RESEARCH ARTICLE

Construction of physical fitness assessment and prediction model for college students based on deep learning and big data

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Received: August 23, 2024; **accepted:** January 3, 2025.

With the development of the economy and the progress of society in recent years, people are paying more and more attention to health issues. This study aimed to develop a multimodal data fusion framework based on deep learning and big data technology to evaluate and predict the physical health of college students. The framework integrated multimodal data including physical fitness test scores, daily activity, sleep quality, dietary preferences, mental health status, and basic physiological parameters to comprehensively and accurately evaluate the health status of college students and provide personalized health advice. The results found that daily activity, physical fitness test, and sleep quality were key factors affecting the health status of college students. The results showed that the health improvement percentages of daily activity, physical fitness test, and sleep quality were ranked from high to low as 12.5%, 10.3%, and 9.8%, respectively. In addition, the user satisfaction and adoption rate of personalized suggestions were also high with the average satisfaction of exercise suggestions of 4.2/5 and the adoption rate of 75%. The average satisfaction of dietary suggestions was 4.0/5 with the adoption rate of 70%, while the average satisfaction of sleep suggestions was 4.1/5 with the adoption rate of 72%. This study provided new methods and technical means for the health management of college students and a useful reference for other fields of health management and disease prevention. Through the application of multimodal data fusion and advanced model architecture, this study expected to promote the development of health assessment and management technology and provide a scientific basis for more accurate personalized health management. These results were of great significance to improve the health level of college students and promote their all-round development.

Keywords: big data; deep learning; physical fitness; assessment models; predictive analytics.

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Introduction

With the development of the economy and the progress of society, people have increasingly focused on health issues. As the future pillars of the country, the physical health of college students is directly linked to their personal development and social progress. However, due to academic pressure, poor living habits, and other factors, the physical fitness of college students has generally declined in recent years. According to the latest "Research Report on Physical Fitness and Health of Chinese Students" provided by the Institute of Sports Science, the State General Administration of Sports, Beijing, China (http://www.sport.gov.cn/), the overall physical fitness level of college students is on a downward trend, particularly in terms of endurance, strength, and flexibility. These issues not only affect students' physical health but may also have a negative impact on their mental health, which, in turn, can influence their academic performance and personal development. The development of science and technology, particularly the rapid advancement of big data and artificial intelligence, offers new possibilities for addressing challenges in college physical training course information transmission through intelligent algorithms [1].

In recent years, as people's awareness of health increases and technology develops, more and more research has begun to focus on how to utilize big data and artificial intelligence technology to improve the health of individuals and groups. Especially in the field of college students' physical health management, there have been some cutting-edge research results worthy of attention. Both domestic and international scholars have made significant progress in utilizing big data and machine learning technologies for health assessment. Liu *et al*. reviewed the application of intelligent governance of physical fitness among college students under the backdrop of big data, suggesting that big data analytics could enhance the effectiveness and personalization of fitness programs [2]. Khan *et al*. advanced this domain by introducing PAR-Net, an enhanced dual-stream convolutional neural networks (CNNs) and echo state networks (ESN) architecture designed specifically for human physical activity recognition, to showcase the potential of deep learning in accurately monitoring daily activities [3]. Huang developed a method based on deep learning algorithms for the accurate recognition of continuous sports actions, offering valuable feedback for athletes during training [4]. Furthermore, Yong explored the simulation of an intelligent system for physical fitness training aimed at sports majors using real-time status updates from wearable Internet of Things (IoT) devices to ensure high data accuracy and effective training outcomes [5]. Despite many advances, current research still faces some challenges including data privacy protection, data quality control, and model generalization capabilities. In addition, how to effectively integrate data from different sources is also a challenge. With the development of 5G communication technology and the IoT, data transmission speeds are faster, and data collection is more convenient, which provides new opportunities for building more accurate health assessment models. Meanwhile, as noted by Zhao *et al*., government and corporate investments in big data for health are increasing, providing sufficient financial support for related research [6]. The integration of internet technology and artificial intelligence has been applied to transform sports training including the prediction of physical fitness test scores for college students. By leveraging machine learning algorithms, it is possible to predict students' physical fitness levels more accurately through analyzing their basic information such as age, gender, weight and combining that information with detailed daily activity data [7]. Such study utilized advanced machine learning algorithms that were able to process large amounts of data and extract useful information from it. However, its shortcoming was that the dataset was mainly derived from Western countries and might not be fully applicable to student populations in Asia or other regions. Lu developed a prediction model for sports performance based on artificial intelligence algorithms by incorporating data simulation to enhance the accuracy and reliability of predictions [8]. Building on this foundation, Wang *et al*. introduced a predictive model for the physical health of college students that integrated semantic web and deep learning under a cloud-edge collaborative architecture [9]. This approach not only addressed various factors affecting physical health but also provided a comprehensive analysis of the interplay between mental and physical health, offering a holistic view of student well-being. Complementing these efforts, Guo explored near-infrared spectral imaging combined with cloud data and wireless network sensing for real-time big data sports and fitness detection [10]. This method offered a non-invasive way to monitor fitness levels continuously, providing immediate feedback to improve training efficiency. Together, these studies highlighted the application of advanced technologies in enhancing sports performance, predicting physical health outcomes, and monitoring fitness levels, while also addressing challenges such as data complexity and privacy protection. Ai's study demonstrated how an artificial intelligence system could be utilized for college students' physical fitness and health management based on big data from physical measurements [11]. Big data analytics is pivotal in college students' fitness and health management. Data cleansing and preprocessing such as removing duplicates and correcting errors ensured data quality [12]. Feature engineering study identified key health factors from student physique tests [13]. Cross-validation assessed model generalization [14]. Gao *et al*. developed a system to predict sports injury risks and offer personalized health advice, leveraging big data [15]. Researchers also used multi-scale methods to predict health risks and customize diet and exercise plans [16]. Guo created a platform for real-time health monitoring and early warning, facilitating timely interventions [17].

