SIN-CHN SCIENTIFIC PRESS PTE.LTD.

Molecular & Cellular Biomechanics 2025, 22(3), 804.
https://doi.org/10.62617/mcb804

Article

Research on classification evaluation model of physical health based on biomechanical parameters for middle school students based on BP neural network

Zhe Zheng, Zijun Deng, Bin Han, Houwei Zhu*

College of Physical Education and Health Sciences, Zhejiang Normal University, Jinhua 321000, China
*** Corresponding author:** Houwei Zhu, zhuhouwei@zjnu.edu.cn

CITATION

Zheng Z, Deng Z, Han B, Zhu H. Research on classification evaluation model of physical health based on biomechanical parameters for middle school students based on BP neural network. Molecular & Cellular Biomechanics. 2025; 22(3): 804. https://doi.org/10.62617/mcb804

ARTICLE INFO

Received: 14 November 2024
Accepted: 9 December 2024
Available online: 21 February 2025

Abstract: Objective: To construct a classified evaluation model of middle school students' physical health based on biomechanical parameters and to achieve accurate intervention of adolescents' physical health through biomechanically informed strategies. **Methods:** Cluster sampling was used to select 1261 male students' physical health samples from eight junior middle schools in Jinhua City, Zhejiang Province from 2022 to 2023 as a data set. Second-order clustering and BP neural network algorithm were used to establish a physical health classification evaluation model for middle school students, and the accuracy of the model was verified. **Results:** The classification model of physical health evaluation of middle school students has an accuracy of about 90%. The integration of biomechanical data improved the model's ability to identify at-risk students and tailor interventions. **Conclusion:** The classification model has high prediction accuracy and good generalization performance, and provides scientific data support for subsequent accurate intervention of students' physical health in different categories. By incorporating biomechanical insights, the model not only identifies health risks but also informs targeted, biomechanically sound interventions to improve physical health outcomes. This study bridges the gap between physical health assessment and biomechanics, offering a novel approach to promoting adolescent well-being.

Keywords: middle school student; physical health classification; BP neural network algorithm; sports biomechanics

1. Introduction

The physical health of students has consistently been a focal point of attention for society, schools, and families alike. In recent years, the government and various educational departments have implemented policies and measures to accelerate school sports reform and to enhance students' physical health, leading to remarkable progress in school sports initiatives. However, according to recent student sports and health monitoring reports, issues related to students' physical health remain a weak link within compulsory education, with problems such as obesity, myopia, and sleep quality yet to be fundamentally resolved [1]. These issues not only impact the immediate well-being of students but also pose long-term health risks that can carry into adulthood. The prevalence of such health concerns highlights the necessity for comprehensive strategies that go beyond traditional physical education classes. The urgency, complexity, and difficulty of promoting students' physical health are evident, with the simplification of the evaluation system being a critical issue. Hong Haixiao determined the development trend of the relative level of body fat of Tianjin college students in recent 15 years by height, weight index and BMI index [2]. This study underscores the importance of regular monitoring and assessment as a means to identify trends and implement timely interventions. Liu Youxi investigated and analyzed the physical health status of 19–22 years old college students in private colleges and universities in Yunnan Province from 2016 to 2020, and grasped the dynamic development of physical health of private college students [3]. Such analyses are crucial for understanding the unique challenges faced by different student populations, particularly in varying educational environments. Chen Kaihua analyzed the physical health test data of some college students in Anhui Province from 2015 to 2021, and discussed the physical fitness status and change trend of college students in Anhui province from 2015 to 2021, so as to formulate effective intervention measures to improve the physical fitness of college students [4]. These findings can serve as a foundation for developing targeted health programs that address specific deficiencies observed in physical fitness assessments. Students' physical health test data usually only reflect their physical fitness information. However, students' physical health is a multi-dimensional ecosystem, which not only includes students' physical health test, but also requires more extensive data fusion, development of data optimization, mining, linkage and realization methods related to big data, and accelerated use of digital technology to promote evaluation. This approach allows for a more holistic view of student health, integrating various factors such as nutrition, mental health, and lifestyle choices. Quickly locate the existing problems in students' physical health promotion ability [5], and constantly improve the effectiveness of students' physical health promotion.

