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Design of Personalized Diet and Exercise Intervention System for Overweight College Students Supported by Intelligent Algorithms

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Abstract: *With the increasing prevalence of overweight and obesity among college students, effective intervention through intelligent means has become a critical issue that urgently needs to be addressed. This paper implements comprehensive health intervention and management through the collaborative work of multiple modules, including real-time data collection, user profile analysis, personalized recommendations, and feedback optimization. The system constructs a personalized recommendation module using an algorithmic model that combines collaborative filtering and content-based filtering. Furthermore, dynamic adjustments are made based on user feedback. The effectiveness of this system is verified in a three-month randomized controlled trial. The experimental results show that participants in the experimental group show significant improvements in both blood glucose and blood lipid levels. All five participants in the experimental group have negative blood glucose levels, ranging from -0.3 mmol/L to -0.4 mmol/L, with an average blood glucose change of -0.33 mmol/L, demonstrating excellent control results.*

Keywords: *Intelligent Perception and Control Technology; Artificial Intelligence; Internet of Things; Deep Learning; Edge Computing*

1. Introduction

With socioeconomic development, improved living standards, and shifts in dietary patterns, the prevalence of overweight and obesity in China is rapidly catching up with that in Western populations. Approximately one-fifth of the world's one billion overweight or obese individuals are Chinese. In particular, the rate of increase in overweight and obesity among Chinese students is significantly faster than in developed countries like Europe and the United States. Obesity has become a significant factor affecting the overall physical and mental development of college students. To address this issue, this paper proposes an intelligent intervention system based on the integration of artificial intelligence and the Internet of Things. This system uses a data acquisition module to collect user information such as weight, body fat percentage, dietary history, and exercise data. It then utilizes deep learning algorithms to analyze users' health needs and generate personalized solutions. Furthermore, it integrates IoT devices to enable real-time data monitoring and feedback optimization.

This paper first introduces the design concept of a personalized diet and exercise intervention system and its application context for overweight college students. It then details the system architecture and the functions of each module. Subsequently, through experimental design and data analysis, the paper verifies the system's effectiveness in improving health indicators and provides a detailed discussion of the experimental data. Finally, the paper summarizes the effectiveness of the system and points out the limitations of current research and the direction of future development, providing a reference for further optimization of personalized health intervention systems.

2. Related Works

In recent years, personalized health interventions have made significant progress in many fields, especially in diet, exercise and disease management. With the continuous development of technologies such as artificial intelligence, deep learning and genomics, more and more studies have begun to explore how to develop precise health intervention plans based on individual differences.

Bermingham et al. compared the effects of Personalized Diet Plan (PDP) and standard dietary recommendations (control group) on cardiovascular metabolic health through a randomized clinical trial. The results showed that PDP significantly reduced serum triglyceride (TG) levels, but low-density lipoprotein cholesterol did not change significantly [1]. Noone et al. explored the effects of molecular transducers of exercise (genome, proteome, transcriptome, metabolome, etc.) on the variability of physiological and health outcomes. They emphasized the challenges of developing personalized exercise prescriptions and pointed out the role of the "Exercise Transducer" Alliance in understanding the variability of exercise responses [2]. Pranoto et al. evaluated the effects of different interventions (including exercise and diet) in the treatment of obesity. The study found that a milk-based diet significantly reduced body weight and fat mass, and alternating day fasting and calorie restriction also significantly reduced body weight. Combining at least 175 minutes of high-intensity exercise per week with a low-calorie diet can significantly reduce weight [3]. Yaffe et al. evaluated the effects of personalized, multi-domain risk reduction interventions on cognitive function and dementia risk in the elderly. The study found that the intervention group had significant improvements in comprehensive cognitive scores, risk factor improvement, and quality of life, especially cognitive function, which was 74% higher than the control group [4]. Dergaa et al. evaluated the effectiveness of exercise prescriptions generated by OpenAI's GPT-4 model in patient profiles with five different health conditions and fitness goals. The evaluation results showed that the model was able to generate generally safe exercise plans, but it was insufficient in terms of accuracy for individual health conditions and goals, often focusing too much on safety and ignoring training effects [5]. Saxena et al. explored the role of the gut microbiome in metabolism and calorie intake, and the impact of diet and lifestyle on them. They emphasized the application of AI in microbiome research, especially the revolutionary progress in multi-omics data analysis [6]. Kothinti explored how deep learning technology can transform medical operations by improving medical diagnosis, personalized treatment strategies, and patient care decision systems. He focused on the application of CNN (Convolutional Neural Network), RNN (Recurrent Neural Network) and Transformer-based models in medical imaging assessment, predictive analysis and drug development [7]. Sampogna et al. discussed the application of personalized treatment plans for patients with major depressive disorder. Innovative measures include intervention strategies for different areas (such as lifestyle intervention and virtual reality to improve the physical symptoms of depression) as well as web-based psychotherapy and digital methods. Treatment should be customized according to the individual needs and preferences of patients to achieve functional recovery [8]. Yurkovich et al. utilized a data-driven personalized approach to assess and optimize each person's health trajectory, combining genetic, behavioral and environmental factors to effectively address these challenges [9]. Zhou et al. aimed to develop a personalized health recommendation framework to help users better discover interventions that suit their needs. The effectiveness of the framework was evaluated using real data sets, and the results showed that its recommendation framework and various design components had good effects [10]. The information stored in the microbiome can be used for early detection and prognostic assessment of high-risk populations, and microbiome regulation may become a tailored, safe and effective treatment method. Ratiner et al. reviewed the progress of the application of microbiome data in precision medicine and discussed its challenges and prospects [11]. Although personalized health interventions have made progress in many fields, existing research still faces challenges in data accuracy, precision of individualized programs, and cross-disciplinary integration, which limits its widespread application and maximization of effects.

