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Research Article

Application and Deconstruction of Exercise Prescription Formulation Based on K-Means Algorithm in the Prevention and Treatment of Chronic Diseases

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Chronic diseases, also known as chronic noncommunicable diseases, have the characteristics of a long period of symptoms, complex and diverse causes, relatively large damage to human health, and a relatively wide impact on the overall safety of society. This study mainly discusses the application of exercise prescription formulation based on K-means algorithm in the prevention and treatment of chronic diseases. Aiming at different groups of people with different physical conditions in different environments, this study established a comprehensive exercise prescription library and feedback channels. By comparing and analyzing the effects of different exercise exercises, people can provide scientifically standardized and suitable exercise and fitness programs for people with chronic diseases. The feasibility of the K-means algorithm in chronic disease prediction is confirmed by experiments, and the experimental time of the improved algorithm and the traditional algorithm is compared, and the efficiency of the improved algorithm is confirmed. Aiming at the privacy, complexity, missing data values, and other issues of chronic disease medical examination data, we have carried out perfect data preprocessing research. After 12 weeks of exercise intervention, the vital capacity of the exercise group increased significantly (5.83%) ($P < 0.01$). The subendocardial myocardial viability rate increased by 9.74% ($P < 0.01$), and the radial artery reflected wave growth index and systolic blood pressure decreased slightly ($P < 0.05$). This indicates that the 12-week exercise training intervention program designed in this study can effectively enhance the cardiopulmonary function of the exercise group, thereby further improving the body's aerobic capacity ($P < 0.05$). This study lays the foundation for the smooth development of chronic disease prevention and treatment.

1. Introduction

The global incidence of chronic diseases continues to increase as the population ages and the prevalence of diabetes, obesity, and hypertension increases. The high prevalence of chronic diseases, huge medical expenses, and easy to combine with cardiovascular and cerebrovascular diseases, high morbidity and mortality, make chronic diseases a silent killer disease. Patients often seek treatment in various ways, but the curative effect is not good, the disease cannot be controlled, and the economy is overwhelmed, which leads to the loss of confidence in life, and then produces serious psychological stress, which often further aggravates the disease. Relief and improvement of chronic diseases are an important source of exercise prescriptions. This is also a solution that requires attention to the exercise prescription process. Do a questionnaire survey of chronic diseases as needed, and add data support to the exercise prescription knowledge base. Organically combining preventive medicine with national fitness exercise prescriptions and guiding the masses in scientific fitness, scientific diet, and scientific prevention is the best choice to effectively alleviate the increasingly prominent subhealth problems.

The prevention and management of chronic diseases have always been the focus of health work. With the promotion of various relevant policies, people's health literacy level for chronic diseases has been continuously improved. Shlisky J highlighted the role of nutritional science in promoting healthy aging and improving outcomes for age-related diseases [1]. Thombs B&D aims to compare commonly used measures of self-efficacy between SSc and other disorders. That is, the score on the Self-Efficacy in Chronic Disease (SEMCD) scale [2]. Marloes explored the solutions for chronic diseases [3]. Acham et al. reviewed the benefits of tropical fruits in the prevention of chronic diseases [4]. Yetley et al. believed that DRI can evaluate dietary health [5]. Their efficiency in the prevention and management of chronic diseases is not very high, so we refer to relevant literature and use the K-means algorithm to optimize the prevention and treatment of chronic diseases.

In medical-related fields, K-means algorithm is used for auxiliary diagnosis of different diseases to facilitate the extraction of knowledge to support clinical experts to make decisions. Qin et al. is very concerned about the development of distributed k-means algorithm for WSN [6]. Mario Haut et al. believed that remote-sensing hyperspectral imaging provides the possibility of collecting images in the region [7]. Kumar et al. believed that data clustering is an important data mining technology [8]. Varadarajan and Xiao focused on projection clustering [9]. Alsmadi believed that early diagnosis of jaw tumor is very important to improve its prognosis [10]. The K-means algorithm can realize the prediagnosis and screening of chronic diseases, and the K-means algorithm will be further discussed later.

The effects of chronic diseases are varied. Many studies have shown that due to the accelerated aging process and the prolongation of life expectancy, the scale of the elderly with chronic diseases continues to expand, and the patients with multiple chronic diseases are more frail and have low self-care ability, which will inevitably lead to an increase in the utilization of health services. K-means algorithm is used to formulate exercise prescriptions, and the purpose is to provide a good way for the prevention and treatment of chronic diseases. Rehabilitation exercise can reduce the incidence of cardiovascular events and improve cardiac function. To explore the effect of exercise prescription on exercise cardiopulmonary function in patients with chronic diseases with different syndromes by observing the indicators of cardiopulmonary exercise test, so as to provide a scientific and effective clinical basis for the rehabilitation exercise treatment of chronic diseases. The cluster analysis with the highest confidence is {chronic pharyngitis => obesity}, and its confidence is as high as 0.9999. Not only that, in this total 360 cluster analysis, the cluster analysis results ranked in the first 131 are obesity, and the confidence level is 0.9999.

2. Chronic Disease Prevention and Treatment

2.1. Chronic Disease. The worldwide prevalence of chronic diseases has become a widespread phenomenon and a rapidly growing public health problem. The problem of multiple chronic diseases is more complicated, and it is very important for clinicians, elderly patients, and policy makers to understand the prevalence status and risk factors of chronic diseases and to explore the prevalence patterns of multiple chronic diseases. Patients with chronic diseases often show changes in cardiac structure, such as myocardial hypertrophy and ventricular hypertrophy, which affect cardiac function. Angiotensin II can increase the synthesis of cardiac contractile protein and reduce the ability of vascular endothelial cells to secrete. At the same time, the smooth muscle cells in the blood vessels are proliferated, the lumen is narrowed, the peripheral blood vessels are constricted, and the perfusion of tissues and organs is reduced. This results in cellular oxidative stress and autophagy, leading to cell damage and ventricular remodeling [11]. Skeletal muscle is the main organ of human energy consumption and plays an important role in human movement and metabolism. In proper exercise, skeletal muscle groups can be exercised through exercise, and the metabolic rate of skeletal muscle cells can be accelerated, thereby maintaining bone homeostasis, increasing bone and joint friction and utilization, and maintaining the flexibility of each joint. The oxidative damage of mitochondria is related to many diseases, which can cause skeletal muscle damage. Exercise can promote the synthesis of mitochondria in skeletal muscle cells and improve oxidative function, thereby alleviating the aging process of skeletal muscle.