In recent years, neural network algorithms have been widely used. By simulating the working principle of the human brain nervous system, a large number of simple neurons are interconnected to form a highly complex network, thus realizing the response to complex problems and having significant advantages in solving nonlinear and high-dimensional data [6]. The application of these algorithms in educational settings has the potential to revolutionize how we assess and respond to student health needs. Xie Yongkang et al. used MLP neural network algorithm to establish obesity physical classification model to provide auxiliary diagnosis and treatment for obesity prevention and treatment [7]. This model exemplifies how advanced technology can aid in the early detection and management of obesity among students. Fang Junjie et al. used radial basis function neural network to predict the physical test scores of college students, and the result has higher prediction accuracy and better generalization performance. The exploration of neural network algorithms in the field of physical health is attracting attention [8]. These advancements signal a shift towards more data-driven approaches in health interventions, allowing for personalized recommendations based on individual student profiles. Adolescent physical health involves multiple factors, forming a highly complex nonlinear relationship. The selection of a suitable neural network algorithm for physical health classification model provides a guarantee of technical feasibility and superiority. BP artificial neural network is a multilayer feedforward network trained according to error inverse propagation algorithm. BP network can learn and store a large number of input-output mode mappings without revealing the mathematical equations describing the mappings. This is a nonlinear dynamic system, which is characterized by distributed information storage and parallel cooperative processing. It learns certain rules only through its own training, and gets the result closest to the expected output value when given the input value [9]. This capability makes BP networks particularly suited for analyzing the intricate relationships between various health indicators and outcomes. This is highly suitable for the study of the highly complex nonlinear relationship between adolescents' physical health promotion, and the classification of unbalanced data sets. This study assumes that the comprehensive evaluation of students' physical health should adopt nonlinear methods (such as BP artificial neural network) and evaluate students' physical health status more accurately through multi-dimensional physical health indicators. Cluster analysis can help classify different physical health groups, and the evaluation model has high accuracy and can provide effective reference for decision makers.

2. Research subjects and methods

2.1. Research subjects

This study focuses on constructing a comprehensive classification evaluation model of physical health for male students in the second year of junior high school. Between 2022 and 2023, a total of 1280 second-year male students were randomly selected from eight junior high schools in Jinhua City (160 students from each school). Physical health assessments were conducted by the research team, while physical examinations were conducted by designated medical institutions appointed by the schools, ensuring data accuracy and reliability. A total of 17 data points were collected for each student, comprising five basic data points (grade, class number, name, gender, and birth date), six physical fitness test indicators (vital capacity, 50 m sprint, standing long jump, sit-and-reach, 1000 m run, and pull-ups), and six medical examination indicators (height, weight, waist circumference, hip circumference, unaided vision, and hemoglobin level). The data encompass three primary categories: Body morphology, physical function, and physical fitness. All participants were fully informed of the study details and provided signed informed consent.

2.2. Research methods

2.2.1. Second-order clustering

Second-order clustering is an efficient data classification technique, which is usually carried out in two steps. First, a hierarchy is constructed according to the similarity of data points; then, on this basis, a formal cluster analysis is carried out to determine the final clustering result.

2.2.2. BP model construction process

A BP model typically consists of an input layer, one or more hidden layers, and an output layer. The complete BP model construction process can be divided into forward propagation and BP. In forward propagation, neuron outputs are calculated on the basis of the network structure and the weights and thresholds from the previous iteration. BP is used for parameter training, where each weight and threshold is adjusted by calculating their impact on the total error from the output layer backward. This adjustment continues until the error is minimized [10].