3. Methods

3.1 System Design Framework

3.1.1 Overall System Architecture

This system, based on intelligent algorithms, aims to provide personalized diet and exercise intervention plans for overweight college students. The system achieves comprehensive health intervention and management through the collaborative work of multiple modules, including real-time data collection, user profile analysis, personalized recommendations, and feedback optimization. The overall architecture includes four parts: data collection, data analysis, personalized recommendation, feedback and optimization: data collection module; user portrait and demand analysis module; personalized diet recommendation module; personalized exercise recommendation module; user

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feedback and optimization module.

3.1.2 Functional Module Division

(1) Data acquisition module

The data acquisition module is responsible for collecting multi-dimensional data from the user's mobile terminal or smart device, including but not limited to:

Basic information: gender, age, height, weight, living habits, etc.

Health data: physiological parameters such as body fat percentage, blood sugar level, blood pressure, etc.

Exercise data: daily exercise volume, exercise duration, exercise intensity, etc.

Dietary data: user's daily diet record, including food types, calories, nutrients, etc.

Data is collected in real time through smart hardware (such as smart bracelets, weight scales, etc.) and user-entered log information to ensure that the data foundation of the recommendation system is accurate and comprehensive.

(2) User portrait and demand analysis module

Based on the user information collection, the system constructs a user portrait and determines the user's diet and exercise needs through data analysis technology. The user portrait can be generated by the following formula:

$$U=f(B,H,E,D,P) \tag{1}$$

Among them, U represents user portrait; B represents basic information; H represents health data; E represents exercise data; D represents diet data; and P represents living habit data. User profiles not only reflect the user's current health status, but also predict the user's needs and preferences.

(3) Personalized diet recommendation module

This module uses an intelligent recommendation algorithm to provide users with personalized diet plans. The recommendation results are calculated by combining a collaborative filtering-based recommendation algorithm and a content-based recommendation algorithm:

$$R_{ij}=\sum_{k=1}^{N} w_{ik}.r_{kj} \tag{2}$$

Among them, R_{ij} represents the score of user i on food j; w_{ik} is the similarity between user i and user k; r_{kj} is the score of user k on food j.

In addition, the diet recommendation model is optimized based on the user's health goals (such as fat loss, muscle gain, and weight maintenance):

$$f_{dict}=\arg\min_{\theta} \sum_{i=1}^{N} (y_i-\hat{y}_i)^2+\lambda\|\theta\|^2 \tag{3}$$

Among them, y_i is the actual diet effect; $\hat{y}_i$ is the predicted diet effect; λ is the regularization parameter; θ is the model parameter.

(4) Personalized exercise recommendation module

The exercise recommendation module uses an optimization algorithm to generate a personalized exercise plan based on the user's health status (such as weight, body fat percentage, and exercise capacity) and goal setting (such as weight loss, improving cardiopulmonary function, etc.). First, the system calculates the difficulty coefficient of the exercise recommendation based on the user's physical data and goal setting:

$$M=\alpha.W+\beta.F+\gamma.I \tag{4}$$

Among them, M is the difficulty coefficient of the exercise plan; W is the user's weight; F is the user's body fat percentage; I is the exercise capacity index; α, Β, γ are weight coefficients.

