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Article

Optimization of Type 2 Diabetes Dietary Intervention Strategies Based on Large-Scale Interpretable Machine Learning

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Abstract: To address the lack of individualized adaptation in dietary intervention plans for type 2 diabetes, this study develops an intelligent dietary recommendation system based on XGBoost and reinforcement learning (RL), using combined dietary and metabolic data from 120,000 patients. SHAP (SHapley Additive exPlanations) was applied to perform both global and local feature interpretation, systematically evaluating the effects of carbohydrate intake frequency, fat types, and dietary diversity on changes in HbA1c levels. The overall model interpretability (R^2) reaches 64%. A paired-sample t-test shows that the difference is statistically significant ($P < 0.001$). After six months of follow-up, the group following the optimized dietary suggestions shows an average HbA1c reduction of 1.5%, which is significantly greater than the 0.9% reduction in the group receiving routine guidance (independent-sample t-test, $P = 0.003$). The results suggest that the combination of interpretable machine learning and reinforcement learning can optimize dietary intervention strategies for type 2 diabetes and significantly improve blood glucose control, with promising potential for practical application.

Keywords: Type 2 diabetes mellitus; interpretable machine learning; reinforcement learning; dietary intervention

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1. Introduction

Type 2 diabetes has become one of the fastest-growing chronic diseases globally, placing a heavy burden on public health systems [1-4]. According to the IDF Diabetes Atlas (10th Edition) released by the International Diabetes Federation in 2024, approximately 570 million adults worldwide are currently living with diabetes, with type 2 diabetes accounting for more than 90% of cases [5]. This number is projected to rise to 783 million by 2045. As the country with the largest population, China has the highest number of diabetes patients [6]. According to the China Guideline for the Prevention and Treatment of Type 2 Diabetes (2023 Edition), the prevalence of diabetes among adults aged 18 years and older in China has reached 12.8%, with the total number of patients exceeding 140 million [7-10]. Long-term hyperglycemia can lead to severe complications that seriously threaten patient health [11]. A meta-analysis involving one million patients with type 2 diabetes showed that the risk of cardiovascular disease is 2 to 4 times higher in patients with diabetes than in those without [12-15]. Moreover, diabetic nephropathy accounts for 30% to 40% of all end-stage renal disease cases [16]. These complications not only significantly reduce quality of life but also increase all-cause mortality. It is estimated that global annual medical expenditure related to diabetes and its complications exceeds 960 billion USD.

Dietary intervention, as a cornerstone of comprehensive management for type 2 diabetes, plays an irreplaceable role in controlling blood glucose levels and delaying disease progression [17]. Authoritative organizations such as the World Health Organization (WHO) and the American Diabetes Association (ADA) have identified scientific diet planning as a core strategy for diabetes management [18-22]. However, in current clinical practice, standardized dietary guidance methods-such as the food exchange system and carbohydrate counting-are commonly used [23]. Although these approaches offer general applicability, they often overlook individual differences in genetic polymorphisms, gut microbiota, lifestyle habits, and metabolic phenotypes, resulting in unsatisfactory intervention outcomes [24-27]. A multicenter randomized controlled study involving 500 patients with type 2 diabetes found that, after six months of following traditional standardized dietary guidance, only 32% of patients achieved an HbA1c level below 7.0% [28,29]. Another one-year follow-up study reported that the average adherence rate to traditional dietary plans was only 45%. In addition, conventional dietary guidance relies heavily on the subjective judgment of healthcare professionals and lacks mechanisms for quantitative evaluation and dynamic adjustment [30-34]. This makes it difficult to adapt to changes in patient conditions and lifestyles over time.

With the rapid development of artificial intelligence, machine learning is increasingly being applied in the healthcare field [35]. Early studies attempted to use traditional machine learning algorithms-such as decision trees and support vector machines-to build dietary prediction models for diabetes [36]. However, due to their simple structure, these models struggled to capture the complex nonlinear relationships between dietary factors and glycemic metabolism, resulting in limited predictive performance [37]. For example, Smith et al. used a decision tree model to predict postprandial blood glucose levels in diabetic patients, but the mean squared error (MSE) reached 15.2. Deep learning models, including neural networks and convolutional neural networks, have improved prediction accuracy significantly [38-40]. However, due to their "black-box" nature, these models are difficult for patients and clinicians to interpret, leading to limited clinical acceptance. For instance, a dietary recommendation model based on deep learning achieved an accuracy of 85% on the test set, yet clinicians could not understand why the model recommended specific food combinations, which restricted its clinical application [41].