2.2. Exercise Prescription. In the study, the exercise group carried out exercise risk assessment, issued exercise prescriptions, implemented exercise interventions, conducted exercise guidance and follow-up management, and the control group carried out chronic disease risk assessment, but did not provide exercise prescriptions. Reasonable exercise can make the body strong, muscles strong, lose weight properly, improve self-resistance, effectively control blood sugar, and blood lipid indicators, thereby reducing the chance of suffering from various chronic diseases. In order to verify the change rules of physiological and biochemical indexes before and after exercise prescription, the t-test was performed on the results by using the hypothesis test method of the difference of the two normal population means in mathematical statistics to verify whether the changes of these indexes have significant changes [12]. Mathematical statistics can be used to study the statistical regularity of a large number of random phenomena.

Take the test statistic

$$T = \frac{\overline{x} - \overline{y}}{S_w \sqrt{1/n_1 + 1/n_2}}. \tag{1}$$

Among them, n_1, n_2 is the sample size [13].

The sample mean before exercise prescription is

$$\overline{X} = \frac{1}{n_1} \sum_{i=1}^{n_1} x_i. \tag{2}$$

The sample mean after exercise prescription is

$$\begin{aligned} \overline{Y} &= \frac{1}{n_2} \sum_{i=1}^{n_2} y_i, \\ S_w &= \sqrt{\frac{(n_1 - 1)S_1^2 + (n_2 - 1)S_2^2}{n_1 + n_2 - 2}}. \end{aligned} \tag{3}$$

The sample variance value before exercise prescription is

$$S_1^2 = \frac{1}{n_1 - 1} \sum_{i=1}^{n_1} \left(x_i - \overline{X}\right)^2. \tag{4}$$

The sample variance value after exercise prescription is [14]

$$S_2^2 = \frac{1}{n_2 - 1} \sum_{i=1}^{n_2} \left(y_i - \overline{Y}\right)^2. \tag{5}$$

Everyone's exercise prescription is also constantly changing with the changes in the individual's own conditions, weather, and places that day. For example, if the weather is good, people can do outdoor sports; if the weather is bad, people can choose indoor sports such as climbing stairs, cycling in the gym. Adjust the exercise frequency, exercise intensity, and exercise time in time according to the exercise effect and ensure the weekly exercise volume of each person. The key points of exercise prescription knowledge for each constitution type were designed by themselves and distributed to the test subjects, including the basic knowledge of traditional Chinese medicine constitution, sports-related knowledge and the content of test process control. The specific embodiment of the exercise prescription is easy for the subjects to understand. The use of the Internet and other media to establish a contact group is convenient for collective participation in watching online videos, and collective communication of the effect and evaluation of exercise prescriptions. Regularly discuss the problems in the implementation of exercise prescription in the group every week, communicate with each other, and improve together. Through the physical test and evaluation of the patient group, the online and offline are combined to build a new health management model in the Internet era and to provide users with professional sports consultation and integrated services of sports prescriptions. After many times of analysis, conception, discussion, and programming, the system finally gets the basic version of the basic realization of the function [15]. The system structure is shown in Figure 1.

2.3. K-Means Algorithm. In this study, K-means algorithm was used to classify chronic diseases, which was convenient for individualized analysis and prediction of chronic diseases. Each class will be assigned for at least one grid to ensure that any class can be found. All grids assigned to the same class will move to the same cluster center and overlap. Therefore, only the grid with the highest density in the same class is kept, other grids are deleted. This can ensure that each class is finally represented by only one grid, and the number of resulting classes and the centers of all classes can be effectively determined. The round corresponding to the optimal grid size is denoted as J, that is [16]:

$$J = \operatorname{argmin}_j \left\{ \frac{|D(3, j)|}{|D(1, j)|} \right\}. \tag{6}$$

Let s_i be a measure of the degree of dispersion of clusters C_i. $d(C_i, C_j)$ indicates the dissimilarity between the two clusters. The similarity index R_{ij} between C_i and C_j is defined as follows:

$$R_{ij} = \frac{s_i + s_j}{d_{ij}}. \tag{7}$$

R_i is defined as follows:

$$R_i = \max_{j=1,2,\ldots m, j \neq i} R_{ij}. \tag{8}$$

The DB metrics are defined as follows:

$$DB_m = \frac{1}{m} \sum_{i=1}^{m} R_i. \tag{9}$$

The dissimilarity between two clusters is defined as follows:

$$\begin{aligned} d_{ij} &= \left\| w_i - w_{jq} \right\| \\ &= \left(\sum_{k=1}^{l} \left| w_{ik} - w_{jk} \right|^q \right)^{1/q}. \end{aligned} \tag{10}$$

The degree of dispersion of clusters is defined as follows:

$$s_i = \left(\frac{1}{n_i} \sum_{x \in C_i} \left\| x - w_i^r \right\| \right)^{1/r}. \tag{11}$$

Assuming that the data set is clustered into k classes, denoted as C=(C_1, C_2,. . ., C_k), the sum of all intraclass dispersions when the samples are divided into k classes is [17]

$$W_k = \sum_{r=1}^{k} \frac{1}{2n_r} D_r. \tag{12}$$

The Gap statistic model is

$$\mathrm{Gap}_n(k) = E_n^*\left(\log\left(W_k^*\right)\right) - \log W_k. \tag{13}$$

The time for a user to access a url link is

$$\mathrm{Time}(\mathrm{user}, \mathrm{url}) = \frac{\mathrm{All\ Time}(\mathrm{user}, \mathrm{url})}{\left(\max_{(\mathrm{visitedUrl})} \mathrm{All\ Time}(\mathrm{user}, \mathrm{url})\right)/\mathrm{Size}(\mathrm{url})}. \tag{14}$$

The similarity of $\mathrm{sim}(u_1, u_2)$ between user u_1 and user u_2 is

$$\begin{aligned} \mathrm{sim}(u_1, u_2) &= \cos(u_1, u_2) \\ &= \frac{u_1 \cdot u_2}{\|u_1\| * \|u_2\|}. \end{aligned} \tag{15}$$

Define the mean of chronic disease treatment outcomes as E_j and the probability of treatment success as p_{ij} [18]:

$$E_j = \sum_i p_{ij} \log\left(p_{ij}\right). \tag{16}$$

Recall rate of K-Means algorithm in chronic disease prevention and treatment:

$$\mathrm{Precision} = \frac{|\{\mathrm{relevant}\}| * |\{\mathrm{retrieved}\}|}{|\{\mathrm{relevant}\}|}. \tag{17}$$

