Kurdish Studies
Jan 2023
Volume: 11, No: 01, pp. 319-331
ISSN: 2051-4883 (Print) | ISSN 2051-4891 (Online)
www.KurdishStudies.net

Received: May 2023 Accepted: September 2023
DOI: https://doi.org/10.58262/ks.v11i1.1024

Analysis of Behavioral Motivation in a Self-Management Model of Physical Activity

Yang Gan[1*]

Abstract

In this paper, we preprocess data in self-management of physical exercise according to different dataset attributes, perform attribute coding commonly used features binary, and use data standardization to scale physical exercise data attributes to mean values. Supervised information of physical exercise can be achieved to minimize the training error. Regression classification based on elastic networks is performed to obtain important physical activity self-management feature sets. Indicators in the database reflecting the impact of physical exercise on the body, and accordingly the set of attributes of the database is noted as attribute values. The metabolic data under the elastic network algorithm is 0.6, and the number of iterations is sustained at a peak of 570 times, which is conducive to the development of physical exercise and self-management outside the physical education classroom.

Keywords*: data normalization, elastic network, physical exercise, self-management, training error*

Introduction

In recent years, the mass of blind physical exercise caused by physical injury cases have been repeatedly reported, the topic of scientific exercise by people generally concerned about the management of physical exercise, especially self-management of physical exercise is rarely mentioned, people participate in physical exercise, physical exercise behavior must be managed in order to reap the desired results (Matsumoto & Takenaka, 2022; Tsai, Chang, Chang, & Lin, 2021). The lack of management of physical activity is blind and random, and it is often futile because of the lack of quality assurance, and in serious cases, it even causes physical and mental damage (Göhler, Hattke, & Göbel, 2022; Hussain & Zhang, 2023). Management is an activity in which people regulate their behavior to achieve the purpose and make it effective. Any purposeful behavior to achieve results must be regulated. Physical exercise is no exception, and physical exercise management is an activity in which pe (Kim & Kwon, 2018)ople regulate exercise behavior in order to achieve the purpose of exercise so as to make it effective (Bebeley, Liu, & Wu, 2017; Petrenko, 2020; Seo, Kim, & Min, 2017). Physical exercise is essentially a sport as the basic means, to exercise the body and mind for the realization of the way to promote health as the fundamental purpose of practical activities, regulate physical exercise behavior is to give full play to the physical exercise to promote physical and mental health function of the inevitable requirements (Iona, Scarfone, Ammendolia, & SEGURA GARCIA, 2018; Lee, 2017; Oliveira et al., 2019).

When people participate in physical exercise, their behavior must conform to the objective laws of sports and follow the basic principles of physical and mental health. The more scientific the regulation of physical activity behavior is, the more the function of physical activity can be given full play, and the more significant its role in serving to promote health and improve the quality of life will be. Literature (Colangelo & Weissbrod, 2019) explored factors associated with exercise behavior to determine how these factors vary in relation to female exercise behavior in order to examine the relationship between exercise social support, exercise self-efficacy, and intrinsic and extrinsic motivation and exercise behavior. A community sample of 357 adult females was used to complete a baseline online survey. Significant differences were found for all

[1] Sports and Health College, Wu Zhou University, Wuzhou, Guangxi, 543001, China. **Email:** wz-gan@163.com

factors in the stages of change with the exception of physical social support. Literature (Qiu & Zhang, 2020) Adopting appropriate measures to strengthen the positive link between implicit attitudes toward exercise may have implications for promoting physical activity. Computerized evaluation of conditioning, a strategy commonly used to change intra-individual cognition, on implicit attitudes and physical activity behavior (Reaume, 2021). Changing Implicit Attitudes Toward Exercise explored whether changes in implicit attitudes toward exercise had any effect on physical activity in the subsequent week, resulting in no significant differences in self-reported physical activity.

Literature (Bebeley, Wu, & Liu, 2017) states that physical activity can be expressed as a public health factor or determinant, related to motor skills of the human musculoskeletal system. Kilocalorie intake and consumption are needed to improve health and healthy lifestyles, thereby reducing mortality and morbidity among college students. The factors measured and assessed under the level of motivation for physical activity among college students were scored using the Motor Behavior Regulation Scale, the Physical Activity Motivation Scale, the Decision Balance Scale, and the Physical Activity Self-Efficacy Scale as the instruments of investigation. Literature (Kotaman & Evran, 2021) tested the effect of two minutes of physical activity at the beginning and in the middle of the class on college students' state motivation and academic performance.

Three cohorts were randomly assigned to the experimental, Hawthorne, and control groups. The results of the study reveal the direct positive effects of physical activity on academic performance. Significant combined effect of physical activity and state motivation on academic performance. In the above literature, individuals have difficulty in controlling the load of physical activity during physical activity and are unable to be able to achieve good results. Inability to produce adaptive responses to new exercise stimuli and difficulty in detecting the effects of physical exercise (ALSHAWY, Ibrahim, Hussein, & Lahlah, 2019).

This paper combines physical exercise and behavioral motivation to design a self-management motivation model for physical exercise. By normalizing the physical exercise data to normalize all the data attributes to the interval, the real influence degree of sports data on the indexes is obtained sorted and labeled. Variable screening and complexity adjustment are performed by controlling parameter entry, so as to evaluate and analyze the sports results. Using the feature selection method of grayscale processing to study the importance of data features and infer the influence of corresponding sports on corresponding physical indicators. The data on physical indicators before and after group training were obtained through measurement, and the data on changes in physical indicators before and after folkloric sports training were calculated. By analyzing the differences in self-management of physical exercise and self-management motivation, the inheritance and development of the traditional management mode, the use of information technology and intelligent technical means. It builds an intelligent management model that meets students' exercise needs by focusing on satisfying students' diversified sports, guided by corresponding policies issued by the government, supervised and operated by colleges and universities, and guaranteed by constant maintenance and updating by technology companies.

