ISSN 2616-7433 Vol. 7, Issue 7: 49-55, DOI: 10.25236/FSST.2025.070708

Intelligent Health Management Solutions for Obese College Students in and out of Class Based on AI Technology

Jian Li[1,a], Zhou Zhou[1,b,*]

[1]College of Physical Education and Health, Guangxi Normal University, Guilin, 541000, Guangxi, China
[a]281792143@qq.com, [b]3842919@qq.com
[*]Corresponding author

Abstract: *Traditional health management programs suffer from insufficient personalization and delayed real-time feedback. To address this, this paper constructs a personalized health management system based on reinforcement learning. Using a Support Vector Machine (SVM), the system collects students' health data in real time and dynamically optimizes health management strategies using a reinforcement learning algorithm. Through intelligent perception and analysis of students' health status, the system adjusts dietary and exercise recommendations in real time, providing personalized health interventions. The experiment involves university students aged 18-24 with a predisposition to obesity (BMI ≥ 24). A group experiment is conducted (the experimental group used this personalized health management system, while the control group follows a fixed exercise plan and dietary recommendations). Results show that after four weeks, the overall weight change in the experimental group ranges from 1.4 kg to 2.0 kg, and the BMI change is from 0.3 to 0.5, demonstrating the effectiveness of this program in weight loss and weight control.*

Keywords: *Personalized Health Management; College Student Obesity; Reinforcement Learning; Support Vector Machine*

1. Introduction

With obesity rates rising globally, particularly among young people, college student obesity has become a critical public health issue that needs urgent attention. This study proposes a personalized health management solution based on reinforcement learning. By collecting students' health data, including weight, BMI, dietary habits, and exercise status, and integrating it with a reinforcement learning model, the system can adjust dietary and exercise recommendations in real time based on the student's health status, achieving more efficient health management.

This paper introduces a personalized health management solution based on reinforcement learning, focusing on the system's design and optimization process, including data collection, model framework, and real-time adjustment of health management strategies. It then presents the experimental design and results analysis, evaluating the effectiveness of this system in a population of obese college students. Finally, the paper summarizes the research findings, discusses the system's strengths and limitations, and proposes future research directions.

2. Related Works

Obesity, as an increasingly serious health problem worldwide, has attracted widespread attention and research. The following are a number of research results that explore the application and effectiveness of different fields and methods in the management, prevention and treatment of obesity.

Adirahma et al. conducted a systematic literature review to explore the training management strategy of using circular training methods to improve the performance of student badminton players. The study analyzed 17 articles that met specific criteria and were screened on Google Scholar from 2019 to 2024, and found that circular training can significantly improve aerobic endurance and maximum strength, thereby improving athletic performance [1]. Hong et al. found that the prevalence of obesity is related to age, gender and region, especially in elementary school. The study called for the