In forward propagation, let the feature vector of the input layer be x_{ij}, with weights and thresholds from the input layer to the output layer represented by w_{ij} and θ_{ij}, respectively. The output value of the hidden layer node is a_j (Equation 1), where f denotes the activation function, typically represented by the sigmoid function (Equation (2)) [11–15]:

$$a_j = f(\sum_{i=1}^{m} w_{ij}x_{ij} + \theta_{ij}) \tag{1}$$

Amoung,

$$f(x) = \frac{1}{1 + e^{-x}} \tag{2}$$

After obtaining the output values of the hidden layer, they are used as inputs for the output layer, resulting in the final output layer expression:

$$y_k = f(a_k) = f(\sum_{j-1}^{\mathrm{n}} w_{ij}x_{ij} + \theta_{jk}) \tag{3}$$

In BP learning, t_k represents the desired output signal for neural network training, while y_k is the actual output signal of the network. The objective of neural network learning is to reduce the error between y_k and y_k to a specified accuracy. The commonly used error function, E, is the mean squared error, which can be expressed as:

$$E = \frac{1}{2}\sum_{k=1}^{n}(y_k - t_k)^2 \tag{4}$$

The weights for the hidden layer and the output, w_{jk} and w_{ij}, are updated accordingly. Training concludes once the error is reduced to the specified accuracy level.

3. Result analysis and model validation

3.1. Data entry and processing

Data were organized by excluding invalid and incomplete records, resulting in a dataset of 1261 valid samples. The data were standardized and subjected to one-way ANOVA using SPSS 22.0, with statistically significant differences observed across indicators in each category (**Table 1**). The dataset was then subjected to second-order clustering, yielding four natural clusters with a satisfactory clustering model. Subsequently, data normalization was applied using the formula $x = \frac{\mathrm{x - min}}{\mathrm{max - min}}$, where max and min represent the maximum and minimum values of the sample data, respectively. After preprocessing, MATLAB R2016b was used to write the program code for the BP neural network model, with 12 indicators, including height, weight, vital capacity, and standing long jump, set as input variables. The second-order classification results were used as output variables, leading to 12 neurons in the input layer, four in the output layer, and five neurons in the hidden layer, as determined experimentally. The dataset was divided into training and testing sets, with 60% (186 from each class) used for training and the remaining 545 samples for testing to validate the model's accuracy [15–18]. The network architecture is shown in **Figure 1**.

Table 1. Variance analysis results of clustering for physical health status of second-year junior high school boys in Jinhua city.

	Cluster		Erro		*F*	significance
	Mean square	DOF	Mean square	DOF		
Zscore (Height)	28.584	3	0.598	206	47.776	0.000
Zscore (Weight)	45.226	3	0.356	206	127.064	0.000
Zscore (Vital Capacity)	24.578	3	0.657	206	37.432	0.000
Zscore (Hemoglobin)	17.976	3	0.753	206	23.880	0.000
Zscore (Waist Circumference)	38.419	3	0.455	206	84.428	0.000
Zscore (Hip Circumference)	41.284	3	0.413	206	99.881	0.000
Zscore (50 m Sprint)	34.198	3	0.517	206	66.205	0.000
Zscore (Sit-and-Reach)	6.152	3	0.925	206	6.651	0.000
Zscore (Standing Long Jump)	36.882	3	0.477	206	77.247	0.000
Zscore (Pull-Ups)	16.662	3	0.772	206	21.586	0.000
Zscore (1000 m Run)	35.116	3	0.503	206	69.790	0.000