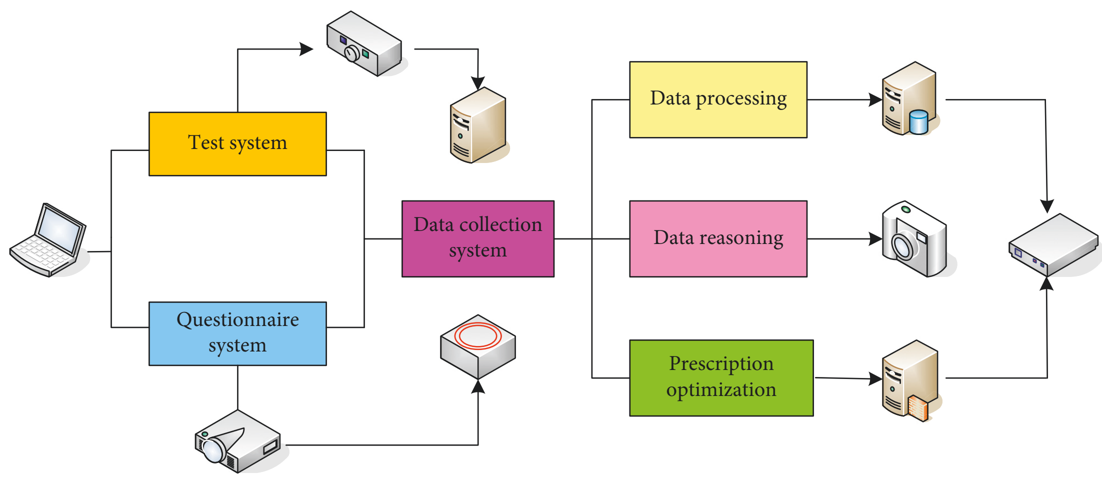

Figure 1: System architecture.

The characteristic measures for all objects are

$$F = \sum_{i} \frac{n_i}{n} \max\{F(i, j)\}. \tag{18}$$

In the formula, $F(i, j)$ represents a collection of categories of chronic diseases.

The purity of the entire clustering result is defined as follows:

$$\text{Purity} = \sum_{r=1}^{k} \frac{n_r}{n} P(S_r). \tag{19}$$

3. Experimental Analysis and Results of Chronic Disease Prevention

3.1. Deconstructing Objects and Detecting Metrics. The test subjects of this experiment are chronic disease patients aged 30–55 years, and the patients who voluntarily participate in the exercise prescription experiment are selected, and the prescription instructions are issued. A total of 40 subjects were divided into 20 cases in the control group and 20 cases in the exercise prescription group.

(1) General item records are measure height, weight, body mass index (BMI), heart rate and blood pressure of admitted patients; test blood routine, urine routine, routine blood biochemical indicators, and glycosylated hemoglobin.

(2) Diet arrangement and daily activity regulations: in the three experimental days of exercise intervention, breakfast and lunch were fixed and the same diet, which was uniformly distributed by the nutrition department. At the same time, it is forbidden to drink strong tea, coffee, and sugar-sweetened beverages, so as not to affect the experimental results. During the experiment, the patients were required to work and rest regularly, not to perform other activities except the exercise in the experiment, and to avoid the influence of stress factors such as mental stimulation and insomnia [19].

3.2. Overall Design of Exercise Experiment. All subjects performed a total of three exercise experiments, divided into 3 days, and the interval between each two experimental days was at least 3 days to avoid the influence of the previous exercise. The content of each exercise is exactly the same, but the time points of the exercise are different, which are 1 h, 2 h, and 3 h after breakfast (calculated by the time when the patient starts to eat the first meal). Therefore, they were defined as 1 h postprandial exercise group, 2 h postprandial exercise group, and 3 h postprandial exercise group. The arrangement sequence of the three exercise experiments of different subjects was randomly rotated to avoid the difference in the influence caused by the exercise sequence. On the day of the exercise experiment, all patients measured their fasting blood glucose at 6.30 am, then immediately ate the delivered meals, exercised at the specified time points, and detected the blood glucose levels before exercise, immediately after exercise, 11 a.m. and 4 p.m., respectively. All venous blood draws were assisted by endocrinology nurses who were uniformly trained and instructed. The blood glucose-level detection and the supervision and guidance of the exercise process were carried out by the researchers themselves. In the experimental stage, in order to fully reflect the role of experimental variables in the basic part, try to avoid interference caused by different aspects of the preparation part and the end part. Therefore, in the preparatory part and the end part, a small amount of exercise is selected for positioning freehand exercises and relaxation and finishing activities [20].

3.3. Exercise Program. The exercise method is brisk walking, and the patient is required to walk briskly at the fastest speed that he can achieve. The total walking distance is 2 km. According to the results of the preexperiment, the preset movement speed is about 4–4.5 km/h, and the movement time is expected to be 25–30 min. 5 minutes of preparatory activities were performed before the exercise, and 5 minutes of finishing exercises were performed after the exercise. During the first exercise, the patient was told in advance to walk at the fastest speed and ability that he could achieve. At the same time, the researchers closely monitored and recorded the distance and time each subject walked (movement time was recorded every 500 m).

Polar watch is one of the most used tools in the sports world and plays a very important role in the training of various sports. The patients who were initially planned to be enrolled were given exercise heart rate monitor (Polar watch), energy monitor, and pedometer to experience exercise with four-level exercise prescription, and the subjects completed a full set of exercise according to the content of exercise prescription CD under the supervision of medical staff. The duration of exercise therapy was 12 weeks. Before the exercise therapy is officially started, the patient's limb coordination ability and proficiency in the prescription will be evaluated first, and the formal exercise therapy and index observation will be started only after the patient can successfully complete each movement of the whole exercise prescription independently. The test flow is shown in Figure 2.

3.4. Statistical Processing. The analysis software SPSS21.0 was used for this analysis, all data results were expressed as mean ($X \pm S$), and the significance test between groups and within groups was carried out by two-factor repeated measures analysis of variance. For significant differences, one-way analysis of variance combined with posthoc test was used to determine the specific location of significance, and P value <0.05 represented a statistical difference. The purpose of the posthoc test study is to be equivalent to the multiple t-test, showing the least significant difference.

CH is used to measure the difference between the classification situation and the ideal classification situation (maximum variance between classes and minimum variance within classes). The CH scores of K-means and DBSCAN under different numbers of clusters are shown in Table 1. Both the K-means method and the DBSCAN method have the highest CH score when the data is divided into two clusters. At this time, DBSCAN sets the parameters MinPts = 86, $\epsilon = 1$ (the parameter ϵ is the neighborhood radius of the data point), and marks 2518 outlier data. Cluster 1 contains 10212 pieces of data, and cluster 2 contains 4783 pieces of data. Through analysis, it is found that all records in cluster 1 do not contain obesity labels, and all records in cluster 2 are obesity. The association rules were mined in the first cluster, and there were 62 disease combinations with support greater than 0.01.