Analysis of the motivation of physical exercise self-management behavior

Constructing a self-management motivation model for physical activity

The degree of effectiveness of physical exercise management depends on school policy orientation, meeting students' needs and evaluation mechanisms. By constructing a self-management motivation model for physical activity, we satisfy students' exercise needs and determine the calculation method for students' physical activity (Helms, Morris, & Griddine, 2021; Prystynskyi, Babych, Zaytsev, Boychuk, & Taymasov, 2020). To solve the school management confusion and form a structural framework guided by school policy and led by students' physical activity self-management, Figure 1 shows the physical activity self-management motivation model. In the model, student demand is the core, and the school management system is the key. The implementation rules of extracurricular sports management are well formulated, the relevant system is developed and improved after the establishment of the management organization, and the software and hardware are well coordinated. Among them, the system is an important guarantee for the implementation of extracurricular physical exercise management, including management and implementation methods, financial security, supervision and management, evaluation and feedback and incentives and rewards. After meeting these conditions, as long as the management department to grasp the implementation of the work, will achieve better results.

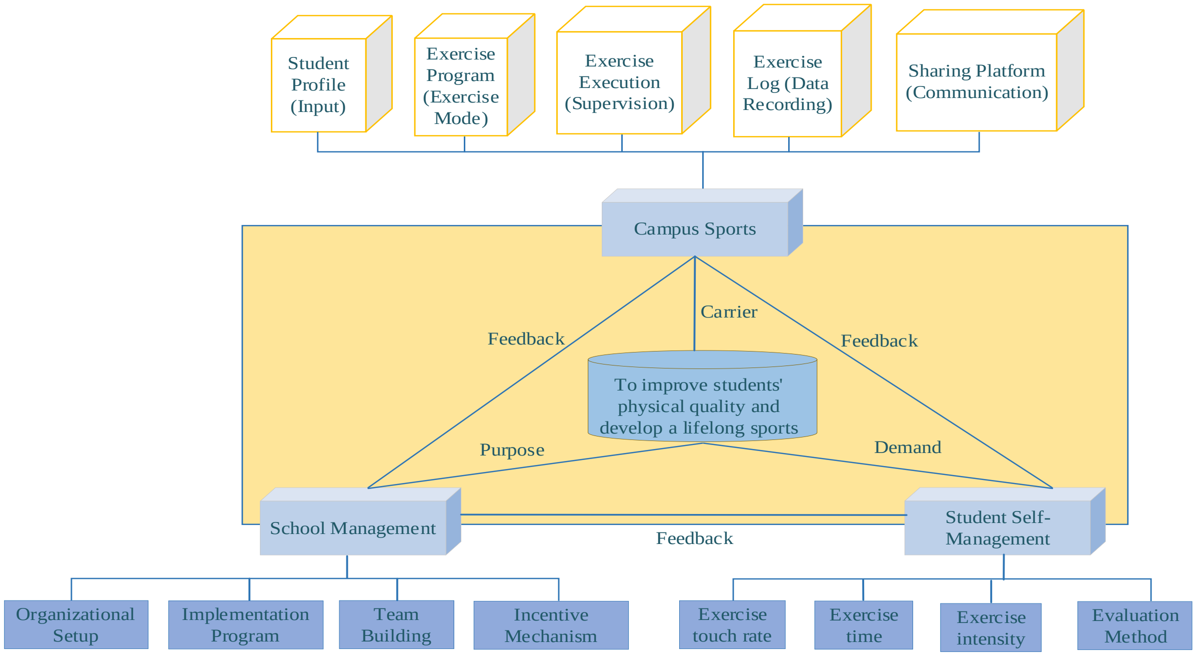


Figure 1: Motivation Model for Self-management of Physical Exercise

Intelligent Platform Architecture for Physical Exercise

In order to promote the participation of students in after-school sports, improve the efficiency of teachers' management and the quality of physical exercise, it is proposed to build an intelligent platform that integrates intelligent data collection and processing, data analysis and data push function (Tucker & Conteh). Figure 2 shows the architecture of intelligent sports platform in colleges and universities, and the intelligent sports platform covers a number of sub-systems such as after-school exercise management system video teaching management system, course management system, stadium management system, club management system and other sub-systems to build an intelligent sports platform.

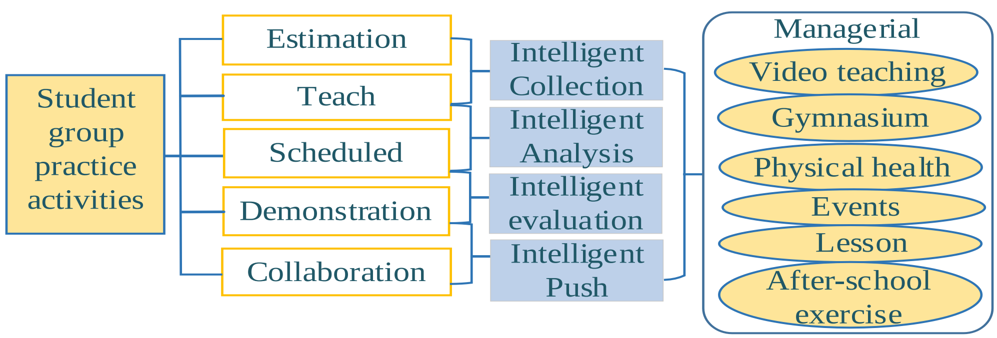


Figure 2: Architecture of Intelligent Sports Platform in Universities

In the intelligent platform architecture, anti-cheating technology and big data technology are widely combined and applied to build into a benign interactive cycle of data collection, data analysis, data application and data collection, to effectively establish a bridge between process management and goal management, to form an effective three-dimensional interactive mode of data collection, intelligent data analysis, and informatized data application, and to enhance the modernization of the school sports governance system and governance capacity. Using the intelligent sports platform to promote the integration of sports classroom teaching, after-school physical exercise, students' physical fitness monitoring, sports club management, etc., to explore an intelligent management model suitable for the development of school sports work, to realize the precise governance of students' physical fitness and health promotion, and to promote the intelligent development of school sports on the basis of overall improvement of students' physical fitness and health level. Stimulate the enthusiasm of students to carry out after-school physical exercise independently, improve the management efficiency of teachers and administrators, give full play to the advantages of Internet-assisted teaching by means of goal management and points management, cultivate students' lifelong sports awareness and habits, and help to improve the quality of physical education teaching (Feng et al., 2021). Regularly releasing students' after-school physical activity and physical fitness and health big data helps to realize the precise governance of students' physical fitness and health promotion. Take the physical education classroom, physical fitness monitoring, and after-school physical exercise as a breakthrough to establish an intelligent physical education service and management platform, and promote the intelligent construction of school physical education(Ghanem et al., 2020).