ISSN 2616-7433 Vol. 7, Issue 7: 49-55, DOI: 10.25236/FSST.2025.070708

formulation of comprehensive and flexible policies to effectively manage and prevent obesity and its related complications [2]. Johnson et al. conducted an electronic survey and focus group interviews with pediatric providers in and around Washington, and found that although more than 90% of doctors said they could provide obesity advice, 52% of doctors lacked confidence in dealing with obesity [3]. Barlas et al. evaluated the reliability of ChatGPT in assessing obesity in type 2 diabetes according to the guidelines of the American Diabetes Association and the American Society of Clinical Endocrinology. Through 20 questions, the results showed that ChatGPT fully complied with the guidelines in the obesity assessment part, with a score of 100% [4]. Lofton et al. pointed out that obesity is more serious in the African American population, especially women, and is not related to socioeconomic status. Structural racism limits their access to healthy food, exercise space, medical insurance and medication, which in turn affects the prevalence and outcomes of obesity [5]. Ahmed et al. explored the attitudes of nursing students towards obese individuals. The results showed that 51.16% of students had a positive attitude towards obese individuals and 48.84% had a negative attitude [6]. Woldemariam et al. used both genotype and phenotype methods to find that omics data can help identify specific biomarkers of individuals at risk of obesity, thereby formulating personalized treatment plans. Comprehensive multi-omics methods can help achieve accurate prevention, treatment and risk reduction of obesity-related diseases, and promote the development of precision medicine [7]. Salminen et al. conducted a three-round Delphi survey in which 43 experts voted on 121 statements on obesity management and reached a consensus on 15 key definitions and reporting statements. A high degree of consensus was reached on different types of surgical procedures (such as Roux-en-Y gastric bypass, sleeve gastrectomy, and endoscopic sleeve gastroenterostomy). They proposed a multimodal treatment algorithm for obese patients [8]. Dayyeh pointed out that obesity is a major global health problem, and Metabolic Bariatric Surgery (MBS) is the gold standard for treating obesity, but it is not suitable for all patients. The international Delphi consensus study showed that experts unanimously agreed on the application of ESG (Endoscopic Sleeve Gastroplasty) in patients with grade I and II obesity and grade III obesity who are unwilling to accept or do not meet the MBS criteria [9]. Okafor pointed out that the personalized food avoidance diet method aims to address the individual's immune tolerance to dietary components to help manage obesity. He proposed a possible T-cell toxin-mediated immune dysfunction disease model, emphasizing that the inflammatory process is associated with epigenetic T-cell dysfunction caused by toxins, verifying this model helps to better understand the role of personalized nutrition in obesity management [10]. Elmaleh-Sachs et al. pointed out that obesity affects about 42% of American adults and is associated with type 2 diabetes, hypertension, cardiovascular disease, sleep disorders, osteoarthritis and premature death. Long-term weight maintenance requires a combination of long-term drug treatment and lifestyle intervention [11]. The bottleneck of existing research mainly focuses on how to provide personalized and effective treatment plans for different types of obese patients, especially in non-surgical treatment and long-term weight maintenance, where there are still significant challenges.

3. Methods

3.1 Classification and Regression Models

3.1.1 Data Collection and Preprocessing

This study collects data on students' lifestyles, dietary habits, and exercise habits, focusing on the following aspects:

Lifestyle: Time allocation between work and study, mental health, etc.

Dietary habits: Average daily calorie intake and dietary types.

Exercise: Frequency, intensity, and duration of exercise.

Physical indicators: Weight, height, BMI, and body fat percentage.

Data processing includes data cleaning (removing missing values and outliers), standardization (e.g., using the standardization formula $X_{norm}=\frac{X-\mu}{\sigma}$), and feature selection (correlation analysis and model-based feature importance).

3.1.2 Feature Engineering

Through expert analysis and data exploration, the following key features are extracted:

ISSN 2616-7433 Vol. 7, Issue 7: 49-55, DOI: 10.25236/FSST.2025.070708

Calorie intake: The student's average daily total calorie intake.

Exercise frequency and intensity: The number and duration of weekly exercise sessions.

Sleep quality: Sleep duration and proportion of deep sleep.

BMI: Calculated using the formula $BMI=\frac{Weight(kg)}{Height(m)^2}$.

Dietary composition: The proportion of nutrients (e.g., intake of high-fat and high-sugar foods).

All features are standardized or normalized to ensure consistent feature scale during model training.

3.2 Classification Model Application

3.2.1 Support Vector Machine (SVM) Model

The goal of an SVM is to find a hyperplane (decision plane) that maximizes the class margin. hyperplane). For binary classification problems, SVM finds the optimal hyperplane by solving the following optimization problem:

$$\text{maximize} \frac{2}{\|w\|} \text{subject to } y_i(w^T x_i+b)\geq 1, \forall I \tag{1}$$

Among them, w is the normal vector of the hyperplane; b is the bias term on the hyperplane; x_i is the training data sample; y_i is the label of the corresponding sample, $y_i \in \{-1,1\}$.

The core of SVM is to ensure classification accuracy by maximizing the margin, so it has strong generalization ability and can perform well in complex classification tasks.

3.2.2 Model Training and Tuning

The training process of SVM usually involves the following steps:

Data mapping: Mapping input features to a high-dimensional space to ensure that the data can be linearly separated in the high-dimensional space.

Kernel function selection: In order to process nonlinear data, SVM uses different kernel functions (such as linear kernel, radial basis function RBF kernel, polynomial kernel, etc.) to map data to a high-dimensional space. Commonly used RBF kernel functions are as follows:

$$K(x_i,x_j)=\exp\left(-\frac{\|x_i-x_j\|^2}{2\sigma^2}\right) \tag{2}$$

Among them, σ is the parameter of the kernel function.