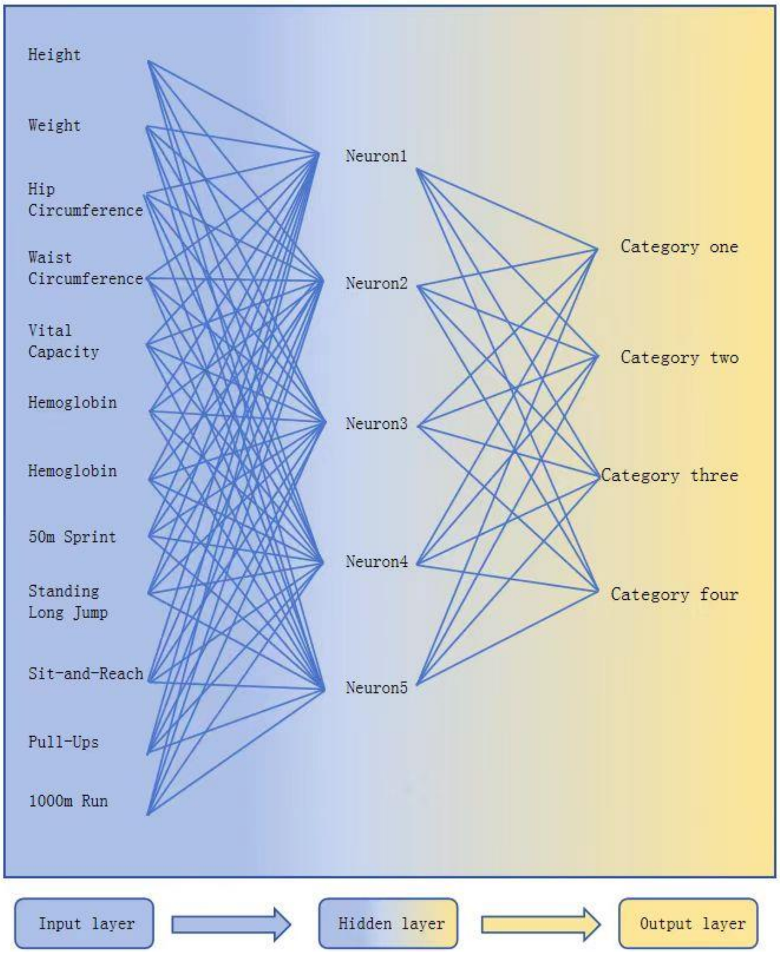

Figure 1. Topology of the BP neural network classification model.

3.2. Classification of student physical health categories

The four clustered groups of students are labeled as Category 1, Category 2, Category 3, and Category 4 (**Table 2**). Height, weight, waist circumference, and hip circumference are classified as body morphology indicators; vital capacity, hemoglobin, and vision are classified as physical function indicators; and the 1000 m run, 50 m sprint, standing long jump, sit-and-reach, and pull-ups are classified as physical fitness indicators. For a more intuitive comparison, each indicator is ranked from 4 to 1 to represent its distribution within the overall dataset. In body morphology and physical function indicators, vital capacity and hemoglobin indices are ranked from highest to lowest (4 to 1) based on actual values. Vision is graded on a four-point scale, with 4 indicating normal vision and 1 indicating severe impairment. For timed events such as the 50 m sprint and 1000 m run, increased times reflect reduced performance; thus, these physical fitness indicators are scored from 4 to 1 for consistency. **Table 3** summarizes these results [18–20].