This study used a variety of data sources including physiological data, activity data, sleep data, and dietary data to conduct a comprehensive analysis through a multimodal data fusion framework using CNNs for analyzing image data such as facial expressions to assess emotional states and recurrent neural networks (RNNs) for processing time series data such as heart rate variability to predict exercise intensity. In addition, machine learning algorithms and deep learning models were combined to improve the efficiency and accuracy of data processing and analysis. This study provided new methods and technical means for the health management of college students and could be a useful reference for other fields of health management and disease prevention. Through the application of multimodal data fusion and advanced model architecture, this study would promote the development of health assessment and management technology and provide a scientific basis for more accurate personalized health management.

Materials and methods

Dataset resource

To construct and validate a comprehensive health assessment model, this study collected data from multiple perspectives that included physical fitness test scores of running, long jump, sit-ups, push-ups; daily activity including steps, activity time, exercise intensity collected through wearable devices; sleep quality data of sleep duration, ratio of deep and light sleep, number of wakings; dietary preferences obtained through questionnaires and dietary logs [18, 19]; mental health status assessed using a standardized PHQ-9 questionnaire assessment provided by the National Institute of Mental Health (NIMH) (Bethesda, Maryland, USA), and physiological parameters of height, weight, and BMI. During the dataset construction, it was ensured that the data were of high quality and diversity, and the laws and regulations on privacy protection were strictly adhered to. The data were obtained from multiple sources including campus health management systems, research projects in which students voluntarily participate, and publicly available health databases. A publicly available database from the Institute of Sports Science, the General Administration of Sport of China (Beijing, China) was used for this study, which covered common health indicators of the college student population. A total of 5,000 data were retrieved from the database, of which 3,500 (70%) were used for model training, 1,000 (20%) were used for model validation, and 500 (10%) were used for model testing. This data was also used to evaluate the performance difference between the proposed deep learning model and the traditional unimodal data processing models that used only fitness test results or a single type of health data for analysis and usually based on traditional machine learning algorithms such as support vector machines (SVM) or random forests.

Construction of physical health assessment and prediction model

A physical health assessment and prediction model for college students based on deep learning and big data technologies was constructed using data from multiple health dimensions. To achieve this goal, the key variables and objective functions were defined [20], which included the input dataset as $X = \{x_1, x_2, \dots, x_n\}$, where x_i was the data vector of the *i*-th individual, and each vector contained multiple features such as physical fitness test scores, step counts, sleep quality scores, *etc.*; the output variable as $Y = \{y_1, y_2, \dots, y_n\}$ to represent health assessment results or predicted values such as overall health scores or predictions of health status over time [21]. The model parameters θ represented the set of learnable parameters in the model including, but not limited to, the weight matrix and bias vector. The goal was to find a set of parameters θ , such that the predicted health status $\hat{Y}$ was as close as possible to the actual health status Y. Then the loss function $L(\hat{Y}, Y; \theta)$ was defined to measure the prediction error [22, 23]. Mean squared error (MSE) was a loss function to quantify the difference between the predicted and true values. MSE is a common loss function for regression tasks, which effectively measures the average of the sum of squares of the deviations between the predicted and true values as shown in equation (1).