Hyperparameter tuning: the hyperparameters of SVM are adjusted through cross-validation (such as K-fold cross-validation), mainly including: C (the width of the classification interval is controlled; too large may lead to overfitting, and too small may lead to underfitting) and σ (the bandwidth of the RBF kernel function, which affects the complexity of the model).

3.3 Linear Regression

Linear regression is a basic regression method that assumes that there is a linear relationship between the target variable (such as weight or BMI) and the input feature. Its goal is to find the optimal regression coefficient by minimizing the squared error. The linear regression model can be expressed as:

$$y=\beta_0+\beta_1 x_1+\beta_2 x_2+\cdots+\beta_n x_n+\epsilon \tag{3}$$

Among them, y is the target variable (such as weight or BMI); β_0 is the intercept term; $\beta_1,\beta_2,\cdots,\beta_n$ are the regression coefficients of the feature; $x_1,x_2,\cdots,x_n$ are the input features (such as diet, exercise, sleep, etc.); ϵ is the error term.

The goal of linear regression is to minimize the following squared error loss function:

$$L(\beta)=\sum_{i=1}^{m} \left(y_i-(\beta_0+\beta_1 x_{i1}+\beta_2 x_{i2}+\cdots+\beta_n x_{in})\right)^2 \tag{4}$$

Among them, m is the number of samples, and y_i is the true value of the i-th sample.

ISSN 2616-7433 Vol. 7, Issue 7: 49-55, DOI: 10.25236/FSST.2025.070708

3.4 Design of Personalized Health Management Program

3.4.1 Reinforcement Learning Model Framework

The core of the personalized health management system is to optimize health management strategies through reinforcement learning (RL) and provide real-time, personalized health recommendations. The system environment includes students' health status, exercise plans, diet records, etc. This information serves as the input of the system to help the model make more accurate decisions.

State definition: The state is the health performance of the system at a certain moment, including students' weight, BMI, body fat percentage, diet records, exercise status, sleep quality, etc. These states reflect the health status of students and provide a basis for the model's decision-making.

Action definition: The action is the health intervention measure taken by the system, including changing students' exercise plans, diet recommendations or sleep recommendations. Each action affects the student's health status.

$$S_t=\{\text{Weight, BMI, diet records, exercise status,}\cdots\} \tag{5}$$

Reward mechanism definition: The reward mechanism is used to measure the behavioral effects of the model and guide the model to learn optimization strategies. For example, health improvement (such as weight loss, BMI reduction, etc.) can be used as positive rewards, while wrong diet choices or insufficient exercise can be used as negative penalties.

$$A_t=\begin{cases} +1,\text{If the student's health improves (e.g. weight loss)} \\ -1,\text{If the student's health deteriorates (e.g. weight gain)} \end{cases} \tag{6}$$

Through these definitions, the system can select appropriate actions based on the student's current status and gradually optimize the health management strategy.

3.4.2 Reinforcement Learning Algorithm Selection

When selecting a reinforcement learning algorithm, Q-learning is an effective model-free reinforcement learning algorithm suitable for the health management optimization task in this study. The Q-learning algorithm guides decision-making by learning the state-action value function (Q value). The core idea is to continuously optimize the Q value to find the optimal strategy.

The update formula of Q-learning is:

$$Q(S_t,A_t)\leftarrow Q(S_t,A_t)+\alpha(R_t+\gamma \max_a Q(S_{t+1},a) -Q(S_t,A_t)) \tag{7}$$

Among them, $Q(S_t,A_t)$ is the Q value of selecting action A_t in state S_t; a is the learning rate, which determines the degree of update of the Q value by new information; R_t is the immediate reward; γ is the discount factor, which indicates the influence of future rewards; $\max_a Q(S_{t+1},a)$ is the maximum Q value in state S_{t+1}. Q-learning optimizes the health management strategy by continuously adjusting the Q value, ensuring that the most appropriate exercise and diet plan is selected under different health conditions.