Return to physical activity using resilient networks

Achieving Minimized Exercise Training Error

Data preprocessing in self-management of physical activity has a standardized and unified process with preprocessing steps based on different dataset attributes (Hamido, Gu, & Itoh, 2021). The common processes for data preprocessing are removing unique attributes, handling missing values, attribute coding and data normalization. Attribute coding is commonly used for feature dichotomization, and data normalization is used to scale the data attributes of a column to the mean value. Data normalization normalizes all data attributes into intervals to obtain the real degree of influence of sports data on the indicator sorted annotation. The physical activity indicator is expressed as:

$$Impact_C(a_P) = \sum_{m=1}^{z} vote(m, a_p) \qquad (1)$$

$Impact_C(a_P)$ represents the importance of the Cnd type of exercise for the prd physical indicator, m represents the mth voter, and z represents the total number of voters, who empirically voted in order based on the effect of this type of exercise on the indicator, and summed the votes.

Supervised information-based physical exercise can be achieved by minimizing training error, by fitting the data as closely as possible, while regularization parameters prevent model overfitting. The model complexity is reduced and the overfitting problem is solved by using regularization terms. The mathematical expression of the limiting loss function by adding a penalty term to the original objective function is given as:

$$\tilde{J}\ (w, X, y) = J\ (w, X, y) + a\Omega(w) \quad (2)$$

X, y is the physical activity training samples and labels, w is the vector of weight coefficients, J is the empirical risk, $\Omega(w)$ is the regularization term, and coefficient a controls the strength of regularization.

Based on the elastic network for regression classification, to obtain the important physical activity self-management feature set, to analyze and evaluate the physical activity effect situation. Through the control parameter into the variable screening and complexity adjustment, so as to evaluate and analyze the results of sports, evaluation index selection characteristics:

$$min\|y - A\beta\|_2{}^2 + \lambda_1\|\beta\|_1 + \lambda_2\|\beta\|_2{}^2 = J\ (w, X, y) + a\|w\|_2 \qquad (3)$$

β is a multidimensional vector of columns of regression coefficients and λ_1, λ_2 is the coefficients before and after obtaining the attributes respectively. This feature selection process obtains the importance ranking of influencing the effect of physical activity, after which experiments are conducted with evaluating the effect.

Information gain is an important criterion for behavioral motivation feature selection, for a feature, the difference in the amount of information about physical activity before and after the change is the entropy, which is used to measure the uncertainty of a random variable using entropy. A finite discrete random variable, a random variable is defined as:

$$H(X) = -\sum_{i=1}^{n} p(x_i)\, log_2\, p\,(x_i) \qquad (4)$$

The more possible variations of a random variable X the more information it X provides and the greater the $p(x_i)$ entropy. For classification or clustering problems, the more variations there are in the category to which the self-managed document belongs, the more informative the category is.

Indicators in the database reflecting the effects of physical activity on the body, and accordingly the set of attributes of the database is noted as attribute values. For the values of the indicator features, the training set is divided by the indicator, which is calculated by the formula:

$$Ent(D) = \sum_{q=1}^{\|y\|} p_q \, log_2 \, p_q \qquad (5)$$

Where p_q denotes the proportion of class q samples in the set of physical activity samples D, and $Ent(D)$ is the information entropy in the physical activity samples. Considering the different number of samples contained in different branch nodes, the branch nodes are given weights, and the weight calculation expression is:

$$Gain(D, a) = Ent(D) - \sum_{v=1}^{V} \frac{|D^v|}{|D|} Ent(D^v) \qquad (6)$$

The information gain obtained from the segmentation of the physical activity sample set D by attribute a, D^v was used to assess the classification performance of self-management, and the mean of the error values was used to indicate the importance of feature V. The inclusion of a random behavioral motivation study to predict changes in exercise patterns selects the features that are important.

Grayscale processing of physical exercise images

Extracting physical activity information

The importance of data features is studied by using the feature selection method of grayscale processing to infer the influence of corresponding sports on the corresponding body indexes. The data of body indexes before and after group training were obtained through measurement, and the data of body index changes before and after folk sports training were calculated to obtain the attribute set of indexes that have a greater impact of physical exercise on body indexes. The matrix of changes in body indicators before and after training is denoted as:

$$P_{t+1} = (x_{t+1}, y_{t+1}) = (x_t, y_t) + (M * w_t)_{\bar{x},\bar{y}} \qquad (7)$$

(x_t, y_t) represents the position where the feature point is located at the moment t, (x_{t+1}, y_{t+1}) represents the position where the feature point is located at the moment, M represents the median filter, and w_t represents the dense optical flow field at the moment, which is used to determine the position of the feature point in the next frame by calculating the change of the optical flow within a certain range.

The description is extracted in the vicinity of the trajectory of the feature point, and all the extracted features are encoded and classified, and finally the recognition of the behavior is achieved. Representing the gray values of the corresponding pixel points in the said before and after frames, the difference image between the two frames can be shown by the following equation (8):

$$D_n(x, y) = |f_n(x, y) - f_{n-1}(x, y)| \qquad (8)$$

f_n is the set behavioral motivation threshold, which is the difference between the pixel points of two frames, and f_{n-1} is the queue value of physical exercise. Based on this to detect the instantaneous rate of the exercise object, the effective extraction of the temporal information in the middle has to maintain the amplitude of movement between neighboring frames. The position of the motion pixel point of the sport exercise is:

$$I(x, y, t) = \frac{\partial I}{\partial x} + \frac{\partial I}{\partial y}\partial y + \frac{\partial I}{\partial t}dt + \varepsilon \qquad (9)$$

$\frac{\partial I}{\partial x}$, $\frac{\partial I}{\partial y}$, and $\frac{\partial I}{\partial t}$ denote the gray value of the pixel point along the partial derivative of the x, y, t direction, and $\boldsymbol{\varepsilon}$ denotes the optical flow vector in the direction. Thus, the ability of describing human behavior is improved to directly affect the effect of behavior recognition, and its spatial and temporal tributaries are structurally improved. After grayscaling and size-unification processing of the sports exercise image, it is subjected to convolution, pooling and other operations to extract the spatial feature information in the image.