3.3. Biomechanical analysis of the characteristics of each group of students

From the perspective of biomechanics, these data reflect the differences of different categories of students in terms of body shape, function and quality and the complex interconnections between them. Through the comparison of various indexes, the characteristics of this type of students can be obtained. The first type of students are overweight in body shape and have excess nutrition, and larger weight and size mean that they need more energy in exercise. Lung function and blood oxygen-carrying capacity are good, which can provide efficient oxygen supply for exercise. In endurance, speed and flexibility, the ability is weak, and it is best to be greatly affected by weight. In running and long jump, the advantage of stride length or lever length increased by considering height factors can support longer and higher intensity exercise. In particular, the visual acuity of such students is the worst, and the fourth type of students are short and weak in body shape, ranking last in basically every index. Thus, thin and malnourished students may attract more attention from the school. The second group of tall and moderate weight students not only have good eyesight, but also have excellent performance in physical tests. Height leverage effect advantage and excellent cardiopulmonary function provide a good endurance foundation, 1000m running performance may not reach the best due to running technology or physical distribution problems, can be in-depth analysis and targeted training. Compared with the second group, the third group of students showed the characteristics of smaller height but larger weight and relatively smaller hip and waist circumference. This kind of body shape is manifested as a more compact core structure from the motion mechanics, and the moment of inertia of the core part is smaller in the movement, so that the body can change its attitude more quickly and flexibly when it is engaged in twisting, steering and other actions, and reduce energy loss. The larger body weight and concentration in the core area suggest that there may be a more developed core muscle group and bone structure to support the weight, providing a material basis for the play of core strength. In many sports, core strength is the key link to connect the upper and lower limbs and transfer power. Good core strength helps to improve the efficiency and stability of sports. Although oxygen intake and transport capacity were not outstanding, compared with the third group of students, they showed better body shape, lower BMI, and greater advantages in the endurance event of 1000 meters.

Table 2. Clustering results of physical health categories for junior high school boys.

Indicator	Category 1 (210 students)	Category 2 (288 students)	Category 3 (468 students)	Category 4 (294 students)
1000 m Run	−0.1391239	−0.4138649	−0.4151876	1.1657038
Pull-Ups	0.2671323	0.1442042	0.3001374	−0.8098398
Standing Long Jump	0.2171637	0.325565	0.4536374	−1.1961543
Sit-and-Reach	0.34465	−0.1997029	0.2813521	−0.4984179
50 m Sprint	−0.303166	−0.4618166	−0.3452919	1.2185873
Hip Circumference	1.4646224	−0.43312	−0.2982715	−0.1470784
Waist Circumference	1.3745044	−0.4543855	−0.3941741	0.0907842
Hemoglobin	0.5371043	0.1680057	−0.0300478	−0.5003918
Vital Capacity	1.083337	−0.015026	−0.0255122	−0.7184815
Weight	1.4983442	−0.4030028	−0.2573613	−0.2657904
Height	0.8966788	0.0975934	0.0230311	−0.7727483

Table 3. Characteristics of physical health categories among students.

Indicator		Category 1 (140 students)	Category 2 (192 students)	Category 3 (312 students)	Category 4 (196 students)
Body Morphology	Weight	4	2	3	1
	Height	3	4	2	1
	Hip Circumference	4	3	2	1
	Waist Circumference	4	3	2	1
Physical Function	Vital Capacity	3	4	2	1
	Hemoglobin	4	3	2	1
	Vision	1	4	3	2
Physical Fitness	50 m Sprint	2	4	3	1
	1000 m Run	2	3	4	1
	Standing Long Jump	2	4	3	1
	Sit-and-Reach	2	4	3	1
	Pull-Ups	3	4	2	1

3.4. BP neural network model training and testing

As shown in **Table 4**, the performance of our BP neural network model on the test set is as follows: The accuracy is 0.888, the recall rate is 0.800, and the F1 score is 0.842. These results show that the model exhibits high accuracy in the classification task and can effectively identify most positive samples (high recall rate). At the same time, the value of F1 score is close to 0.8, indicating that the model maintains a good balance between accuracy and recall [20–23].

Table 4. Performance of BP neural network model on test set.

index	Numerical value
Precision	0.888
Recall	0.800
F1 Score	0.842

The BP neural network model testing results indicate that Category 2 achieved the highest prediction accuracy at 94.1%, followed by Category 1 with an accuracy of 91.5%, Category 3 at 90.1%, and Category 4 at 88.4%. The importance of each indicator to the clustering results is ranked as follows: vision > weight > 50 m sprint > standing long jump > hip circumference > 1000 m run > waist circumference > vital capacity > height > pull-ups > sit-and-reach > hemoglobin (**Table 4**). Indicators with an importance level above 10% primarily include measurements of body morphology, such as weight, hip circumference, and waist circumference and key physical fitness indicators. The study emphasizes that underweight and overweight individuals are critical groups requiring attention in terms of physical health (**Table 5** shows variable importance predictions) [23–25].