4. Results and Discussion

4.1 Experimental Subjects and Data Collection

Experimental Subjects: A certain number of college students, both male and female, aged 18-24, with a predisposition to obesity (BMI $\geq$ 24), are selected as experimental subjects. Participants are required to voluntarily participate and agree to provide health data (such as weight, BMI, diet records, and exercise status).

Data Collection: The following data is collected for model training and evaluation:

Basic health data: weight, BMI, body fat percentage, daily calorie intake, weekly exercise time, etc.

Health behavior data: diet records, exercise type and frequency, sleep quality, etc.

Individual characteristics: age, gender, mental health status, etc.

ISSN 2616-7433 Vol. 7, Issue 7: 49-55, DOI: 10.25236/FSST.2025.070708

4.2 Experimental Grouping

Participants are divided into two groups, each receiving a different health management strategy:

The experimental group uses a personalized health management system based on reinforcement learning. The system adjusts the health management strategy in real time based on the students' health data, providing personalized exercise and diet recommendations.

The control group uses a traditional static health management program, with fixed exercise plans and dietary recommendations, and no strategy adjustments based on student feedback.

4.3 Data and Statistical Methods

Hypothesis Testing: t-tests are used to compare the differences in various health indicators (such as weight and BMI) between the experimental and control groups to verify whether the personalized health management strategy of the experimental group is superior to the traditional approach of the control group.

Regression Analysis: Regression analysis is used to assess the impact of various factors (such as exercise volume and dietary structure) on changes in weight and BMI, and to analyze which factors have the greatest impact on weight loss outcomes.

Table 1 Initial health assessment data

Student ID	Gender	Age	Initial Weight (kg)	Initial BMI	Initial Body Fat Percentage (%)	Initial Exercise Frequency (times/week)	Initial Calorie Intake (kcal)
1	Male	20	75.2	27.4	22.5	2	2300
2	Female	22	68.5	26.3	25.1	3	2100
3	Male	21	82	28.1	24.3	1	2400
4	Female	23	72	25.8	22.9	2	2200

The initial health assessment data in Table 1 shows significant variation in participants' underlying health status. Factors such as weight, BMI, body fat percentage, and exercise frequency all influence the effectiveness of health management interventions to some extent. Male participants generally have higher weights (e.g., student No. 003's initial weight is 82.0 kg), as well as higher BMI and body fat percentage, indicating a clear tendency toward obesity. Female participants, on the other hand, have lower initial weights (e.g., student No. 002's weight was 68.5 kg), but their BMI and body fat percentage remain high, suggesting that factors other than weight also influence their health.

Exercise frequency is relatively high, with student No. 002 exercising three times a week, potentially indicating less scope for health management intervention. Other participants (e.g., Nos. 001, 003, and 004) exercise less frequently, potentially leading to more significant improvements in subsequent health management. Regarding calorie intake, the data shows that most participants have a high average daily calorie intake, particularly No. 003, who consumes 2400 kcal, suggesting that a high-calorie diet may be a major contributor to their obesity.

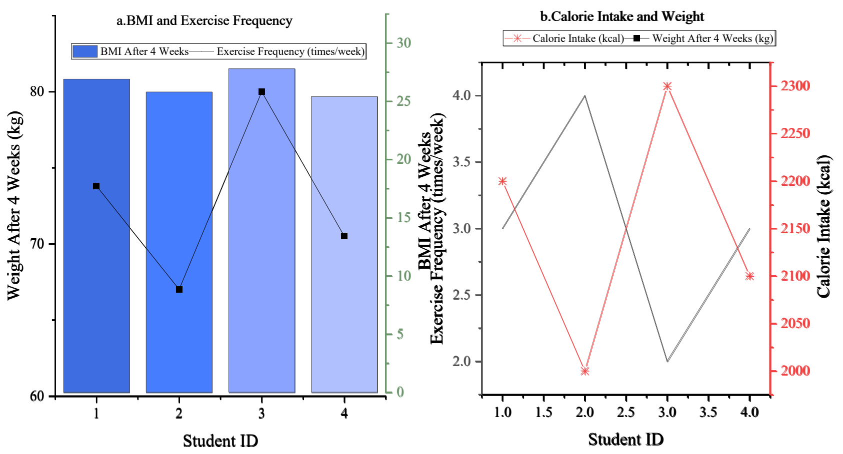

Figure 1 Health data of the experimental group (after 4 weeks)