Physical exercise process

For the detection and tracking of moving targets, firstly, a static image of physical exercise is intercepted as a background, and secondly, this background is compared with the intercepted image of the next time period. By sensing whether there is a large change or not, and then according to the gray scale median filtering to determine the moving target, to complete the tracking of physical exercise moving target. Figure

3 shows the grayscale processing physical exercise process, which ensures the effective advancement of the physical exercise self-management model. The process is as follows:

(1) Use the computer terminal to perform grayscale operation on the physical exercise image sequence, and then select multiple frames from the physical exercise image sequence to form the training image sequence (Wdowiak-Okrojek, Lipiec, Wejner-Mik, Bednarkiewicz, & Kasprzak, 2021). The respective corresponding gray-level feature sets of the pixel points in the physical exercise image sequence were extracted, and then the individual gray-level feature sets were filtered to obtain the physical exercise self-management motivation model.

(2) Then the subsequent video surveillance images in the image sequence are subjected to motion target detection, and then the images containing the motion targets are subjected to morphological filtering and connectivity region detection to obtain the contours and locations of the motion targets. For motion targets searching in the set of gray-scale features corresponding to pixel points without complex parameter estimation and probability calculation not only simplifies the detection process to improve the detection accuracy, but also reduces the time overhead to improve the operation efficiency.

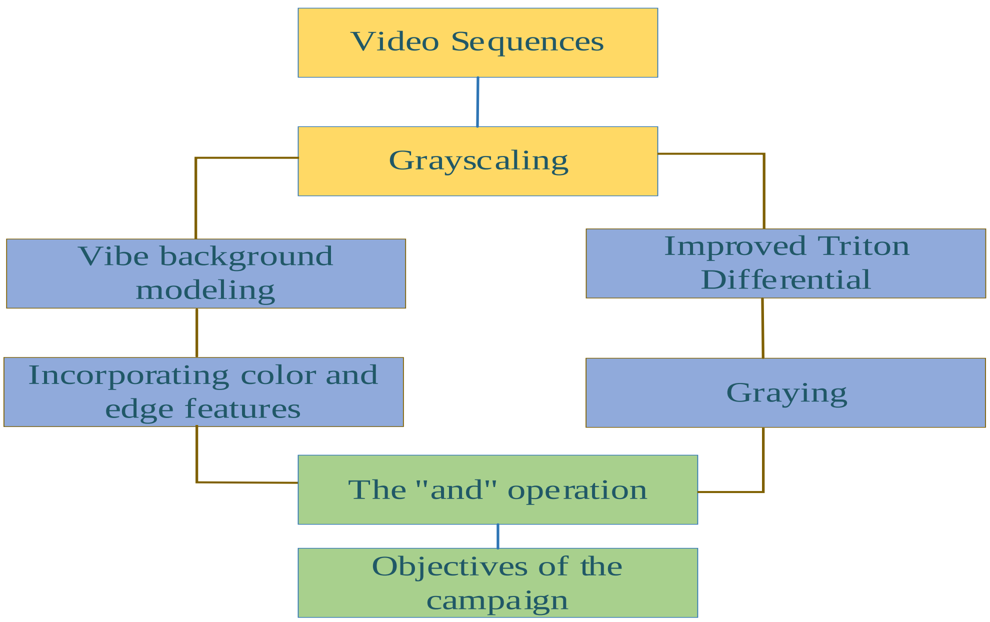


Figure 3: Flow Chart of Grayscale Processing for Physical Exercise

Elastic network convolutional feature dependence

Compressed channel characterization vector

Convolutional features based on elastic networks using channel attention for discovery of convolutional features are used to focus on regions of significant behavioral motion for efficient behavior recognition. A channel attention mechanism is introduced to improve the recognition capability of the network by explicitly modeling the interdependencies between convolutional channel features. The global spatial information is compressed and expressed as a channel feature description vector. Global average pooling is defined as follows:

$$U_c = \frac{1}{H \times W} \sum_{i=1}^{H} \sum_{j=1}^{W} X_{c,i,j} \qquad (10)$$

$X_{c,i,j}$ denotes the response value at the position in the feature map of the Cnd channel, and U_c is the Cth element of the channel feature description vector. Based on the global average pooled aggregated channel information, a set of convolution operations are subsequently applied to learn the dependencies between the channels as in the following equation:

$$a = f(W_u \delta(W_d U)) \qquad (11)$$

W_d is the weight parameter of the downsampled convolutional layer for the channel with a reduction scale of r, δ denotes the activation function, W_u is the weight parameter of the upsampled convolutional layer for the channel with a zoom scale of r, and f denotes the bending activation function. The weight representations generated by the channel attention module are used to adjust the output feature maps of the convolutional layers:

$$\hat{X}_c = \varphi(X, a) \quad (12)$$

φ represents the product operation between the channel feature map and the corresponding channel weights. $\hat{X}_c$ is the convolutional feature map after being calibrated. Using the channel attention module, the resilient network is able to learn the variability of different feature channels and improve the behavioral motivation performance of physical exercise by enhancing the recognition of channel features.

In the proposed spatio-temporal point-of-interest attention module, the feature representation of a particular convolutional layer in a sequence of dynamic images will be mapped in the spatial dimension of the convolutional feature map from that dynamic image to come up with the corresponding mapping points:

$$\begin{cases} x_k' = \frac{w}{w_D} \times x_k \\ y_k' = \frac{H}{H_D} \times y_k \end{cases} \quad (13)$$

x_k', y_k' is the coordinate position of the knd mapping point in the feature map space, W is based on the mapping points in the feature map space, and H is the number of mapping points for each position in the computational space dimension. x_k is the number of mapping points located at the position of row and column i in the feature map space, and y_k is the number of mapping points reflecting the activity level of the corresponding position on the feature map.

Calculate the clustering criterion function

Correlation calculations

The influence of redundant points is attenuated by retaining the maximum weights, and the convolutional layer features similar to the feature space are selected to induce the maximum weights to be sufficient to focus on the salient movement regions of physical activity behavior. The adjusted spatio-temporal point-of-interest attention is uniformly distributed, then the spatio-temporal point-of-interest attention weighted feature is defined as:

$$\hat{X}_s = \varphi_s(X, \beta') + X \qquad (14)$$

φ_s denotes the weighting operation of the channel convolutional feature map with the adjusted spatio-temporal point-of-interest attention weights, β' denotes the preservation of spatial information in the original convolutional features, and X denotes the introduction of residual concatenation to add the input convolutional features. With the generated spatio-temporal point-of-interest attention weighted feature maps, the spatio-temporal point-of-interest attention can discover significant spatio-temporal motion regions in dynamic images, which helps to improve the performance of behavior recognition.