Then, based on the setting of the optimization problem, the optimal exercise plan is generated using methods such as genetic algorithm or particle swarm algorithm:

$$\min_{x} f(x)=\sum_{i=1}^{n} w_i.(x_i-d_i)^2 \tag{5}$$

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Among them, x is the parameter set of the exercise plan; d_i is the target exercise intensity; w_i is the weight of the exercise intensity.

(5) User feedback and optimization module

This module makes real-time adjustments to diet and exercise recommendations based on user feedback and changes in health data. User feedback is obtained through questionnaires, exercise data, weight changes, etc. The system makes dynamic adjustments based on the following optimization model:

$$\min_{\theta} \sum_{i=1}^{N} (\mathrm{Feedback}_i - f(\mathrm{Input}_i,\theta)^2 + \lambda \|\theta\|^2) \tag{6}$$

Among them, $\mathrm{Feedback}_i$ is the user's feedback on diet and exercise; $f(\mathrm{Input}_i,\theta)$ is the recommended output based on user input; λ is the regularization term; θ is the adjusted parameter. In this way, the system can achieve dynamic adaptation and continuously optimize personalized intervention plans to improve intervention effects and user satisfaction.

3.2 Application of Intelligent Algorithms in Diet and Exercise Intervention

3.2.1 Intelligent Algorithm Support for Diet Intervention Strategies

Intelligent algorithm support for diet intervention strategies aims to provide users with personalized diet plans to help them achieve health goals, such as weight loss, muscle gain, or weight maintenance. The diet intervention algorithm generates the best diet recommendations for each user by analyzing multi-dimensional data such as the user's basic information, health data, and eating habits.

For content-based recommendations, the recommendation algorithm can be calculated using the following formula:

$$R_{ij} = \frac{\sum_{k=1}^{N} w_{ik} \cdot f_{kj}}{\sum_{k=1}^{N} |w_{ik}|} \tag{7}$$

Among them, R_{ij} is the recommendation degree of user i for food j; w_{ik} is the similarity between user i and user k; f_{kj} is the feature value of food j; N is the number of users. By calculating the similarity of food, the most suitable food can be recommended to the user.

In order to consider the matching of the nutritional content of different foods with health goals, the diet recommendation algorithm also needs to introduce the calculation of nutritional content. Assuming that the nutrient vector of food j is $C_j=(c_1,c_2,,\cdots,c_k)$, where c_k represents the content of the kth nutrient, the system makes recommendations through the following optimization function:

$$f_{dict} = \arg\min_{\theta} \sum_{i=1}^{N} \left(y_i - \hat{y}_i\right)^2 + \lambda \|\theta\|^2 \tag{8}$$

Among them, y_i is the actual diet effect; $\hat{y}_i$ is the predicted diet effect; λ is the regularization parameter; θ is the optimization parameter. By minimizing the error, the system can recommend the most suitable diet for the user.

3.2.2 Establishment and Management of Food Database

(1) Collection of food data

There are two main sources of food data:

Public databases: such as the United States Department of Agriculture (USDA) food database or other public nutrition databases.

User input: Users input their daily diet through the application, and the system identifies the food based on food recognition technology and enter it into the database.

The main contents of food data include: food name, nutrient content (such as protein, fat, carbohydrates, vitamins, etc.), calories, and food category (such as staple food, vegetables, fruits, etc.).

(2) Data management and update

The management of the food database needs to solve the problems of data accuracy and timeliness. In order to ensure the accuracy of the data, the food data in the database can be verified and updated using the following formula:

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$$\text{Accuracy}_{ij}=\frac{1}{N}\sum_{k=1}^{N}\left(\frac{|d_{ij}-\hat{d}_{ij}|}{d_{ij}}\right) \tag{9}$$

Among them, Accuracy_{ij} represents the accuracy of food j in database i; d_{ij} is the actual food data; $\hat{d}_{ij}$ is the predicted food data. By calculating the error of the data, the food database can be quality controlled and corrected and updated accordingly.

4. Results and Discussion

4.1 Experimental Design Type

Randomized Controlled Trial (RCT): The experimental group and the control group are selected, and the personalized diet and exercise intervention system and the traditional diet and exercise program are used for intervention respectively.

Longitudinal Tracking Experiment: The experimental period is 3 months, and the user's health data are collected and analyzed regularly to compare the changes at different stages.

4.2 Experimental Subjects and Grouping

Experimental Subjects: Overweight college students with a BMI (body mass index) between 24 and 29.9.

Grouping:

Experimental group: a personalized diet and exercise intervention system supported by intelligent algorithms.

Control group: traditional diet and exercise recommendations (e.g., diet plans provided by nutritionists, exercise programs recommended by conventional fitness trainers).