$$L(\hat{Y}, Y; \theta) = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (1)$$

where $\hat{y}_i$ was the model's predicted health status for the *i*-th individual, while y_i was the true health status. To find the best parameter θ, the loss function by optimization algorithms was minimized. Commonly used optimization algorithms include gradient descent (GD) and its variants. The GD method was used to update the model parameters θ, and the update rule was shown in equation (2) [24, 25].

$$\theta_{t+1} = \theta_t - \eta \cdot \nabla_\theta L(\hat{Y}, Y; \theta_t) \quad (2)$$

Model design ideas

This study designed an innovative multimodal data fusion framework with excellent ability to unify and integrate multiple data types into a coherent representational space. The core of the framework was an advanced attention mechanism that intelligently recognized and learned the significance of different data sources to provide a more comprehensive and accurate picture of an individual's overall health. Utilizing the cutting-edge transformer architecture to handle diverse data modalities, it adaptively assigned appropriate weights to each type of data through its powerful attention mechanism, ensuring that key health indicators were adequately valued and parsed. A deep learning architecture was crafted with the ability to automatically extract key features from complex data sources. The architecture not only specialized in capturing fine-grained features within a single data modality, but also dug deeper into the interactions and correlations between different modalities to significantly improve the predictive performance of the model. Combining the strengths of CNN and RNN, CNN focused on extracting local features in image and sequence data such as inferring the emotional state through facial expression analysis, while RNN focused on capturing dynamic changes in time-series data such as monitoring the fluctuation of heart rate. In addition, graph neural networks (GNN) were introduced to build a correlation network between health indicators to further strengthen the expressive power of features. Generative adversarial networks (GANs) or reinforcement learning (RL) techniques were further utilized to tailor health recommendations to individuals. These cutting-edge technologies could generate personalized health interventions such as customized diet plans and exercise guidance based on an individual's unique situation and historical data. Specifically, a system based on GANs was built, where the generator was responsible for outputting personalized health recommendations and the discriminator was responsible for evaluating the accuracy and applicability of these recommendations. Another option was to use

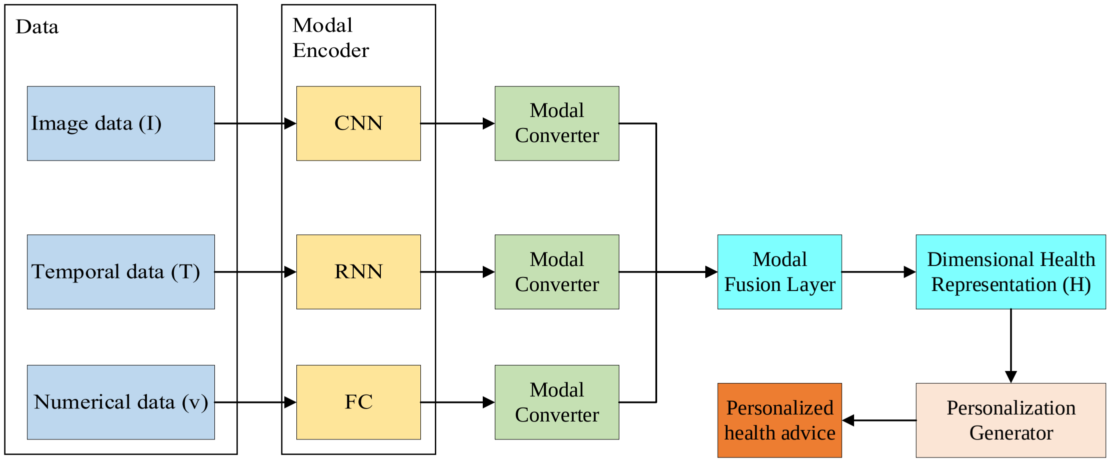

Figure 1. Modeling framework.

reinforcement learning, which took the changing health data as the environment state and learned through trial and error of the agent to find the optimal health advice strategy. Such a design aimed to provide users with more accurate and personalized health management solutions. The advanced machine learning techniques such as recurrent convolutional neural networks (RCNN) that could analyze time-series data from physical health standard tests to predict future outcomes accurately was another option. Scientist has demonstrated how RCNN could be used for principal component analysis and prediction of students' physical health test results, enabling the identification of personalized health management strategies based on historical and real-time data [26]. Furthermore, Ma *et al*. constructed a teaching system that integrated big data and artificial intelligence to promote the physical health of students, which used reinforcement learning to adaptively provide optimal health advice to enhance the accuracy and personalization of health management solutions through continuous learning and adjustment [27].