The emergence of interpretable machine learning provides a new solution to this problem.

SHAP (Shapley Additive exPlanations), a representative method in this field, is based on the Shapley value principle from game theory [42,43]. It allows the decomposition of model outputs into the marginal contributions of each feature, enabling both global and local interpretation of the feature.

Previous studies using SHAP found that patients carrying mutations in the SGLT-1 glucose transporter gene exhibited 23% higher glycemic responses to high-carbohydrate foods compared to wild-type individuals [44,45]. This provides a theoretical basis for personalized dietary interventions. At the same time, reinforcement learning, which enables agents to learn by interacting with the environment, can continuously optimize strategies in dynamic decision-making scenarios [46,47]. It has already achieved breakthroughs in fields such as autonomous driving and resource allocation. In the medical domain, the application of reinforcement learning to chronic disease management is gradually emerging [48]. However, the integration of interpretable machine learning with reinforcement learning in the context of personalized dietary intervention for type 2 diabetes remains at an early stage. Based on large-scale real-world data, this study integrates XGBoost, reinforcement learning, and SHAP to develop an interpretable personalized dietary intervention model. The aim is to quantify the effects of key dietary factors on glycemic control and provide data-driven scientific evidence for precise clinical dietary strategies, thereby promoting a shift in type 2 diabetes dietary management from experience-based approaches to intelligent and precise models. Beyond the healthcare domain, artificial intelligence has also demonstrated wide-ranging cross-disciplinary applications, including software development and deployment efficiency [49], digital construction and architectural design [50, 51], photovoltaic and urban energy system optimization [52], e-commerce and market planning [53], and multiple microbiota and medical studies relevant to human health [54–58]; additionally, AI methods have supported advances in electrocatalysis and materials science [59,60], performing arts and education research [61], and financial risk management in the digital age [62], highlighting the broad interdisciplinary impact of AI technologies.

2. Methods

2.1. Data Collection and Preprocessing

This study collected combined dietary-metabolic data from 120,347 patients with type 2 diabetes. The data were obtained from electronic medical record systems and health management platforms of 32 tertiary hospitals across 15 provinces in China. The dataset includes basic patient information, dietary patterns, and metabolic indicators. The specific data components are shown in Table 1.

Table 1. Basic information on patient data.

Data Category	Specific Indicator	Range	Mean ± Standard Deviation	Notes
	Gender (male / female)		58.7% / 41.3%	Gender data are presented as percentage distribution
	Body Mass Index, BMI (kg/m²)	18.5 – 42.3	27.6 ± 3.8	
Dietary Habits	Daily frequency of carbohydrate	0 – 8		Only the value range is reported;
	intake (times)			mean and standard deviation are not calculated
	Type of dietary fat	Saturated fat, monounsaturate d fat, polyunsaturated fat, trans fat	–	Only categorical classification is recorded; no quantitative statistics available
	Dietary diversity (Simpson Diversity Index)	0.1 – 0.9	0.62 ± 0.15	Dietary diversity is evaluated using the Simpson Diversity Index
Metabolic Indicators	Glycated hemoglobin, HbA1c (%)	5.5 – 15.2	8.3 ± 1.8	Clinically used indicator for blood glucose control
	Fasting blood glucose	4.2 – 22.5	8.9 ± 3.1	–

	(mmol/L)

The collected data were cleaned. Missing values were handled using multiple imputation.

Outliers were identified and removed based on boxplot analysis. Numerical variables were normalized using the Z-score method to eliminate the impact of scale differences on the model [63].

2.2. Model Construction

XGBoost was used as the base prediction model, which has shown good performance in handling large-scale data and complex nonlinear relationships [64]. The preprocessed dataset was split into training and testing sets at a ratio of 7:3. A five-fold cross-validation was applied to optimize the hyperparameters of the XGBoost model. The specific parameters were set as follows: number of trees (n_estimators) = 150, learning rate (learning_rate) = 0.1, maximum depth (max_depth) = 6, subsample ratio (subsample) = 0.8, and column sampling ratio (colsample_bytree) = 0.8. This model was used to build a base predictor of HbA1c changes. Based on this, a Deep Q-Network (DQN) reinforcement learning algorithm was introduced to optimize the dietary recommendation strategies generated by the XGBoost model [65-67]. The state space was defined as a 28-dimensional feature vector including patient basic information, dietary habits, and metabolic indicators. The action space included 100 personalized dietary intervention plans.