4.3 Experimental Data Analysis Methods

Statistical Analysis: Using paired t-tests or ANOVA to analyze changes in body weight, body fat percentage, and other metrics between the experimental and control groups, comparing the efficacy differences between the two groups.

Regression Analysis: Researchers conduct regression analysis based on individualized user data (such as basal metabolic rate, exercise intensity, etc.) to evaluate the impact of various factors on intervention outcomes.

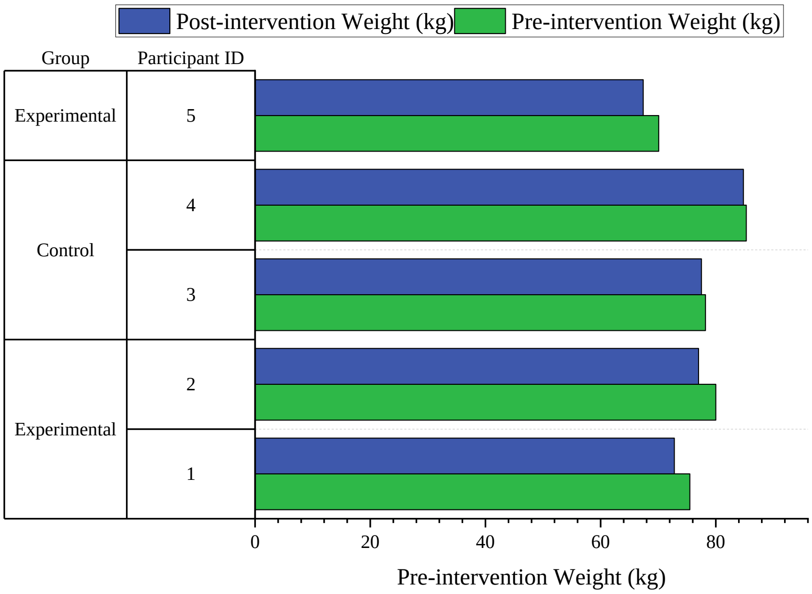

Figure 1 Weight change data

In Figure 1, the weight changes of the participants in the experimental group after the intervention generally demonstrated a significant downward trend, while the weight changes in the control group were relatively small. First, all five participants in the experimental group experienced negative weight changes, ranging from -2.7 kg to -3.0 kg, with an average weight change of -2.8 kg and a percentage change of -3.66%.

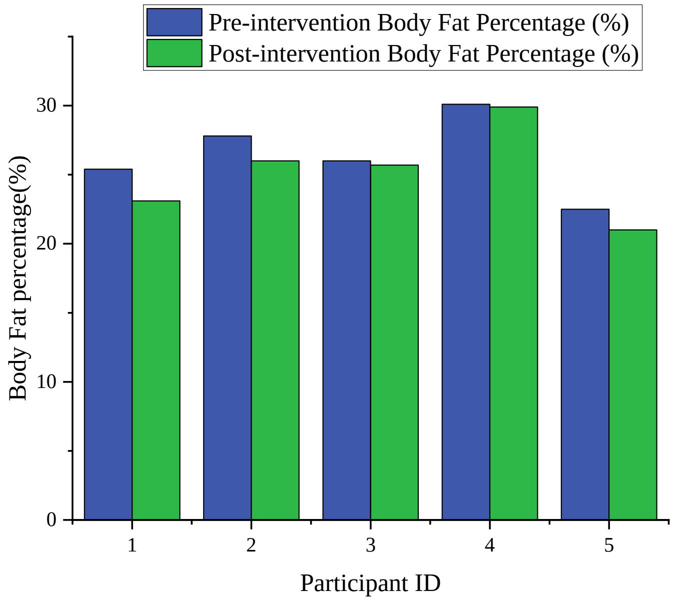

Figure 2 Body fat percentage change data

All five participants in the experimental group experienced negative body fat percentage changes, ranging from -1.5% to -2.3%, with an average change of -1.8% and a percentage change of -7.17%. Figure 2 demonstrates that, with the support of personalized diet and exercise intervention, the experimental group achieved a significant reduction in body fat percentage, demonstrating a significant fat loss effect.