Models of innovation

The proposed multimodal data fusion framework contained several core components including the modal encoder equipped with specialized encoders for different data modalities using CNNs to process image data and RNNs to process temporal data [28], the modal converter that dynamically fused the features of each modality by using the Transformer's self-attention mechanism and adjusted the weights according to the relevance and importance of the data, the modality fusion layer that integrated the information of all modalities to form a unified high-dimensional health representation, and the personalization generator that generated personalized health advice for individuals based on the fused health representation using GANs or RL techniques [29] (Figure 1). For each modality m (where $m \in M$, M was the set of all modalities), an encoder E_m was defined to extract the features of modality m. Suppose x_m was the original input of modality m and $E_m(x_m)$ was the feature representation after encoder processing. The image data was represented as equation (3).

$$f_I = E_I(I) = \text{CNN}(I) \quad (3)$$

For the time-series data T, a RNN was used as an encoder E_T as follows.

$$f_T = E_T(T) = \text{RNN}(T) \quad (4)$$

For other modal data, such as numerical data V, the fully connected layer (FC) was used as an encoder E_V and was shown in equation (5).

$$f_V = E_V(V) = FC(V) \quad (5)$$

The modal converter was based on the Transformer architecture, which used a self-attention mechanism to fuse the features of different modalities. The feature representation of each modality f_m was defined, which was linearly transformed to obtain the query vector Q_m, the key vector K_m, and the value vector V_m. For modality *m*, its formula was shown in equations (6)-(8).

$$Q_m = W_Q f_m \quad (6)$$

$$K_m = W_K f_m \quad (7)$$

$$V_m = W_V f_m \quad (8)$$

where (W_Q, W_K, W_V) were the learnable weight matrix. The multi-head attention mechanism $MultiHead(Q, K, V)$ was then defined and shown below in equations (9)-(12).

$$\text{MultiHead}(Q, K, V) = \text{Concat}(head_1, \ldots, head_h)W^O \quad (9)$$

where $head_i = \text{Attention}(QW_i^Q, KW_i^K, VW_i^V)$ (10)

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (11)$$

$$d_k = \text{dimension}(K) \quad (12)$$

where *h* was the number of attention heads. $(W_i^Q, W_i^K, W_i^V, W^O)$ were the learnable weight matrix. The final attention output A_m was shown in equation (13).

$$A_m = \text{MultiHead}(Q_m, K_m, V_m) \quad (13)$$

The task of the modal fusion layer was to fuse the attentional outputs of the different modalities A_m into a unified representation *H*, which was done by simple weighted averaging or by more complex nonlinear transformations. A simple approach was to use weighted averaging as shown in equation (14).

$$H = \sum_{m \in M} w_m A_m \quad (14)$$

where w_m was the weight of modality *m*, which could be learned by training outside the amount. A personalized generator generated personalized health advice based on the fused health representation *H*. GANs were used to achieve this functionality, which consisted of a generator *G* and a discriminator *D*. The purpose of generator *G* was to generate personalized suggestions *S* from the fused health representations *H*, while the purpose of the discriminator *D* was to differentiate between the real suggestions and the generated suggestions. The loss function L_G of generator *G* was shown in equation (15) and the loss function L_D of discriminator *D* was shown in equation (16).

$$L_G = -\mathrm{E}_{H \sim p_H(H)}[\log D(G(H))] \quad (15)$$

$$L_D = -\mathrm{E}_{S \sim p_S(S)}[\log D(S)] - \mathrm{E}_{H \sim p_H(H)}[\log(1 - D(G(H)))] \quad (16)$$

where $p_H(H)$ was the distribution of health representations. $p_S(S)$ was the distribution of real suggestions. By jointly optimizing L_G and L_D, models that generated high quality personalized suggestions were trained [30].