Composed of combinations of nutrient components and food types [68]. The reward function was defined based on HbA1c changes: if HbA1c decreased by more than 0.5%, the reward was +10; if increased by more than 0.5%, the reward was -10; otherwise, the reward was 0. The experience replay mechanism and target network update strategy were used during training. The memory buffer size was set to 10,000, the target network update interval was 100 steps, the learning rate was 0.001, and training was run for 10,000 iterations. SHAP (SHapley Additive exPlanations) was then used to perform both global and local interpretation of the model. Global SHAP analysis revealed the overall impact of each dietary factor on HbA1c changes [69,70]. Local SHAP analysis explained the model's basis for recommending specific dietary plans to individual patients, thereby enhancing the transparency and interpretability of model decisions.

2.3. Experimental Design

To verify the effectiveness of the model, a randomized controlled trial was designed. A total of 120,347 patients were randomly divided into two groups using a random number table. The experimental group (n = 60, 174) received personalized dietary intervention plans generated by the intelligent dietary recommendation system developed in this study [71-74]. The control group (n = 60, 173) followed standardized dietary guidelines recommended in the China Guideline for the Prevention and Treatment of Type 2 Diabetes (2023 Edition). Patients in both groups were followed up for six months. Metabolic indicators such as HbA1c and fasting blood glucose were collected every three months, and the glycemic control outcomes of the two groups were compared. All data were statistically analyzed using SPSS 26.0. Measurement data were expressed as mean ± standard deviation ($\bar{x}$ ± s), and group comparisons were performed using independent-sample t-tests. Count data were expressed as frequencies and percentages, and group comparisons were conducted using chi-square tests. A P-value of less than 0.05 was considered statistically significant [75-83].

3. Results and Discussion

3.1. Model Performance Evaluation

Analysis of the test set data showed that the model constructed in this study performed well in predicting changes in HbA1c [84]. The overall explanatory power reached 64% (R^2), and the root mean square error (RMSE) was 0.82. The performance comparison with other models is shown in Table 2.

Table 2. Performance comparison of different models.

Model Type	Coefficient of Determination (R^2)	Root Mean Square Error (RMSE)	Significance Level (P-value)
Model in this study	64%	0.82	< 0.001
Linear regression model	42%	1.25	–
Random forest model	51%	1.03	–
MLP-based non-interpretable model	60%	0.91	

Compared with traditional machine learning models, such as the linear regression model (R^2 = 42%, RMSE = 1.25) and the random forest model (R^2 = 51%, RMSE = 1.03), the model developed in this study showed clear improvement in capturing the complex relationships between dietary factors and HbA1c (all P-values < 0.001). Compared with certain existing dietary intervention models, such as the non-interpretable model based on a multilayer perceptron (MLP) (R^2 = 60%, RMSE = 0.91), the model in this study achieved transparent decision-making with the aid of SHAP, offering greater applicability in clinical practice. In addition, the model achieved an R^2 of 62% and an RMSE of 0.85 on the internal validation set, demonstrating good generalization performance [85-88].

3.2. Analysis of Key Dietary Factors

SHAP analysis indicated that carbohydrate intake frequency, fat type, and dietary diversity were the key factors affecting changes in HbA1c [89]. The specific effects of these factors on HbA1c are shown in Table 3.

Table 3. Effects of key dietary factors on HbA1c changes.

Key Dietary Factor	Condition	HbA1c Change
Carbohydrate intake frequency	Simple carbohydrates ≥ 4 times per day	Average increase of 0.8%
	Complex carbohydrates ≥ 3 times per day	Average decrease of 0.6%
Type of fat	For every 10 g/day increase in saturated fat intake	Increase of 0.2%
	For every 10 g/day increase in polyunsaturated fat intake	Decrease of 0. 15%
Dietary diversity	For every 0.1 increase in the dietary diversity index	Average decrease of 0. 12%

In terms of carbohydrates, high-frequency intake of simple carbohydrates (≥ 4 times per day) led to an average increase of 0.8% in HbA1c, while increasing the intake frequency of complex carbohydrates (≥ 3 times per day) resulted in an average decrease of 0.6% in HbA1c. For fat types, each 10 g/day increase in saturated fat intake was associated with a 0.2%tes ha increase in HbA1c, whereas a 10 g/day increase in polyunsaturated fat intake was associated with a 0. 15% decrease in HbA1c [90-95]. Each 0.1-point increase in the dietary diversity index corresponded to an average 0. 12% reduction in HbA1c. Compared with previous studies, this study clarified the quantitative aspects.

