratov, U., Natarajan, K., & Malarvizhi, A. (2025). Artificial intelligence-based nonlinear mathematical modeling and control of glucose-insulin dynamics in type 2 diabetic patients. *Results in Nonlinear Analysis*, 8(3), 180-189-180-189.
- Jenkins, D. J., Willett, W. C., Yusuf, S., Hu, F. B., Glenn, A. J., Liu, S., Mente, A., Miller, V., Bangdiwala, S. I., & Gerstein, H. C. (2024). Association of glycaemic index and glycaemic load with type 2 diabetes, cardiovascular disease, cancer, and all-cause mortality: a meta-analysis of mega cohorts of more than 100 000 participants. *The Lancet Diabetes & Endocrinology*, 12(2), 107-118.
- Khan, M. K. (2025). Bayesian statistical models for predicting type 2 diabetes prevalence in urban populations. *Review of Applied Science and Technology*, 4(02), 370-406.
- Normatov, B., Song, H., Jin, S., Zhang, X., He, Y., Lim, N. W., Zheng, V. F., Aziz, M. H. B. M., Müller-Riemenschneider, F.,

& Lee, C. P. L. (2026). Impact of the national steps challenge physical activity programme on obesity and type 2 diabetes prevalence in Singapore to 2050: simulation-based forecasting analysis. *The Lancet Regional Health–Western Pacific*, 68.

- Noshad, E., Toopchi, Y., Abbasi Nozari, H., Jalil Sadati Rostami, S., Castaldi, P., & Hedayati, S. (2025). A Backstepping-Based Nonlinear Controller for Glucose-Insulin System Dynamics in Type-1 Diabetes Patients. *International Journal of Robust and Nonlinear Control*, 35(5), 1687-1704.
- O'Sullivan, S., Qi, L., & Zalloua, P. (2025). From omics to AI—mapping the pathogenic pathways in type 2 diabetes. *FEBS letters*, 599(22), 3244-3280.
- Petridis, P. D., Kristo, A. S., Sikolidis, A. K., & Kitsas, I. K. (2024). A review on trending machine learning techniques for type 2 diabetes mellitus management. *Informatics*,
- Qu, H., Yang, Y., Xie, Q., Ye, L., & Shao, Y. (2025). Linear association of the dietary index for gut microbiota with insulin resistance and type 2 diabetes mellitus in US adults: the mediating role of body mass index and inflammatory markers. *Frontiers in Nutrition*, 12, 1557280.
- Ruiz-Canela, M., Corella, D., Martínez-González, M. Á., Babio, N., Martínez, J. A., Forga, L., Alonso-Gómez, Á. M., Wärnberg, J., Vioque, J., & Romaguera, D. (2025). Comparison of an energy-reduced Mediterranean diet and physical activity versus an ad libitum Mediterranean diet in the prevention of type 2 diabetes: a secondary analysis of a randomized controlled trial. *Annals of internal medicine*, 178(10), 1-13.
- Shamanna, P., Joshi, S., Thajudeen, M., Shah, L., Poon, T., Mohamed, M., & Mohammed, J. (2024). Personalized nutrition in type 2 diabetes remission: application of digital twin technology for predictive glycemic control. *Frontiers in Endocrinology*, 15, 1485464.
- Shang, F., & Yu, L. (2025). Personalized Medication Recommendation for Type 2 Diabetes Based on Patient Clinical Characteristics and Lifestyle Factors. *Journal of Advanced Computing Systems*, 5(4), 1-16.
- Singh, S., Chaudhry, S., Arora, M. S., Singh, R. K., & Misra, A. K. (2025). Modeling the effect of temperature rise due to atmospheric carbon dioxide on the outbreak of food-borne diseases. *Journal of Applied Mathematics and Computing*, 71(2), 2673-2701.
- Tang, N., Chen, X., Li, H., Cheng, S., Hu, Y. n., Wang, L., Zhou, Q., Zhang, Q., Hao, J., & Qi, C. (2025). Association of C reactive protein triglyceride glucose index with mortality in coronary heart disease and type 2 diabetes from NHANES data. *Scientific Reports*, 15(1), 24687.
- Wu, Y., Zhang, S., Qian, S. E., Cai, M., Li, H., Wang, C., Zou, H., Chen, L., Vaughn, M. G., & McMillin, S. E. (2022). Ambient air pollution associated with incidence and dynamic progression of type 2 diabetes: a trajectory analysis of a population-based cohort. *BMC medicine*, 20(1), 375.
- Yang, B., Li, J., Haller, M. J., Schatz, D. A., & Rong, L. (2023). Modeling the progression of Type 2 diabetes with underlying obesity. *PLoS computational biology*, 19(2), e1010914.
- Yang, J., Yin, X., Tobias, D. K., Chen, Z., Sun, Q., Manson, J. E., Chavarro, J. E., Willett, W. C., Hu, F. B., & Zhang, C. (2025). Ultra-processed Foods and Diet Quality in Association With Long-term Weight Change and Progression to Type 2 Diabetes Among Individuals With a History of Gestational Diabetes Mellitus—A Prospective Study. *Diabetes Care*, 48(10), 1827-1836.
- Yildirim, V., Sheraton, V. M., Brands, R., Crielaard, L., Quax, R., van Riel, N. A., Stronks, K., Nicolaou, M., & Sloot, P. M. (2023). A data-driven computational model for obesity-driven diabetes onset and remission through weight loss. *Iscience*, 26(11).
- Zhang, D., Chen, X., Huang, K., Zheng, Q., Fu, Y., Ma, J., Ren, X., Xu, B., Liu, P., & Liu, J. (2023). Urinary essential and toxic metal mixtures, and type 2 diabetes mellitus: telomere shortening as an intermediary factor? *Journal of Hazardous Materials*, 459, 132329.
- Zhuang, P., Wu, Y., Yao, J., Liu, X., Liu, H., Wan, X., Jia, W., Wang, T., Zhang, Y., & Jiao, J. (2025). Marine n-3 polyunsaturated fatty acids slow sleep impairment progression by regulating central circadian rhythms in type 2 diabetes. *Cell Reports Medicine*, 6(5).