ISSN 2616-7433 Vol. 7, Issue 7: 49-55, DOI: 10.25236/FSST.2025.070708

Based on the health data of the experimental group after 4 weeks, the personalized health management program achieves significant results in promoting weight and BMI reduction. All participants experience varying degrees of weight and BMI reduction, demonstrating the positive impact of the personalized intervention strategy on obese college students. Overall, weight changes range from 1.4 kg to 2.0 kg, and BMI changes range from 0.3 to 0.5, demonstrating the effectiveness of the program in weight loss and weight control (see Figure 1a).

Analysis in Figure 1b reveals that changes in participants' exercise frequency and calorie intake play a key role in their health improvements. Most students increase their exercise frequency (an average of three times per week) and reduce their daily calorie intake, particularly for participants 002 and 004. The increased exercise frequency and reduced calorie intake significantly contribute to their weight and BMI reductions. Furthermore, reduced calorie intake also plays a significant role in weight control, particularly for participant 003, who experiences a significant weight loss despite a lower exercise frequency and no significant reduction in calorie intake.

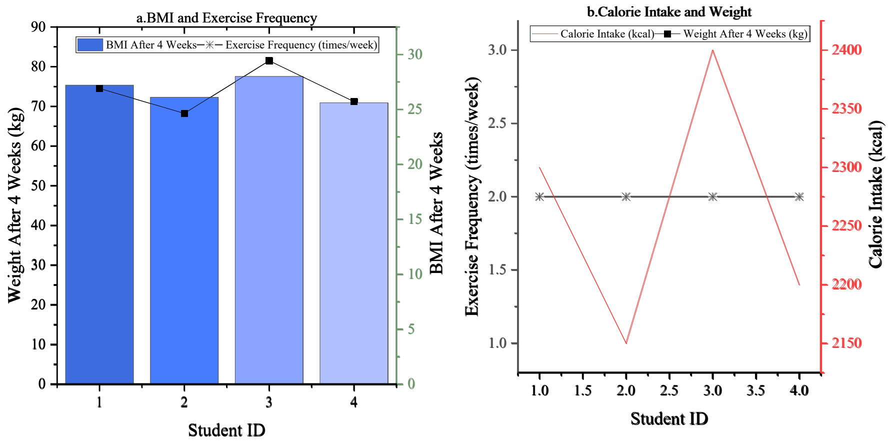

Figure 2 Health data for the control group (after 4 weeks)

Based on the health data for the control group after 4 weeks, the overall intervention effect is relatively limited. Although weight and BMI decrease for all participants, the magnitude of change is small, indicating that the traditional static health management program is less effective than the personalized health management program in improving weight and BMI. Weight changes range from 0.3 kg to 0.8 kg, and BMI changes range from 0.1 to 0.2, demonstrating relatively limited improvements, as shown in Figure 2a.

Figure 2b shows that participants in the control group show little change in exercise frequency and calorie intake, maintaining an average of 2 weekly exercise sessions, and calorie intake remains relatively unchanged from the initial data. Although weight decreases over the 4-week period, the small magnitude of change may be closely related to the lack of flexibility in exercise frequency and dietary adjustments. Compared to the experimental group, the control group lacks personalized adjustments, resulting in a more modest overall health management effect.

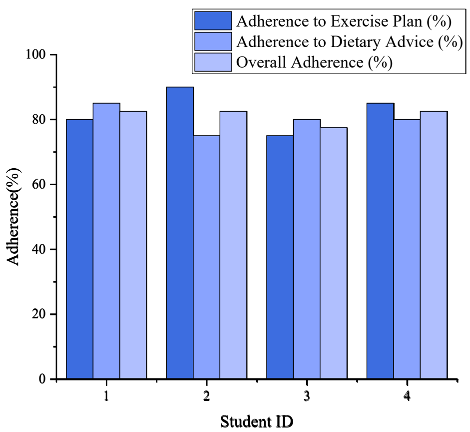

Figure 3 Health management strategy adherence (experimental group)

The experimental group records participants' adherence to the health management intervention,

ISSN 2616-7433 Vol. 7, Issue 7: 49-55, DOI: 10.25236/FSST.2025.070708

including compliance with diet and exercise.