Using the average of minimizing the squared Euclidean distance of each element to its cluster center, the clustering criterion function is used to measure the clustering results of behavioral motivation, calculated as the sum of squared cluster center errors of all objects in the dataset with respect to their respective clusters, and the expression for the clustering criterion function:

$$RSS = \sum_{i=1}^{k} \sum_{p \in c_i} |p - m_i|^2 \qquad (15)$$

c_i denotes the set of data objects in category i, p is the data objects in cluster c_i, m_i is the average value of cluster c_i, and k indicates that the dataset can be divided into k clusters. A new relevance constraint is added to the confidence and support of the association rule, and the relevance is calculated as:

$$Intr(X \Rightarrow Y) = \frac{P(X \cap Y)}{P(X)P(Y)} \qquad (16)$$

X, Y indicates the degree of interest and closeness of the correlation calculation value, when the correlation rule's posterior is a single data item has a clearer decision-making guidance, to ensure the application value of the rule, and to reduce a large number of redundant correlation rules. Consider the support and confidence indexes to analyze the behavioral motivation of physical exercise to obtain inter-attribute information, so as to calculate the interest degree value to analyze the deep relationship between behavioral attributes and self-management (Law et al., 2021). In addition to circumventing the matrix problem, it can also effectively exclude negative influences in physical exercise.

Optimization of processes

In order to efficiently determine the two important parameters of elastic network regression, Figure 4 shows the optimization of the elastic network regression process, so as to optimize the parameters of behavioral motivation in the self-management model and further ensure the robustness of the model.

Based on the elastic network regression steps can be summarized as:

(1) Firstly, the parameters are randomly generated, and the self-management group performance values are obtained through elastic network regression.

(2) Obtain the probability distribution through Gaussian process regression and Bayes' theorem, and according to the acquisition function, weigh the exploration and exploitation to select the parameters that are most likely to maximize the acquisition function next time.

(3) Add the collection of known parameters and repeat the steps to update the probability distribution. Until the ideal combination of parameters physical exercise behavior motivation is obtained.

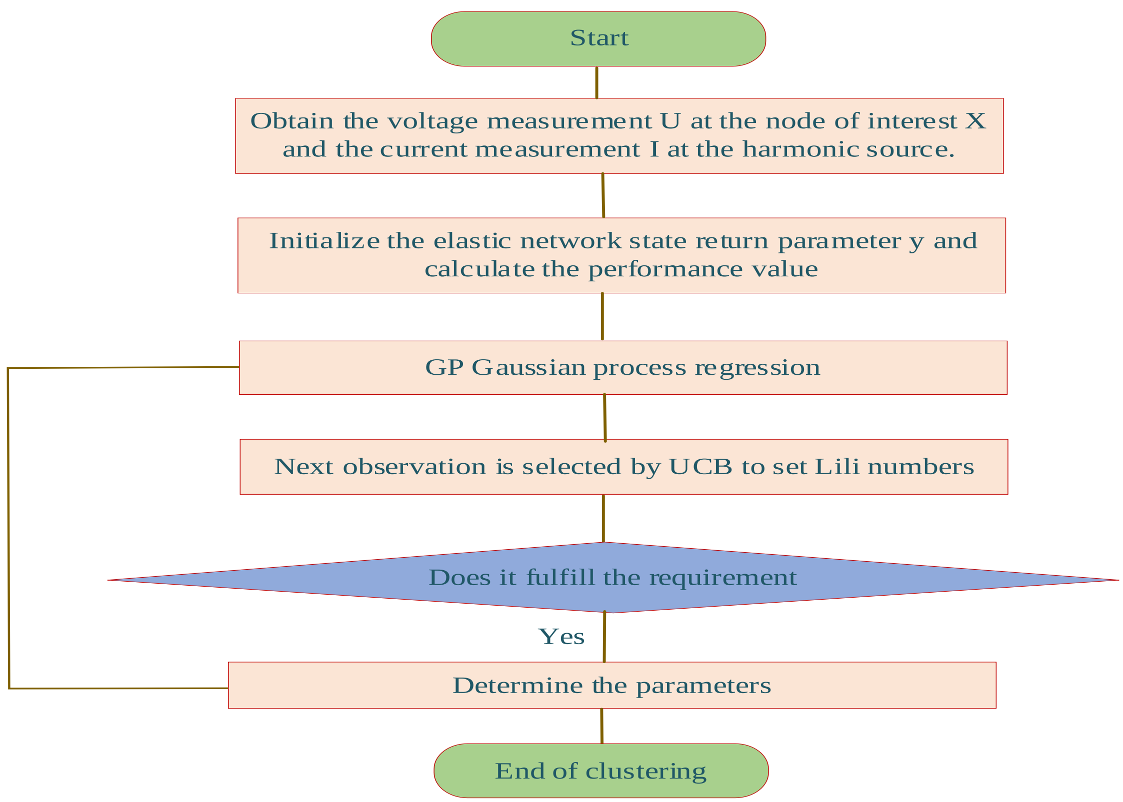


Figure 4: Optimization of Elastic Network Regression Process

Analysis of differences in self-management of physical activity

Variance test

To analyze the improvement in physical fitness after students' participation in self-managed courses. ANOVA test was performed on the measured and calculated physical fitness results using grade level and course participation as factors, and Table 1 shows the self-management of physical activity. The main effect of the grade variable reached a statistically significant level, $F=3.532$, $p<0.05$, and the main effect of the course participation variable reached a statistically significant level, F=3.489, $p<0.05$, and the interaction between grade and course participation did not reach a statistically significant level, F=1.254. The sum of the squared deviations was 3.675 for the case of course participation, and the interaction was 3.816. a further post-hoc analysis was conducted for the post hoc tests for each of the two significant main effects, there was a significant difference in the level of physical fitness improvement, with more physical fitness improvement in classes where the self-management course was taught. Students' participation in the self-management course will increase the students' motivation to participate in sports, which is conducive to improving the level of self-management, thus improving the teaching effect on students' physical and mental qualities. Teachers' correct guidance and instruction, in practice, enable students to reach the ultimate goal of self-improvement and self-transcendence, and cultivate students' self-learning, self-education, and self-management ability.