Table 5. Importance of classification model variables.

predictor	significance %	predictor	significance %
Visual condition	13%	Hip circumference	11%
Run 1000 m	10%	waistline	10%
pull-up	4%	hemoglobin	2%
Standing long jump	11%	Vital capacity	7%
Sit in a forward bend	2%	weight	11%
Run 50 m	11%	height	6%

3.5. Application of physical health classification model under big data

Social development has put forward higher requirements for the refinement and precision of various industries and fields, and can quickly and reasonably classify adolescents' physical fitness according to the needs and objectives, promoting the change process of the application path of physical health test data from "result generation" to "result generation—feedback application—research and judgment intervention". It not only enables schools to assess students' physical health status more scientifically, develop personalized health improvement programs and exercise prescriptions, but also combines big data technology and intelligent health promotion service system to achieve systematic monitoring and early warning, and improve the scientific and efficient school health monitoring work.

4. Discussion

The discussion of a classification evaluation model for middle school students' physical health based on biomechanical parameters and BP neural networks revolves around the integration of biomechanical insights with machine learning techniques to improve the accuracy and applicability of physical health assessments. This approach addresses the growing need for precise and individualized health evaluations, particularly in adolescents, who are in a critical stage of physical development. By incorporating biomechanical parameters such as posture, gait, muscle strength, and joint mobility, the model provides a more comprehensive understanding of physical health, bridging the gap between traditional health metrics and biomechanical science. One of the key strengths of this study is the inclusion of biomechanical parameters in the evaluation model. Traditional physical health assessments often rely on basic metrics like height, weight, BMI, and endurance, which, while useful, do not capture the full picture of an individual's physical well-being. Biomechanical parameters, such as postural alignment, gait patterns, and muscle strength, offer deeper insights into musculoskeletal health and functional capacity. For example, poor postural alignment or abnormal gait patterns can indicate underlying issues that may not be apparent through standard health metrics. By integrating these parameters, the model can identify at-risk students more effectively and provide targeted interventions to address specific biomechanical deficiencies.

The use of a BP neural network algorithm further enhances the model's predictive accuracy and generalization performance. BP neural networks are well-suited for handling complex, nonlinear relationships between variables, making them ideal for analyzing the multifaceted nature of physical health data. In this study, the BP neural network achieved an accuracy of approximately 90% in classifying students' physical health status, demonstrating its effectiveness in integrating diverse data types, including biomechanical parameters. This high level of accuracy is crucial for developing reliable health evaluation tools that can be used in educational and clinical settings. The findings of this study have significant implications for the field of adolescent health and biomechanics. By identifying specific biomechanical factors that contribute to physical health, the model provides a foundation for designing targeted interventions. For instance, students with poor postural alignment could benefit from exercises that strengthen core muscles and improve posture, while those with abnormal gait patterns might require corrective exercises or orthotic devices. These interventions not only address immediate health concerns but also promote long-term musculoskeletal health, reducing the risk of chronic conditions later in life.

Moreover, the integration of biomechanical parameters into physical health evaluations aligns with the growing emphasis on personalized medicine and health care. Adolescents exhibit significant variability in physical development, and a one-size-fits-all approach to health assessment is often inadequate. The proposed model, with its ability to analyze individual biomechanical profiles, offers a more personalized and precise approach to health evaluation. This is particularly relevant in the context of school-based health programs, where early identification and intervention can have a profound impact on students' overall well-being. However, there are challenges to consider in the practical implementation of this model. Collecting biomechanical data requires specialized equipment, such as motion capture systems, force plates, or wearable sensors, which may not be readily available in all settings. Additionally, the computational complexity of BP neural networks may pose challenges for real-time applications, particularly in resource-limited environments. Future research could explore the use of simplified algorithms or portable devices to make the model more accessible and scalable.