According to the health management strategy adherence data for the experimental group in Figure 3, overall, participants perform well in terms of exercise and dietary recommendations, demonstrating the effectiveness of the personalized health management system in encouraging students to adhere to health intervention measures. The overall average adherence rate is 80%, with most students showing high adherence to exercise and diet, which contributes to achieving health management goals.

With regard to the exercise plan, adherence varies among participants. Student 002 has the highest adherence rate, reaching 90%. This high adherence rate may be related to their high interest and participation in exercise. In contrast, student 003's adherence rate is lower, at only 75%, possibly related to their relatively low motivation to exercise. Regarding dietary recommendations, student numbers 001 and 004 show high adherence rates of 85% and 80%, respectively, demonstrating their effective adherence to personalized dietary recommendations. The dietary compliance rate for patient No. 002 is 75%, which may be related to their dietary habits and personal taste preferences. This also indicates that the implementation of personalized dietary recommendations still faces certain challenges.

5. Conclusions

This study, based on the integration of artificial intelligence and the Internet of Things (IoT) technologies, proposes a personalized health management solution designed to optimize health management strategies for obese college students using a reinforcement learning algorithm. By collecting students' health data (such as weight, BMI, exercise, and dietary records) in real time and combining it with personalized interventions, the study evaluates the effectiveness of this system in improving obesity among college students. Despite initial success, the study still has certain limitations. The experimental period is short, only four weeks, and future studies can extend the experimental period to further verify the long-term effects of the health management system. With the development of intelligent hardware technology, the system's real-time monitoring and feedback capabilities are expected to be further enhanced, thereby providing more precise health management solutions.

References

[1] Adirahma, A. S., Widiyanto, W. E., Setyawan, H., et al. (2024). Badminton training management strategy with circuit training method to improve athlete performance among students. Retos: Nuevas tendencias en educación física, deporte y recreación, 61, 108-120.
[2] Hong, Y., Ullah, R., Wang, J. B., et al. (2023). Trends of obesity and overweight among children and adolescents in China. World Journal of Pediatrics, 19(12), 1115-1126.
[3] Johnson, S., Gupta, S., Mackey, E., et al. (2023). "We feel like we are in it alone": A mixed-methods study of pediatric primary care barriers for weight management. Childhood Obesity, 19(1), 3-12.
[4] Barlas, T., Altinova, A. E., Akturk, M., et al. (2024). Credibility of ChatGPT in the assessment of obesity in type 2 diabetes according to the guidelines. International Journal of Obesity, 48(2), 271-275.
[5] Lofton, H., Ard, J. D., Hunt, R. R., et al. (2023). Obesity among African American people in the United States: A review. Obesity, 31(2), 306-315.
[6] Ahmed, M. M., Ibrahim, R. M., & Younis, N. M. (2024). Assessment of nursing students' attitudes toward obese individuals. Journal of Current Medical Research and Opinion, 7(05), 2468-2476.
[7] Woldemariam, S., Dorner, T. E., Wiesinger, T., et al. (2023). Multi-omics approaches for precision obesity management: Potentials and limitations of omics in precision prevention, treatment, and risk reduction of obesity. Wiener Klinische Wochenschrift, 135(5), 113-124.
[8] Salminen, P., Kow, L., Aminian, A., et al. (2024). IFSO consensus on definitions and clinical practice guidelines for obesity management—An international Delphi study. Obesity Surgery, 34(1), 30-42.
[9] Dayyeh, B. K. A., Stier, C., Alqahtani, A., et al. (2024). IFSO bariatric endoscopy committee evidence-based review and position statement on endoscopic sleeve gastroplasty for obesity management. Obesity Surgery, 34(12), 4318-4348.
[10] Okafor, M. T. (2024). Personalized nutrition for obesity management: A mini-review. International Journal of Medicine and Health Development, 29(4), 285-288.
[11] Elmaleh-Sachs, A., Schwartz, J. L., Bramante, C. T., et al. (2023). Obesity management in adults: A review. Jama, 330(20), 2000-2015.