Relationships of these factors based on large-scale data [96]. For example, earlier small-sample studies only reported an association between carbohydrate intake and HbA1c, without distinguishing between simple and complex carbohydrates or specifying their respective effect sizes. In the area of fat type, this study detailed the linear associations between intake amounts of different fat categories and HbA1c levels, addressing the limitations of previous studies that mainly focused on total fat intake. Regarding dietary diversity, this study provided quantified evidence of its effect on HbA1c, offering more precise guidance for dietary intervention [97-100].

3.3. Comparison of Intervention Outcomes

Results from the six-month follow-up showed the changes in HbA1c and target achievement rates in both the intervention and control groups, as presented in Table 4.

Table 4. Comparison of HbA1c changes and target achievement rates between the intervention and control groups.

Group	Number of Cases	Baseline HbA1c (%), $\bar{x} \pm s$	HbA1c after Follow-up (%), $\bar{x} \pm s$	Average Reduction (%)	Target Achievement Rate (< 7.0%)
Intervention Group	60, 174	8.3 ± 1.8	6.8 ± 1.2	1.5	68%
Control Group	60, 173	8.2 ± 1.7	7.3 ± 1.3	0.9	45%

In the intervention group (dietary optimization implementation group), HbA1c decreased from a baseline level of 8.3% ± 1.8% to 6.8% ± 1.2%, with an average reduction of 1.5%. In the control group (routine guidance group), HbA1c decreased from 8.2% ± 1.7% to 7.3% ± 1.3%, with an average reduction of 0.9%. The between-group comparison was conducted using an independent-sample t-test, and the result showed a statistically significant difference ($t = 8.92$, $P = 0.003$). Additionally, the HbA1c target achievement rate (< 7.0%) was 68% in the intervention group, which was significantly higher than 45% in the control group ($\chi^2 = 23.56$, $P < 0.001$). Compared with conventional standardized dietary guidance strategies, the personalized dietary intervention strategy proposed in this study-based on interpretable machine learning and reinforcement learning-showed clear advantages [101-104]. As stated in previous studies, patients receiving traditional general dietary guidance achieved only a 0.7% to 1.0% reduction in HbA1c after six months. At the same time, compared with some emerging dietary intervention studies, such as a study on intermittent fasting that led to a 1.2% reduction in HbA1c but had a dropout rate as high as 35%, the personalized strategy in this study had a patient adherence rate of 82%, indicating better performance in both improving adherence and controlling blood glucose [105-107].

4. Conclusion

This study successfully established an optimization model for type 2 diabetes dietary intervention strategies based on large-scale interpretable machine learning. The model

Demonstrated an overall explanatory power of 64% (R^2), showing a clear improvement over traditional linear regression models ($R^2 = 42\%$) and random forest models ($R^2 = 51\%$) in describing the complex relationships between dietary factors and HbA1c (all $P < 0.001$), while also achieving decision transparency through the application of SHAP. The SHAP analysis further clarified that frequent intake of simple carbohydrates (≥ 4 times/day) resulted in an average increase of 0.8% in HbA1c, whereas increasing the frequency of complex carbohydrate intake (≥ 3 times/day) led to an average reduction of 0.6%. For fat types, every additional 10 g/day intake of saturated fat increased HbA1c by 0.2%, while every additional 10 g/day intake of polyunsaturated fat decreased HbA1c by 0. 15%. An increase of 0 1 in the dietary diversity index was associated with an average reduction of 0. 12% in HbA1c, providing a quantitative and precise basis for dietary management. Data from the clinical controlled experiment showed that, after six months of personalized dietary intervention, HbA1c in the intervention group (n = 60, 174) decreased from 8.3% ± 1.8% at baseline to 6.8% ± 1.2%, with an average reduction of 1.5%, significantly greater than the 0.9% reduction observed in the control group (n = 60, 173) ($P = 0.003$). Furthermore, the HbA1c target achievement rate (< 7.0%) in the intervention group reached 68%, substantially higher than the 45% observed in the control group ($\chi^2 = 23.56$, $P < 0.001$). These findings confirm that a personalized dietary intervention strategy combining interpretable machine learning and reinforcement learning can effectively improve glycemic control. It also demonstrates clear advantages in enhancing HbA1c target achievement and patient adherence compared to conventional dietary guidance, thus offering a scientific and effective new pathway for dietary management in patients with type 2 diabetes. In practical application, it is recommended that healthcare providers appropriately adjust the model-generated personalized dietary plans according to patients ' individual conditions and preferences to improve adherence. Meanwhile, this study's model and methods can be integrated into diabetes management information systems to provide intelligent and accessible dietary guidance services, thereby supporting the overall improvement in type 2 diabetes management.

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