Table 1 Analysis of Self-management of Physical Exercise

	Sum of Squares of Deviations	**Degree of Freedom**	**Mean Square Deviation**	**F-Value**
Grade	1.296	3	6.473	3.532
Course Participation	3.675	2	6.759	3.489
Interaction	3.816	3	5.801	1.254
Error Term	3.968	2	6.384	1.376

Tests of Difference

In order to study the differences in self-management of physical activity among college students, the differences on self-management of physical activity among college students were analyzed by using elastic networks. According to the significance calculation of method management, time management, content management, motivation management and self-management dimensions, the differences in self-management of physical activity among college students are shown in Table 2. There are significant differences in the four dimensions of method management, time management, content management, and motivation management in self-management of physical activity among college students.

The highest significance was 32.605 regarding appointments in method management, 12.583 in socialization in time management, 9.865 in fitness in content management, and in motivation management. It affects the four dimensions in the self-management of physical activity and the fitness and the purpose of appointment scored higher. It is through the self-management of their own self-management that they can be more effective in educating the users better and improve their self-management skills. Improving students' own management skills is the main initiative of the school at this stage, after localized self-management courses can improve students' motivation and self-management.

Resulting in the strengthening of physical and mental health, the use of classroom teaching to teach students self-management courses, effectively strengthen the level of self-management, so that the effect of classroom teaching can be twice the result with half the effort.

Table 2 Differences in Self-management of Physical Exercise among College Students

Dimension	**Body Building**	**Teach**	**Social**	**Significance**
Method Management	29.348	32.605	27.265	6.015
Time Management	13.096	14.053	12.583	4.324
Content Management	9.865	10.758	9.264	2.789
Motivation Management	11.974	12.242	11.394	2.713
Self-management	16.442	19.691	12.167	5.477

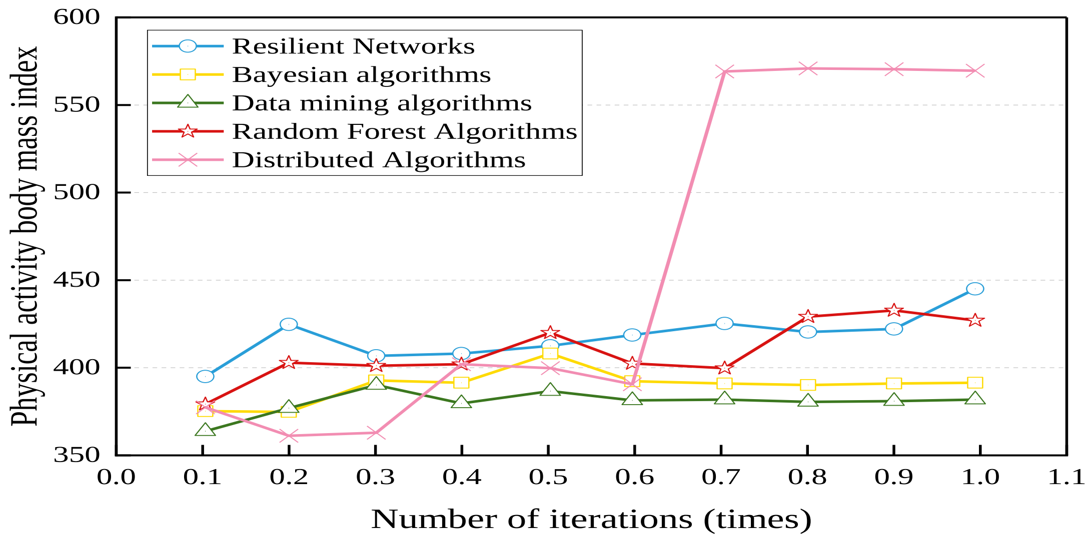
Behavioral Motivation Analysis of Physical Activity

Iterative analysis

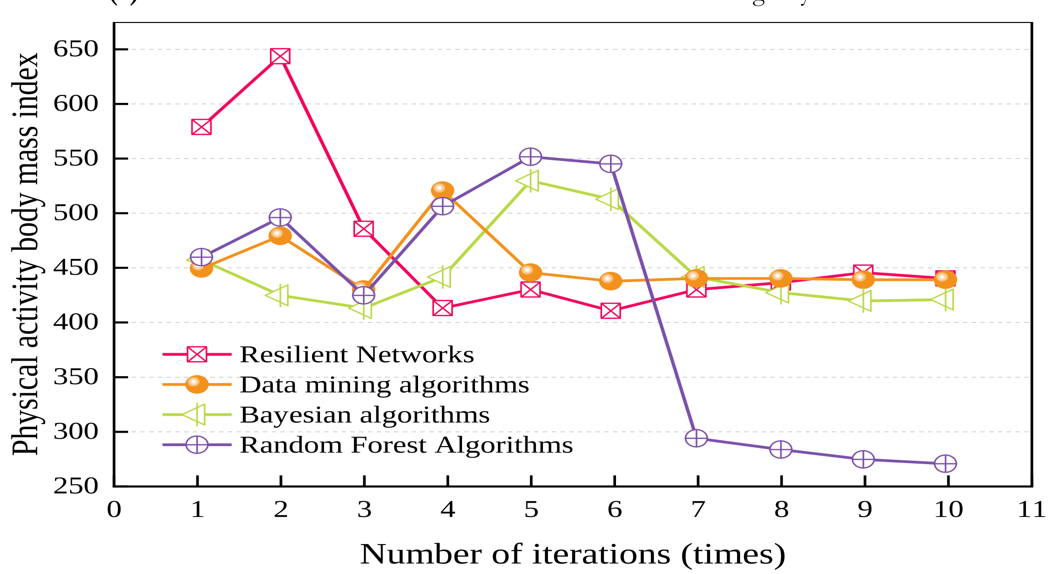
In order to study the clustering stability of elastic networks, it is helpful to select the right combination of parameter values to improve the quality of clustering according to the physical activity metabolic data and body mass index. The parameters of elastic network method, Bayesian algorithm, data mining algorithm, random forest algorithm and distributed algorithm are used by getting the parameter range of behavioral motivation. Figure 5 shows the comparison of the number of selected generations of different algorithms for the size of physical activity data types, which ensures that the arrangement of physical activity improves the comprehensive impact of social adaptation and feeds back into the development of healthy behaviors.