The disease combination with the highest support degree is shown in Table 2, among which the combination of fatty liver and hypertriglyceridemia has the highest support degree, reaching 0.0415. Among them, fatty liver and hemorrhoids have the highest number of disease combinations, with 14 types.

In the second cluster, the mining of cluster analysis is carried out, in which there are 360 disease combinations with a support degree greater than 0.01. There were 143 disease combinations including two items, 167 disease combinations including three items, and 49 disease combinations including four items. Table 3 below shows the top ten disease combinations ranked by support, among which the combination of obesity and hypertriglyceridemia has the highest support, reaching 0.1971. Among them, the number of disease combinations related to obesity was the highest, which was 191 kinds. The mining results of cluster analysis in the second cluster are shown in Table 3.

From the disease combination in cluster 2, there are 360 rules with a confidence greater than 0.1 in the cluster analysis, among which the cluster analysis with the highest confidence is {chronic pharyngitis => obesity}, and its confidence is as high as 0.9999. Not only that, in this total 360 cluster analysis, the cluster analysis results ranked in the first 131 are obesity, and the confidence level is 0.9999. The cluster analysis results of the top six cluster analysis confidence rankings mined in cluster 2 are shown in Table 4.

The result is that the cluster analysis of obesity and fatty liver is the largest proportion of all the rules mined, and they intersect with each other. The results can intuitively see the relationship between obesity and fatty liver, and obesity and fatty liver have a very serious impact on physical health. The confidence level indicates that once people have obesity, there is a great chance to accompany diseases such as chronic pharyngitis, hemorrhoids, and fatty liver, but it does not rule out the possibility of this result due to too few data samples of chronic pharyngitis and hemorrhoids in this dataset. Analysis of the cluster analysis mining results in the two clusters, some chronic diseases including asthma, gout, cervical spondylitis, and other diseases did not find any related disease combination and cluster analysis. Analyzing the reasons, on the one hand, these diseases may occur alone and are not closely related to other diseases; on the other hand, the number of data samples may be too small. For example, there are only 28 cases of asthma and only 88 cases of gout in this dataset. In contrast, there are 5338 cases of obesity with the most comorbidity combination.

When trying to find the best parameters for K-means, a grid search method is used to determine the best parameters. When using grid search, a set of parameters is randomly selected and trained with the selected set of parameters, and then repeated until a certain number of iterations is reached to obtain performance metrics for each run. In this subsection, the micro-average F1 (MicroF1) is used as the evaluation metric (ReLU is shown in Figure 3(a)). In this experiment, the maximum number of iterations is set to 1000, the learning rate is set to 0.01, 0.05, 0.075, and 0.1, the number of hidden layers is set to 2, and each layer has 100 neural nodes. At the same time, multiple dropout layers are introduced, including 0 dropout layers, 1 dropout layer and 2 dropout layers before the output layer, and the dropout ratio of each dropout layer is set to 0.4. Finally, the Sigmoid and ReLU activation functions are set for comparison to evaluate the respective cases. Overall, under the same hyperparameters, the ReLU function performs better than the Sigmoid activation function (the Sigmoid activation function is shown in Figure 3(b)).

In order to confirm the reliability of the association rules obtained by the experiment, the multinomial logistic regression method was used to analyze the correlation of the

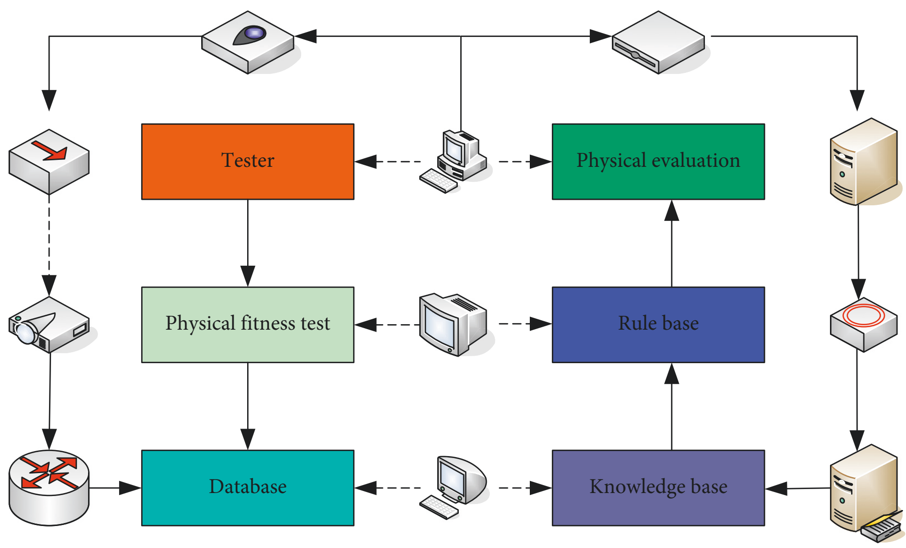

Figure 2: Test flow.

Table 1: CH scores under different numbers of clusters for K-means and DBSCAN.

Number of clusters	K-Means	DBSCAN
2	3514	3600
3	3017	3300
4	2917	3100
5	2816	2900
6	2660	2800
7	2520	2780
8	1900	2250

Table 2: Disease combinations ranked by support.

Association rules	Confidence
{Diabetes => fatty liver}	0.4554
{Hyperuricemia => fatty liver}	0.4018
{Hypertension => atherosclerosis}	0.3832
{Dental disease => hemorrhoids}	0.3789
{Disordered lipoprotein metabolism => fatty liver}	0.3701
{Chronic rhinitis => chronic pharyngitis}	0.3702

Table 3: Mining results of cluster analysis in the second cluster.

Disease combination	Support
Obesity, hypertriglyceridemia	0.1934
Hypertriglyceridemia, fatty liver	0.1355
Obesity, hypertriglyceridemia, fatty liver	0.1312
Obesity, fatty liver	0.4967
Obesity, gallbladder disease	0.1047
Fatty liver, gallbladder disease	0.0523

Table 4: Cluster analysis results of the top six cluster analysis confidence rankings mined in cluster 2.