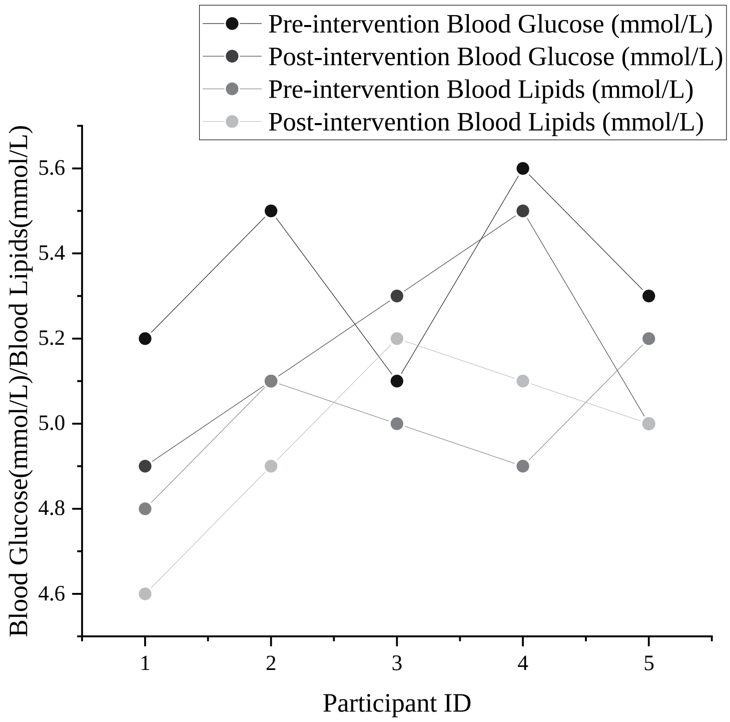

Figure 3 Health indicator change data

Participants in the experimental group showed significant improvements in both blood sugar and blood lipids. For all five participants in the experimental group, changes in blood glucose were

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negative, ranging from -0.3 mmol/L to -0.4 mmol/L, with an average change of -0.33 mmol/L, demonstrating good control. For example, Participant 1 and Participant 2 saw blood glucose decreases of -0.3 mmol/L and -0.4 mmol/L, respectively, with percentage changes of -5.77% and -7.27%, respectively. Regarding blood lipids, changes in the experimental group were also negative, ranging from -0.2 mmol/L to -0.2 mmol/L, with an average change of -0.2 mmol/L, demonstrating significant lipid improvement. In contrast, changes in blood glucose and lipid profiles were more limited in the control group. Blood glucose levels increased in the control group, ranging from +0.2 mmol/L to -0.1 mmol/L, with an average change of +0.05 mmol/L, indicating that without personalized intervention, blood glucose levels in the control group fluctuated. Regarding changes in blood lipid levels, the control group generally experienced increases, ranging from +0.2 mmol/L to +0.2 mmol/L, with an average change of +0.2 mmol/L, indicating a negative trend, as shown in Figure 3.

Table 1 User satisfaction and feedback

Participant ID	Group	Diet Recommendation Satisfaction (1-5)	Exercise Recommendation Satisfaction (1-5)	System Usability (1-5)	Overall Satisfaction (1-5)
1	Experimental	4	4	5	4
2	Experimental	5	5	4	5
3	Control	3	3	4	3
4	Control	3	2	3	2
5	Experimental	4	4	4	4

Based on the user satisfaction and feedback data in Table 1, a comparative analysis was conducted between the experimental and control groups regarding satisfaction with diet recommendations, exercise recommendations, system usability, and overall satisfaction. The experimental group generally performed well across all satisfaction indicators, while the control group's satisfaction scores were lower.

The experimental group generally received high scores for satisfaction with diet recommendations, exercise recommendations, system usability, and overall satisfaction. Specifically, three participants in the experimental group gave their diet recommendations a score of 4 and 5, respectively, for an average score of 4.33. For exercise recommendations, the scores were 4 and 5, with an average score of 4.33. For system usability, all participants in the experimental group gave high scores of 4 and 5, with an average score of 4.33. Overall satisfaction was also high in the experimental group, with scores of 4 or higher, for an average of 4.33. Participant 2's scores were particularly strong, with scores of 5 for each of these indicators, demonstrating high approval of the system.

5. Conclusions

This paper presents and designs a personalized diet and exercise intervention system integrating artificial intelligence and the Internet of Things, aiming to help overweight college students effectively manage their weight and improve health indicators. By combining deep learning and IoT technology, this study realizes precision interventions tailored to individual differences. The system enables personalized dietary and exercise plans based on users' health data, continuously optimizing intervention outcomes through real-time data feedback. The experimental sample is limited to overweight college students, with an intervention period of three months. Future research may expand the sample size and extend the intervention duration to evaluate the system's long-term effectiveness and adaptability across broader populations. While personalized intervention programs demonstrate advantages in health management, enhancing the system's intelligence to address more complex health management needs remains a key direction for future research.

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