Figure 5(a) shows the number of iterations in the physical exercise metabolic data, the elastic network algorithm with the increase of metabolic data, the more iterations, and after the metabolic data of 0.6, the number of iterations continued in the peak 570 times, this time period of the clustering quality is higher. Bayesian algorithm, data mining algorithm, random forest algorithm and distributed algorithm have the highest number of iterations of 410, 380, 440 and 450, respectively, and the fewer iterations required for convergence, the higher the clustering efficiency and clustering quality.

Figure 5(b) shows the number of iterations in the physical activity body quality index, and the number of iterations for the elastic network method increases as it decreases, with a maximum value of 640 iterations. The maximum value of Bayesian algorithm iterations is 530 times, data mining algorithm iterations are 510 times, and random forest algorithm iterations are 550 times. It makes the whole physical exercise self-management motivation activity higher and accelerates the management mode. Carrying out physical exercise is the core of cultivating students to develop good physical exercise, and strengthening students' guidance on physical exercise so that they can establish the correct motivation for physical exercise. Enhance students' activity to physical exercise, enhance physical health and improve skills, and increase the atmosphere of school sports culture.



(a) Number of Generations Selected for Metabolic Data during Physical Exercise



(b) Number of Generations Selected for Physical Exercise Body Mass Index

Figure 5: Number of Generations Selected for the Scale of Physical Exercise Types

Analysis of motivational disincentives

In order to analyze the factors hindering the motivation of physical exercise behavior, a questionnaire survey was carried out for students of a university using the elastic network method. Through the physical education teacher's guidance to the students, excluding sports majors and long-term exercise students to fill out the questionnaire, physical activity behavior motivation factors shown in Figure 6. In order to analyze and promote students to develop the habit of physical exercise, so as to enhance their physical fitness to maintain physical and mental health, and enrich the after-school life to improve the quality of life. Physical exercise impediment factors are basically similar; the physical environment is the main factor affecting students' participation in physical exercise. The percentage of students with social environment hindering factors in the elastic network is 19.32%, followed by Bayesian algorithm at 16.84%, and the percentage of students with data mining algorithm in the physical environment hindering factors is 24.33%, and the percentage of students with random forest algorithm is 29.35%. The percentage of students of distributed algorithm in intensity of exercise hindering factor is 22.06%, elastic network algorithm is 39.81%, and the percentage of students of Bayesian network algorithm in frequency of exercise hindering factor is 30.63% and data mining algorithm is 23.52%. The percentage of students in Random Forest Algorithm for movement time hindering factor is 31.44% and Distributed Algorithm is 30.72%. Develop appropriate exercise programs for students with different types of problems, and answer students' questions about exercise by interacting with them at any time. The development of targeted development of teaching plans to improve the efficiency of teachers in terms of management, but also to allow students to have more relatively free time to carry out their favorite after-school exercise, thus enhancing the enthusiasm of students to exercise.

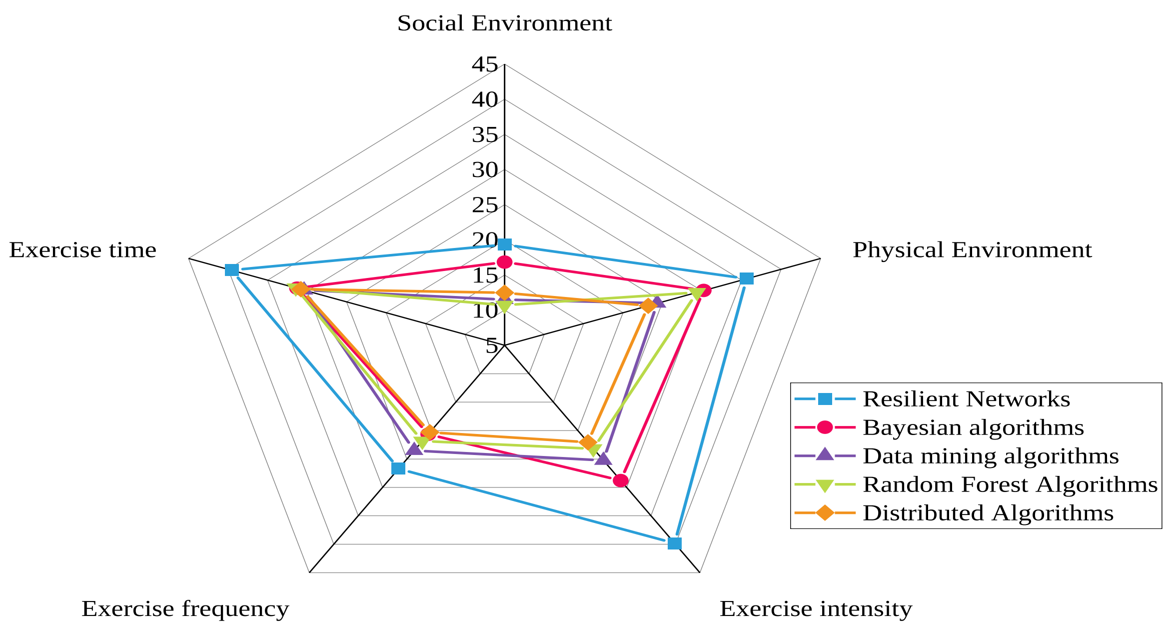


Figure 6: Factors that Hinder the Motivation of Physical Exercise Behavior

Conclusion

In this paper, based on the self-management of physical exercise, the physical exercise images are grayed out to obtain the set of indicator attributes that physical exercise has a large impact on the physical indicators. Based on this to detect the instantaneous rate of the physical exercise movement object, keeping the movement amplitude between neighboring frames. The results are as follows:

(1) The sum of squared deviations of physical exercise for course participation is 3.675, and the interaction is 3.816. Extracurricular physical exercise can be an important way to ensure the physical and mental health of all students, and to enhance the physical fitness of all students, so as to achieve self-realization and transcendence.