Association rules	Confidence
{Chronic pharyngitis => obesity}	0.9999
{Hemorrhoids => obesity}	0.9999
{Heart disease => atherosclerosis}	0.9221
{(Diabetes, lipoprotein metabolism disorder) => fatty liver}	0.8330
{(Obesity, lipoprotein metabolism disorder, diabetes) => fatty liver}	0.8542
{(disordered lipoprotein metabolism, snoring) => fatty liver}	0.8014

incidence factors of chronic kidney disease, and the validity of the rules obtained by the improved algorithm was evaluated. Select the 23 physical examination feature items contained in Table 5 as independent variables, and set the final classification result as the dependent variable. The discretized data set was submitted to the data statistical analysis software IBMSPSSStatistics22 developed by IBM for multinomial Logistic regression analysis. Logistic regression analysis is a generalized linear regression analysis model, which is often used in data mining and automatic disease diagnosis. In the experiment, the final classification result of chronic kidney disease was set as the dependent variable, and the related physical examination items of chronic kidney disease were analyzed. By comparing the specific experimental results and comparing the specific odd ratio (OR) value, it can also be regarded as an accurate estimate of the relative risk of chronic kidney disease. It was concluded that the four main factors affecting the incidence of chronic kidney disease were hypertension, diabetes, urine specific gravity, and albumin content. Among them, the highest correlation with chronic kidney disease was hypertension, OR = 2.754, and the weakest was urine specific gravity, OR = 1.262. The results of logistic regression analysis are shown in Table 5.

In the case of the same minimum support threshold and different number of case items, comparing the running time of the two algorithms. It can be seen from Figure 4 that the running time of the two algorithms increases with the number of case records, and there is a more obvious distinction from 6000 records, and with the increase in the

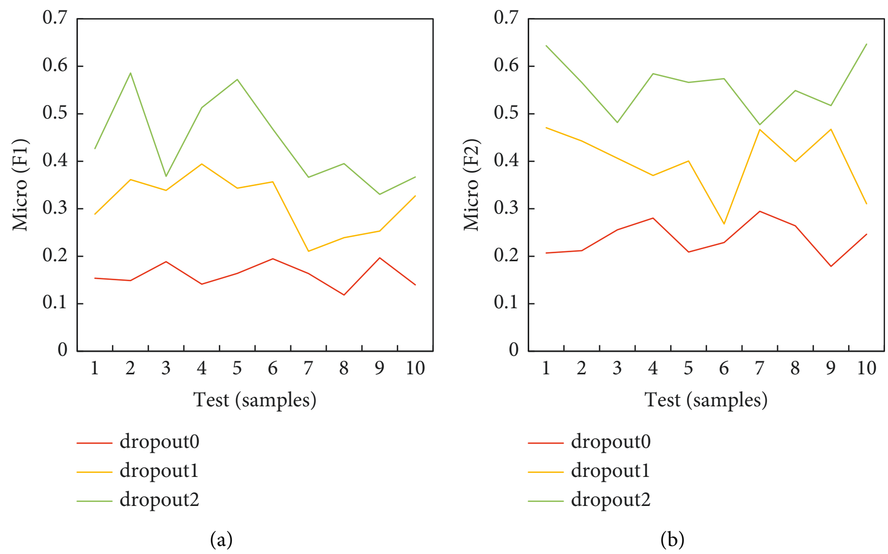

Figure 3: Activation function performance. (a) ReLU. (b) Sigmoid activation function.

Table 5: Logistic regression analysis results.

Feature item	Standard error	OR
Hypertension	0.133	2.743
Diabetes	0.187	2.044
Albumin content	0.231	1.732
Urine specific gravity	0.115	1.266

number of case records, the time difference between the two algorithms will gradually widen. When the number of case records decreases, the time gap between the two algorithms will gradually shorten. For example, when the number of case records is 4000, the running time of the traditional vertical data format algorithm is almost the same as the running time of the K-means algorithm, both of which are about 23 s. The main reason is that in the case of a small number of data pieces, although the K-means algorithm reduces a large number of cyclic comparison operations in the orthogonal process, there is a process of calculating the difference set table in the algorithm flow, which will take a certain amount of time. Even when the number of case records is 2000, there is a situation where the traditional data format takes less time. However, with the increase of the number of records, the advantage of K-means algorithm can be manifested when the time to find the difference table is negligible compared to the time spent by a large number of loop comparisons. The comparison of K-means and DSE is shown in Figure 4.

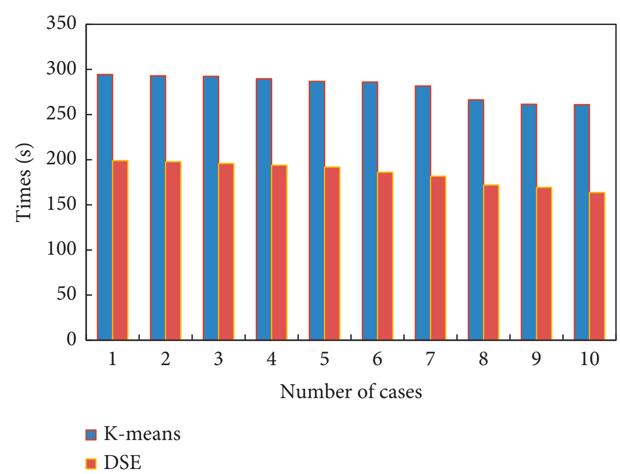

Figure 4: Comparison of K-means and DSE.

The time required for both algorithms to run decreases as the minimum support threshold increases, because the size of the minimum support threshold affects the generated candidates. Under different minimum support thresholds, the results of the running time of the two algorithms are compared, in which there are a total of 8000 transaction data. It can be seen from this that when the support is increasing, the number of candidates generated by the algorithm is correspondingly reduced, and the time consumption is also reduced (as shown in Figure 5(a) per second). As can be seen from Figure 5, when the support threshold is before 3%, the K-means algorithm has a great reduction in the running time compared with the traditional vertical data format algorithm (the algorithm can construct an ordered search list and use the depth-first search strategy to simultaneously generate the candidate set and the support of the candidate set). This shows that in the case of a large number of candidate item sets, the time efficiency of the K-means algorithm is nearly doubled. When the support threshold is increased to 3%, the running time of the two algorithms will gradually tend to be flat due to fewer and fewer candidate item sets generated (the response efficiency is shown in Figure 5(b)).