Experimental design

A series of preprocessing operations on the data were performed, which included thorough data cleaning to remove missing values, outliers, and noise; precise feature selection using the recursive feature elimination (RFE) method to extract metrics that were highly relevant to the health assessment; and standardized data transformations using Z-score standardization to ensure that all the numerical features had a uniform metric. Two groups with one as experimental group and the other as control group were set up in this study. The experimental group adopted proposed multimodal data fusion framework, which was capable of processing and integrating health data from different sources, covering a wide range of data types. The control group followed the traditional unimodal model, which relied on a single data source to assess

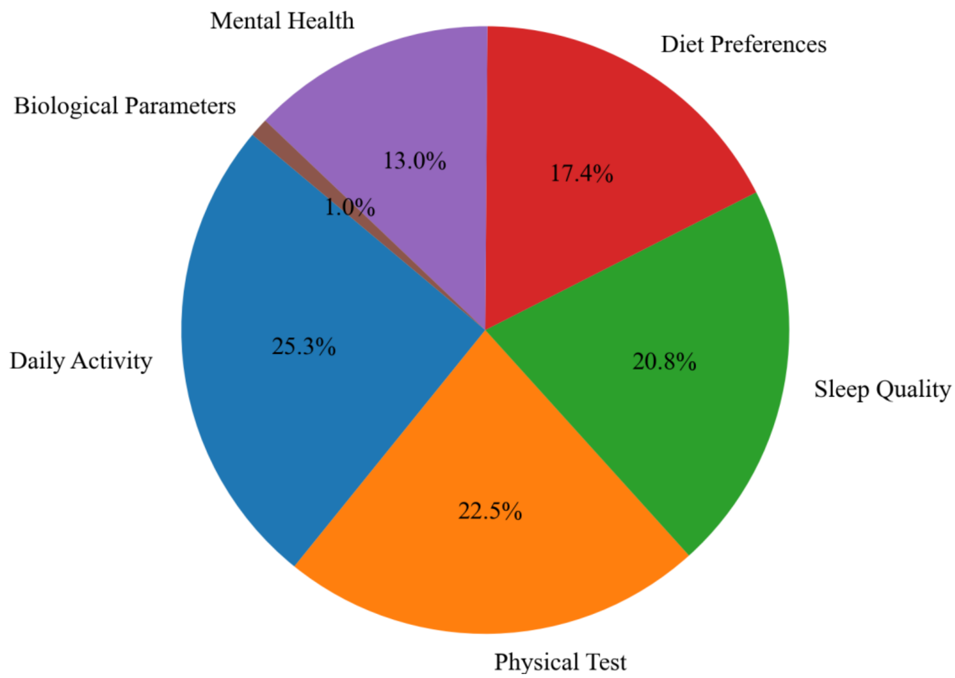

Figure 2. Relative importance of different factors of modal data.

health status. Python programming language and the Scikit-learn library were used for all operations. This study involved 150 college students from multiple universities in Beijing, Shanghai, and Guangzhou in China. User feedback was collected through an online questionnaire including satisfaction with the recommendation system and the accuracy of recommendation results. All procedures of this study were approved by the Ethics Committee of Peking University (Beijing, China) (Approval No. IRB00001052-20240812).

Results and discussion

Modal importance analysis

The performance results of different modal data in health assessment showed that the mean health score of daily activity demonstrated the highest score of 79.3, while dietary preference had the lowest score of 76.9, which suggested that the amount of daily activity might have a higher reference value in health assessment. The results of mean square error (MSE) showed that the daily activity volume had the smallest error of 0.049, while sleep quality had the largest error of 0.058, suggesting that the predictive accuracy of daily activity volume data was high. The standard deviation of individual health scores reflected the degree of dispersion of the scores with dietary preference having the largest standard deviation of 4.1, indicating that dietary preference data were relatively unstable in health assessment. The importance of different modal data was analyzed and the results showed that the relative importance scores of the amount of daily activity was the highest one as 25.3%, which indicated that focusing on and improving the amount of daily activity was important for improving health in daily health management. The physical fitness test, the sleep quality, the dietary preferences, mental health status, and the physiological parameters demonstrated the relative importance scores of 18.7%, 15.6%, 12.4%, 10.2%, and 8.1%, respectively (Figure 2), which reflected their contributions to health assessment and their helps to identify and optimize key health assessment factors, thereby formulating more effective health management strategies.

Table 1. Results of the personalized recommendations assessment.

	Average satisfaction	Average adoption rate	Number of users' feedback
Exercise recommendations	4.2/5	75%	150
Dietary recommendations	4.0/5	70%	150
Sleep Recommendations	4.1/5	72%	150

Table 2. Results of users' feedback and acceptance.