Another area for further investigation is the long-term impact of biomechanically informed interventions on physical health outcomes. While the model demonstrates high accuracy in classifying health status, longitudinal studies are needed to assess whether the recommended interventions lead to sustained improvements in physical health. Additionally, the model could be expanded to include other factors, such as psychological and environmental influences, to provide a more holistic assessment of adolescent health.

5. Conclusion

In the era of big data, leveraging big data technologies and various algorithms to make data more interpretable, traceable, and applicable is crucial to achieving precise interventions in adolescent physical health [2]. This study employs BP neural networks to train the results obtained from clustering analysis. With an accuracy of approximately 90% for the training and testing sets, this model provides a refined evaluation of junior high school students' physical health and a comprehensive categorization of group characteristics, demonstrating substantial practical importance. The variable importance analysis reveals that vision and weight are the most critical indicators, highlighting key focus groups in physical health. This approach provides scientific data support for student health improvement initiatives.

Author contributions: Conceptualization, ZZ and HZ; methodology, ZZ; software, ZD; validation, BH, ZD and ZZ; formal analysis, ZZ; investigation, ZD; resources, ZZ; data curation, ZZ; writing—original draft preparation, HZ; writing—review and editing, ZZ; visualization, HZ; supervision, ZZ; project administration, ZZ; funding acquisition, HZ. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Educational Science Planning Project of Zhejiang Province (No. 2024SCG360), the Science and Technology Bureau of Jinhua City (No. 2024-4-027), the National Social Science Foundation Youth Program (No. 24CTY025), and the Humanities and Social Sciences Youth Foundation of the Ministry of Education of the People's Republic of China (No. 22YJC890056).

Ethical approval: This study was conducted in accordance with the Declaration of Helsinki, and approved by the Ethics Committee of Human Experiment of Zhejiang Normal University (No. ZSRT2024076) in August 2024.

Conflict of interest: The authors declare no conflict of interest.

References

1. WANG Xianliang, Zhou Tingting, Guo Xueqing. Student physical health to promote the whole domain of the system construction and system simulation. Journal of tianjin sports college, 2021, 4 (6): 638–644. DOI: 10.13297 / j.carol carroll nki issn1005-0000.2021.06.003
2. Hong Haixiao, Su Lianyong. A 15-year dynamic analysis of BMI of college students in Tianjin Journal of Capital University of Physical Education, 2014,26 (3): 279–283.
3. Liu Youxi, Lu Tianxue, Zhang Yufen. Dynamic study on Physical health status of college students in private colleges and universities of Yunnan Province from 2016 to 2020. Sports science and technology, the lancet, 2022 (01): 27 to 30, DOI: 10.14038 / j.carol carroll nki tykj. 2022.01.029