(2) The highest significance of appointment in method management is 32.605, and the significance of fitness in content management is 9. 865.Fully mobilize the students' enthusiasm and creativity in exercise, so that the students' physical fitness can be really improved. Ensure that students can participate in all, and promote the continuous development of extracurricular sports.

(3) The proportion of students in the elastic network with social environment hindering factors is 19.32%, followed by Bayesian algorithm as 16.84%, which improves the exercise behavior of college students and improves the self-discipline of college students participating in exercise. Improving the self-management ability of college students' physical exercise behavior is extremely important for the healthy growth of college students.

Funding

This research was supported by the 2021 Guangxi Higher Education Undergraduate Teaching Reform Project: Research and Practice of Ideological and Political Teaching in Public Physical Education Courses in Colleges and Universities (2021JGA323).

Reference

ALSHAWY, F. A., Ibrahim, A., Hussein, C., & Lahlah, M. (2019). First record of arrow bulleye, Priacanthus sagittarius Starnes, 1988 from the Syrian marine waters (Eastern Mediterranean). *FishTaxa, 4*(2), 21-24.

Bebeley, S. J., Liu, Y., & Wu, Y. (2017). Physical exercise self-efficacy for college students' level of motivation in physical activity. *International Journal of Science and Research, 6*(8), 81-85.

Bebeley, S. J., Wu, Y., & Liu, Y. (2017). Motivational level of college students' in physical activity: a concern for public health education. *International Journal of Science and Research, 6*(10), 816-821.

Colangelo, A. M., & Weissbrod, C. S. (2019). The role of social support, self-efficacy, and motivation in the exercise behavior of women. *Exercise Medicine, 3*.

Feng, X., Li, J., Hu, S., Zhao, Y., Chen, L., & Wang, N. (2021). An approach to the permeation mechanism of learning transfer and teaching strategy in physical education based on complex network. *Plos one, 16*(1), e0243906.

Ghanem, H., Jaskani, S., Alloush, M., Hanbal, I., Albader, M., Safar, H., . . . Asfar, S. (2020). Stiff to dilate and risky to cut through: iliac radiation arteritis. *Vasc Endovasc Rev, 3*, e06.

Göhler, G.-F., Hattke, J., & Göbel, M. (2022). The mediating role of prosocial motivation in the context of knowledge sharing and self-determination theory. *Journal of Knowledge Management, 27*(3), 545-565.

Hamido, S., Gu, X., & Itoh, K. (2021). The Impact of Self-monitoring Physical Activity on The Awareness and Behaviour of University Students. *Journal of Japan Industrial Management Association, 72*(2E), 134-148.

Helms, K., Morris, D., & Griddine, S. A. (2021). Exercise causality orientation, motivation, and adherence in an incentive walking program. *Journal of Physical Activity Research, 6*(1), 28-35.

Hussain, T., & Zhang, Y. (2023). The influences of cross-cultural adjustment and motivation on self-initiated expatriates' innovative work behavior. *Personnel Review, 52*(4), 1255-1272.

Iona, T., Scarfone, R., Ammendolia, A., & SEGURA GARCIA, C. (2018). Motivation in non-sedentary subjects over fifty age: state of physical and mental health. *Medicina dello Sport, 71*(4), 617-626.

Kim, J., & Kwon, C. (2018). How self-management affects exercise satisfaction and exercise adherence for Taekwondo players. *Korean Journal of Sports Science, 27*(2), 361-371.

Kotaman, H., & Evran, D. (2021). Impact of physical exercise on teacher candidates academic learning performance and state motivation. *Learning and Motivation, 73*, 101709.

Law, R.-J., Langley, J., Hall, B., Burton, C., Hiscock, J., Williams, L., . . . Gallanders, J. (2021). 'Function First': how to promote physical activity and physical function in people with long-term conditions managed in primary care? A study combining realist and co-design methods. *BMJ open, 11*(7), e046751.

Lee, J. M. (2017). A study on the motivation of pre-service teachers to participate in physical activity-society. *Journal of Fisheries and Marine Sciences Education, 29*(5), 1480-1490.

Matsumoto, H., & Takenaka, K. (2022). Relationship between basic psychological needs and exercise motivation in Japanese adults: An application of self-determination theory. *Japanese Psychological Research, 64*(4), 385-396.

Oliveira, D., Ladeira, Â., Giacomin, L., Pivetta, N., Antunes, M., Batista, R., & Nascimento Júnior, J. (2019). Depressão, autoestima e motivação de idosos para a prática de exercícios físicos. *Psicologia, Saúde e Doenças, 20*(3), 803-812.

Petrenko, N. (2020). Pidvishennya motivaciyi na zanyattyah z fizichnogo vihovannya v agrarnomu universiteti [Increasing motivation in physical education classes at an agrarian university]. Continuing Professional Education: Theory and Practice, 1, 30–36. In.

Prystynskyi, V., Babych, V., Zaytsev, V., Boychuk, Y., & Taymasov, Y. (2020). Impact of updated curriculum content on 6th-7th graders' motivation in physical education. *Physical Education Theory and Methodology, 20*(2), 117-123.

Qiu, Y., & Zhang, G. (2020). Make exercise easier: a brief intervention to influence implicit attitudes towards exercise and physical activity behavior. *Learning and Motivation, 72*, 101660.

Reaume, A. G. (2021). Drug Repositioning as a Pharmaceutical Strategy: The Obvious Benefits are Real but Beware of Pitfalls That May be Less Apparent. *Journal of Commercial Biotechnology, 26*(4). doi:https://doi.org/10.5912/jcb1011

Seo, H.-J., Kim, & Min. (2017). Motivation and characteristics of participation in college nighttime liberal physical education. *Journal of the Korean society for Wellness, 12*(1), 299-308.

Tsai, T.-H., Chang, Y.-S., Chang, H.-T., & Lin, Y.-W. (2021). Running on a social exercise platform: Applying self-determination theory to increase motivation to participate in a sporting event. *Computers in Human Behavior, 114*, 106523.

Tucker, H. J., & Conteh, M. Epidemiological Surveillanceof College StudentsPhysical Activity Motivation.

Wdowiak-Okrojek, K., Lipiec, P., Wejner-Mik, P., Bednarkiewicz, Z., & Kasprzak, J. (2021). Exercise stress echocardiography with probe fixated on patient's chest. *European Heart Journal, 42*(Supplement_1), ehab724. 062.