Among male medical examiners with hypertension, the confidence level of being diagnosed with kidney disease is about 81%. The reason is that high blood pressure will lead to atrophy of the blood supply and excretion function of the kidneys, lesions of the renal arteries, resulting in proteinuria, and blood pressure will continue to increase. Thus, a vicious

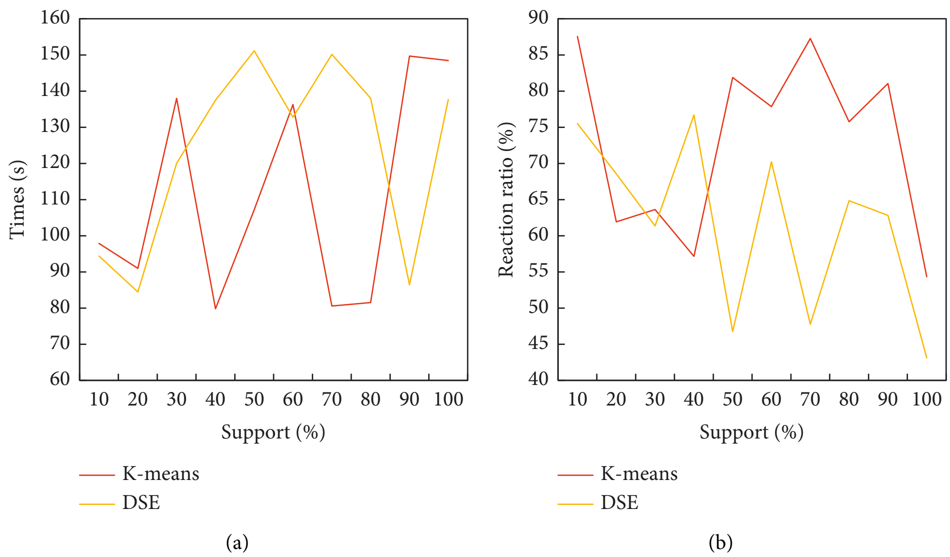

Figure 5: Minimum support threshold. (a) Runs per second. (b) Reaction efficiency.

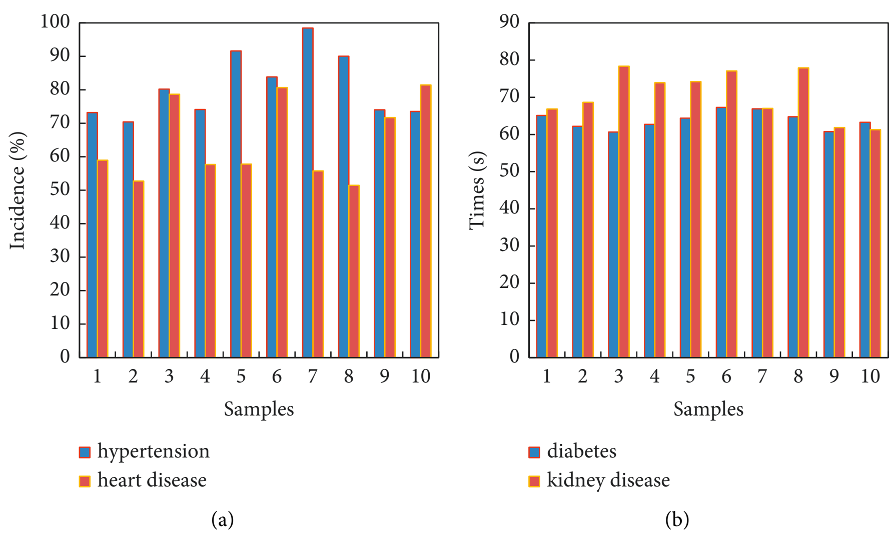

Figure 6: Probabilities of different diseases. (a) Hypertension and heart disease. (b) Kidney disease and diabetes.

circle (high blood pressure and heart disease are shown in Figure 6(a)). The cause of high blood pressure in men is often caused by staying up late, drinking alcohol, and irregular eating habits for a long time. Therefore, maintaining a good routine of work and rest and healthy eating habits, and drinking less alcohol are of great help in preventing and reducing kidney disease. Among male medical examiners with diabetes, the urine specific gravity is greater than 1.025, and the albumin content in urine is more than 5.5 g/d, the confidence level of being diagnosed with kidney disease is about 73%. These two values are higher than the normal values, both because of glomerular filtration problems, resulting in disorders of the body's metabolism, increased protein content in the urine. In this case, it is necessary to go to the hospital for treatment in time, and irregular physical examination is also a very important cooperative measure (nephropathy and diabetes are shown in Figure 6(b)).

Taking hypertension as the dependent variable, the correlation analysis between chronic diseases was carried out. The experimental results are shown in Figure 7. According to the experimental results, comparing the OR value, the analysis concluded that there are five chronic diseases affecting the occurrence of hypertension, namely hyperlipidemia, diabetes, fatty liver, coronary heart disease, and stroke. Among them, the chronic disease with the strongest correlation with hypertension was hyperlipidemia, $OR = 3.826$, and the weakest was stroke, $OR = 1.415$. According to the results of the above statistical analysis, it can be seen that chronic diseases such as hyperlipidemia and diabetes have a promoting effect on the occurrence of hypertension, and they are all risk factors for hypertension (the standard error is shown in Figure 7(a)). Similarly, using several other chronic diseases as the dependent variable for analysis, it was found that when any one chronic disease was

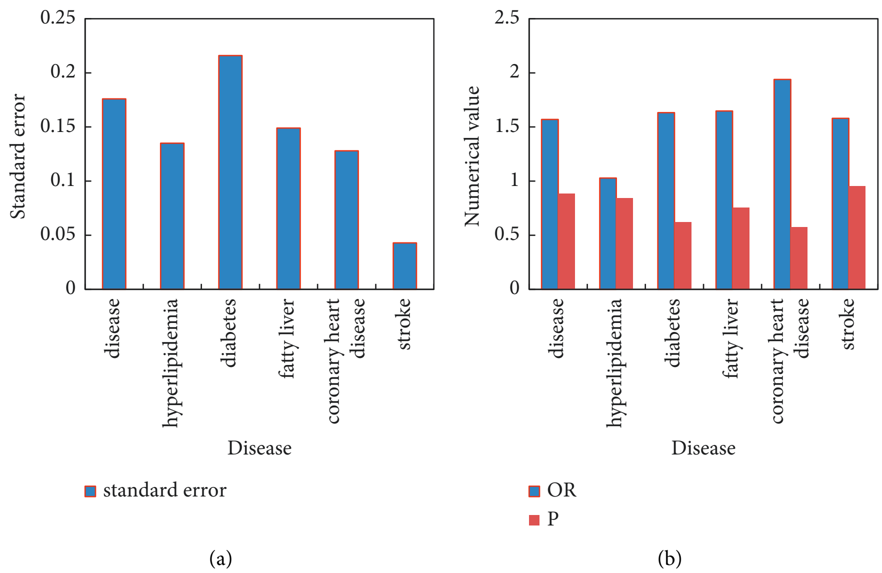

Figure 7: Experimental results. (a) Hypertension and heart disease. (b) Kidney disease and diabetes.

used as the dependent variable, several other chronic diseases had an impact on it (OR and P are shown in Figure 7(b)).