Evaluation indicators	Customer satisfaction	Acceptability	Number of participating users
Usability	4.4/5	82%	150
Accuracy	4.3/5	80%	150
Degree of personalization	4.5/5	84%	150

Personalized recommendations assessment

The evaluation results of personalized suggestions showed that the average satisfaction of exercise advice was the top one on the list with a score of 4.2/5, indicating that users were more satisfied with exercise advice. On the other hand, the average adoption rate showed that the exercise suggestions had the highest adoption rate of 75%, indicating that users were more inclined to follow exercise suggestions (Table 1). The total number of user's feedback for all indicators was 150, which ensured the representativeness and reliability of the assessment results. These data reflected the effectiveness of personalized advice in promoting health behavior change among users.

Users feedback and acceptance

The users' feedback and acceptance of the ease of use, accuracy, and degree of personalization of the health management system showed that the ease of use had the highest user satisfaction of 4.4/5 and the highest acceptance level of 82%, which indicated that users found the system easy to operate and easy to use. The degree of personalization showed the highest user satisfaction of 4.5/5 and acceptance of 84%, which indicated that users were very satisfied with the personalization services provided by the system (Table 2). Overall, users' feedback on the system was positive, and the acceptance was high, which laid a good foundation for further promotion and use of the system.

Modal contribution and health improvement effect

The contribution of different modal data to health improvement was analyzed with the smaller the ranking number, the greater the contribution. The results demonstrated that the daily activity level ranked first in terms of percentage of health improvement with a contribution of 12.5%, which again emphasized the importance of daily activity level in health management. In contrast, physiologic parameters ranked the last with a contribution of only 2.2%, which might indicate that physiologic parameters played a relatively small role in health improvement (Table 3). This data helped to identify and optimize key factors in health management.

User preferences and behavioral changes

The users' preferences for different health recommendations and their impact on behavior change demonstrated that the exercise advice had the highest user preference of 4.3/5, and the highest percentage of behavior change of 78%,

Table 3. Modal contribution and health improvement effect.

Modal (computing, linguistics)	Improvement in health (%)	Improvement ranking
Daily activity level	12.5%	1
Fitness test	10.3%	2
Sleep quality	9.8%	3
Dietary preference	8.1%	4
Mental health status	7.4%	5
Physiological parameter	2.2%	6

Table 4. User preferences and behavioral changes.

Recommendation	User preference	Behavior change (%)	Number of users' feedback
Exercise recommendations	4.3/5	78%	150
Dietary recommendations	4.1/5	73%	150
Sleep recommendations	4.2/5	75%	150

indicating that users not only preferred exercise advice but also more inclined to act on it. The user preference and behavior change ratio for sleep suggestions were 4.2/5 and 75%, respectively, indicating that users had a positive attitude towards suggestions to improve sleep quality (Table 4). The data provided an empirical basis for user behavior change and helped better customize and promote health advice.

This study proposed a multimodal data fusion framework for college students' physical health management. By comparing the results of the experimental group with the control group, the results suggested that the multimodal data fusion framework demonstrated significant advantages in health assessment. The proposed framework was able to integrate multiple sources of data such as physical fitness test scores, daily activity level, and sleep quality to more accurately assess an individual's health status, which had higher accuracy and lower mean square error than that of the unimodal model used in the control group. Relatively high percentages of health improvement were observed for the three modalities of daily activity amount, physical fitness test, and sleep quality, suggesting that these factors played a key role in the health management of college students. In particular, the amount of daily activity not only scored the highest in the modal importance analysis, but also ranked first in the health improvement effect, which emphasized the importance of increasing daily physical activity in improving college students' health. In addition, the assessment results of personalized advice showed that users had high satisfaction and acceptance rates for advice on exercise, diet, and sleep, which indicated that personalized health management strategies based on the multimodal data fusion framework could effectively promote behavioral changes among users. The users' feedback and acceptance analysis further confirmed the advantages of the proposed health management system in terms of ease of use, accuracy, and degree of personalization, which was important for improving user engagement and adherence.

Acknowledgements

This research was supported by China University of Mining and Technology (Beijing) Central Universities Fundamental Scientific Research Operating Expenses Project (Grant No. 2021YQTY03) and China University of Mining and Technology (Beijing) Central Universities Basic Scientific Research Operating Expenses Project (Grant No: 2023SKPYTY02).

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