The selected important influencing factors for the occurrence and development of hypertension are age, environmental factors, other diseases, season, gender, BMI, fasting blood glucose, triglycerides, occupation, smoking history, drinking history, genetics, potassium, systolic blood pressure, abnormal indicators, individual factors, high-density cholesterol, low-density cholesterol, diastolic blood pressure, sodium, kidney disease, endocrine, uric acid, total cholesterol, primary and secondary hypertension etc., totaling 26. Changes in heart rate and increased peripheral resistance can lead to low pressure. Because the degree of obesity reflected by the ratio of height factor to weight factor is included in BMI index, it is no longer selected as an important influencing factor. Since there are still many influencing factors selected, and there is a certain overlap between them, the affiliation is not clear. In order to carry out in-depth research, preliminarily determine the degree of influence of various important factors, and gradually clarify the etiological evidence of the occurrence and development of hypertensive diseases, which can be used for risk prediction of the occurrence and development of hypertensive diseases. In this study, the system structure model was used to perform hierarchical clustering analysis on the selected important influencing factors to construct a hierarchical structure of the important influencing factors of hypertension disease management, and then calculate the influence weight of each factor. The proportion of important factors affecting the occurrence and development of hypertension is shown in Figure 8.

After 12 weeks of exercise intervention, the weight of the exercise group decreased by 3.11%, waist circumference decreased by 2.48%, and the decrease was very significant compared with the previous one ($P < 0.01$). Waist-to-hip ratio and body fat percentage decreased significantly

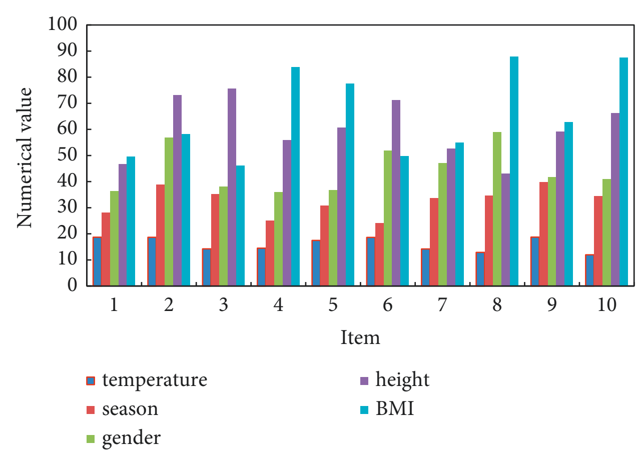

Figure 8: Proportion of important factors affecting the occurrence and development of hypertension.

compared with those before exercise ($P < 0.05$). Compared with before intervention, hip circumference showed a slight downward trend, but the difference was not significant ($P > 0.05$). The control group decreased by 0.60% ($P > 0.05$).

Waist circumference is an easy, inexpensive way to measure abdominal obesity. Computed Tomography (CT), MRI, ultrasound, bioelectrical impedance analysis, and dual-energy X-ray are also methods for quantitatively detecting abdominal fat. There is an indisputable link between visceral adipose tissue (VAT) and cardiometabolic risk, and normal normative body weight, BMI and waist circumference are the main indicators of nonpharmacological lifestyle health management. The exercise management regimen of this study played a role in reducing body weight and waist circumference in the managed population. Weight loss is based on lifestyle changes, including diet and increased physical activity. The comparison of body shape before and after the experimenter's intervention is shown in Figure 9.

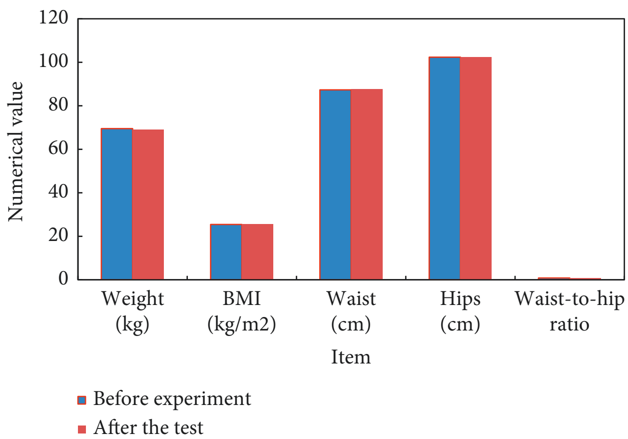

Figure 9: Comparison of body shape before and after the experimenter's intervention.

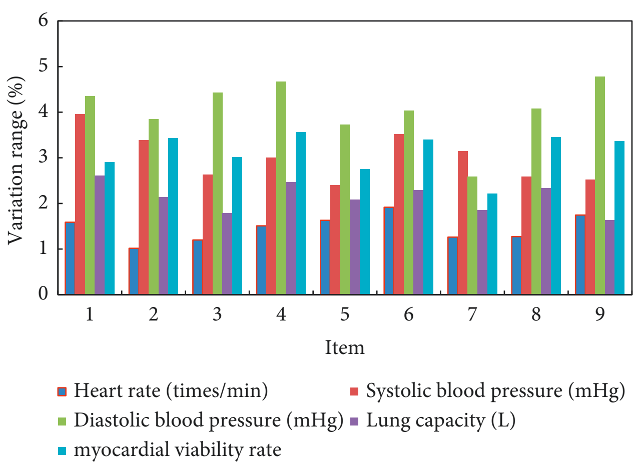

Figure 10: Range of physical function changes after intervention.

After 12 weeks of exercise intervention, the vital capacity of the exercise group increased significantly (5.83%) ($P < 0.01$); the subendocardial myocardial vitality rate increased by 9.74% ($P < 0.01$), and the radial artery reflected wave growth index and systolic blood pressure decreased slightly ($P < 0.05$). It shows that 12 weeks of exercise training intervention can effectively enhance the cardiopulmonary function of the exercise group, thereby significantly improving the body's aerobic capacity ($P < 0.05$). Exercise affects both the development of atherosclerosis and the incidence of primary and secondary cardiovascular events, including myocardial infarction and stroke. Exercise also plays an important role in improving other chronic vascular diseases, including diabetes and dementia. Worldwide, the proportion of elderly people suffering from coronary heart disease is relatively high. The range of physical function changes after the intervention is shown in Figure 10.

4. Conclusion

Chronic diseases are characterized by complex causes, high morbidity, and high mortality. Once diagnosed, they are difficult to eradicate. The management of chronic diseases is mainly based on prevention and control, and only early diagnosis and early treatment can effectively reduce the risk of disease. Therefore, after people's routine physical examination, in-depth chronic disease risk prediction is carried out on their physical examination data, and citizens' understanding of chronic diseases will be strengthened, which will effectively reduce the incidence of chronic diseases. With the increase of age, the related indicators of chronic diseases also showed an upward trend. At the same time, the comorbidity rate of chronic diseases in the overweight and obese population was also significantly higher than that in the normal population. However, whether it is a senior or an overweight or obese population, there are differences between their exercise ability and normal physique adults. Based on the formulation of exercise prescriptions, this study conducts exercise ability assessment, provides scientific guidance through health management model, and uses K-means algorithm to classify and intervene training for chronic disease patients with different symptoms. It solves the problem of insufficient athletic ability and lack of scientific guidance for these people. The K-means algorithm proposed in this study has greatly improved the efficiency of case data analysis. The physical examination health data used in this paper only includes the basic data and laboratory biochemical data of the physical examination personnel and does not fully consider the physical examination personnel's eating habits, exercise habits, drug use, and other medical records and other data. Therefore, a wider range of feature dimensions can be used in the next research to improve the performance of the model. Constructing a unified medical database specification is beneficial to the data sharing of different medical institutions.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The author declares that there are no conflicts of interest.

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References

[1] J. Shlisky, D. E. Bloom, A. R. Beaudreault, K. L. Tucker, H. H. Keller, and Y. F. Levi, "Nutritional considerations for healthy aging and reduction in age-related chronic disease," *Advances in Nutrition An International Review Journal*, vol. 8, no. 1, pp. 17–26, 2017.

[2] B. D. Thombs, L. Kwakkenbos, K. E. Riehm, N. Saadat, and C. Fedoruk, "Comparison of Self-Efficacy for Managing Chronic Disease between patients with systemic sclerosis and

other chronic conditions: a systematic review," *Rheumatology International*, vol. 37, no. 2, pp. 281–292, 2017.

[3] M. Vooijs, M. C. Leensen, J. L. Hoving, H. Wind, and M. H. F. Dresen, "Perspectives of people with a chronic disease on participating in work: a focus group study," *Journal of Occupational Rehabilitation*, vol. 27, no. 4, pp. 593–600, 2017.

[4] I. O. Acham, S. Ahemen, M. T. Ukeyima, and A. T. Girgih, "Tropical fruits: bioactive properties and health promoting benefits in chronic disease prevention and management," *Asian Food Science Journal*, vol. 3, no. 1, pp. 1–13, 2018.

[5] E. A. Yetley, A. J. Macfarlane, L. S. G. Finestone, C. Garza, and J. D. Ard, S. A. Atkinson, D. M. Bier, A. L. Carriquiry, W. R. Harlan, D. Hattis, and J. C. King, "Options for basing Dietary Reference Intakes (DRIs) on chronic disease endpoints: report from a joint US-/Canadian-sponsored working group," *American Journal of Clinical Nutrition*, vol. 105, no. 1, pp. 249S–285S, 2017.

[6] J. Qin, W. Fu, and H. Gao, "Distributed k-means algorithm for sensor networks based on multi-agent consensus theory," *IEEE Transactions on Cybernetics*, vol. 47, no. 3, pp. 772–783, 2017.

[7] J. Mario Haut, M. Paoletti, J. Plaza, and A. Plaza, "Cloud implementation of the K-means algorithm for hyperspectral image analysis," *The Journal of Supercomputing*, vol. 73, no. 1, pp. 1–16, 2017.

[8] A. Kumar, D. Kumar, and S. K. Jarial, "A hybrid clustering method based on improved artificial bee colony and fuzzy C-means algorithm," *International Journal Of Artificial Intelligence*, vol. 15, no. 2, pp. 40–60, 2017.

[9] K. Varadarajan and X. Xiao, "On the sensitivity of shape fitting problems," *Louisiana History the Journal of the Louisiana Historical Association*, vol. 24, no. 4, pp. 377–388, 2012.

[10] M. K. Alsmadi, "A hybrid Fuzzy C-Means and Neutrosophic for jaw lesions segmentation," *Ain Shams Engineering Journal*, vol. 9, no. 4, pp. 697–706, 2017.

[11] O. Alessandro, A. Filho, E. M. Rodriguez, M. G. Carta, and S. Machado, "Physical exercise for Parkinson's disease: clinical and experimental evidence," *Clinical Practice & Epidemiology in Mental Health Cp & Emh*, vol. 14, no. 1, pp. 89–98, 2018.

[12] H. Anne, P. Werner, R. Friederike, and M. Tim, "Repeated testing for the assessment of individual response to exercise training," *Journal of Applied Physiology*, vol. 124, no. 6, pp. 1567–1579, 2018.

[13] K. M. Mustian, C. M. Alfano, C. Heckler, and A. S. Kieckner, "Comparison of pharmaceutical, psychological, and exercise treatments for cancer-related fatigue: a meta-analysis," *JAMA Oncology*, vol. 3, no. 7, pp. 961–968, 2017.

[14] R. B. Batacan, M. J. Duncan, V. J. Dalbo, P. S. Tucker, and A. S. Fenning, "Effects of high-intensity interval training on cardiometabolic health: a systematic review and meta-analysis of intervention studies," *British Journal of Sports Medicine*, vol. 51, no. 6, pp. 494–503, 2017.

[15] P. Williamsn, G. Atkinson, and A. M. Batterham, "Inter-individual responses of maximal oxygen uptake to exercise training: a critical review," *Sports Medicine*, vol. 47, no. 8, pp. 1501–1513, 2017.

[16] M. Klompas, N. M. Cocoros, J. T. Menchaca et al., "State and local chronic disease surveillance using electronic health record systems," *American Journal of Public Health*, vol. 107, no. 9, pp. 1406–1412, 2017.

[17] T. Vandiver, T. Anderson, B. Boston, C. Bowers, and N. Hall, "Community-based home health programs and chronic disease: synthesis of the literature," *Professional Case Management*, vol. 23, no. 1, pp. 25–31, 2018.

[18] G. S. Birkhead, "Successes and continued challenges of electronic health records for chronic disease surveillance," *American Journal of Public Health*, vol. 107, no. 9, pp. 1365–1367, 2017.

[19] K. S. Almberg, L. S. Friedman, D. Swedler, and R. A. Cohen, "Mine safety and health administration's part 50 program does not fully capture chronic disease and injury in the Illinois mining industry," *American Journal of Industrial Medicine*, vol. 61, no. 5, pp. 436–443, 2018.

[20] A. B. Neiman, T. Ruppar, M. Ho et al., "CDC Grand Rounds: improving medication adherence for chronic disease management - innovations and opportunities," *American Journal of Transplantation*, vol. 18, no. 2, pp. 514–517, 2018.