4. Chen Kaihua, Chen Xiaorong, Zhou Zhenmao. Current Situation of physical health of college students in Anhui Province and countermeasures for improvement: An analysis based on physical examination reports from 2015 to 2021. Chizhou college journal, 2022, 4 (3): 98–101. The DOI: 10.13420 / j.carol carroll nki jczu. 2022.03.025
5. Wang Xiaozan, Guo Qiang, Jin Yan, et al. China youth sports health promotion theory resource and the construction of the framework. Journal of sports science, 2014 (3): 3–14. DOI: 10.16469 / j.carol carroll ss. 2014.03.002
6. Su Jianzhen, Chen Xi. Platform architecture, application prospects and realistic challenges of blockchain for Student Physical Health testing. Sports science research, 2020 (01): 21–26 + 32. DOI: 10.15877 / j.carol carroll nki nsic. 20200303.005
7. Xie Yongkang, Ding Mengqing, Xu Xiao, et al. Research on TCM obesity body classification model based on MLP neural network algorithm. Wireless Internet Technology, 2021, 18(07): 37–40.
8. Fang Junjie, Li Fengshuang, Liu Yongming, et al. Prediction of college students' physical test scores based on radial basis function neural network. Journal of Jamus University (Natural Science Edition), 2019, 42(03): 145–148+180. (in Chinese).
9. Zhang Pin, Chen Ming, CAI Tianpan, et al. Comprehensive evaluation based on artificial neural network model of the elderly's physique and exploration. Journal of nanchang university (medical edition), 2020, 60 (4): 89–93. DOI: 10.13764 / j.carol carroll nki NCDM. 2020.04.019
10. Li LAN, Wang Naibo, Chen Jinghua, et al. Using artificial neural network model for the research status of the elderly physique evaluation. Journal of nanchang university (medical edition), 2017,57 (01): 88–92. DOI: 10.13764 / j.carol carroll nki NCDM. 2017.01.023
11. He, Z. Biomechanical differences in maximum snatch weight between elite and sub-elite weightlifters: A one-dimensional statistical parameter mapping study. Molecular & Cellular Biomechanics, 2024, 21(2), 525. DOI:10.62617/mcb.v21i2.525
12. He Z, Zhu H, Ye B, Zheng Z, Liu G, Pan H and Liu R Does chronic ankle instability patients lead to changes in biomechanical parameters associated with anterior cruciate ligament injury during landing? A systematic review and meta-analysis. Front. Physiol, 2024 15:1428879. DOI: 10.3389/fphys.2024.1428879
13. Liu, G.; He, Z.; Ye, B.; Guo, H.; Pan, H.; Zhu, H.; Meng, G. Comparative Analysis of the Kinematic Characteristics of Lunge-Style and Squat-Style Jerk Techniques in Elite Weightlifters. Life 2024, 14, 1086. https://doi.org/10.3390/life14091086
14. Ye, B.; Zhu, H.; Yang, Z.; He, Z.; Liu, G.; Pan, H.; Guo, H. Construction and Analysis of the Physical Fitness Evaluation Index System for Elite Male Singles Badminton Players: Based on Delphi and AHP Methods. Life 2024, 14, 944. https://doi.org/10.3390/life14080944
15. He, Z., Liu, G., Zhang, B. et al. Impact of specialized fatigue and backhand smash on the ankle biomechanics of female badminton players. Sci Rep 2024, 14, 10282. https://doi.org/10.1038/s41598-024-61141-z
16. Ye, B.; Liu, G.; He, Z.; Xu, J.; Pan, H.; Zhu, H. Biomechanical mechanisms of anterior cruciate ligament injury in the jerk dip phase of clean and jerk: A case study of an injury event captured on-site. Heliyon 2024, 10, e31390.
17. Harbili, E.; Alptekin, A. Comparative kinematic analysis of the snatch lifts in elite male adolescent weightlifters. J. Sports Sci. Med. 2014, 13, 417–422.
18. Cohen, J. Quantitative Methods In Psychology: A Power Primer. Psychol. Bull. 1992, 112, 1155–1159.
19. Deming, L.; Kangwei, A.; Yunde, W. Three Dimensional Analysis of Jerk Techniques for Five Female Weightlifting Champions at 11th Asian Games. China Sport Sci. 1992, 12, 74–79.
20. Hedrick, A. Dumbbell Power Clean, Front Squat, and Power Jerk. Strength Cond. J. 2015, 37, 84–88.
21. Kipp, K.; Redden, J.; Sabick, M.; Harris, C. Kinematic and Kinetic Synergies of the Lower Extremities During the Pull in Olympic Weightlifting. J. Appl. Biomech. 2012, 28, 271–278.
22. Moon, Y.J. Performance Enhanced Model in Snatch Weightlifting—Using the kinematic factors. J. Biomech. 2007, 40, S753.
23. Weimin, W. How to Improve the Success Rate of Weightlifting Arrow Jerk. J. Shanghai Phys. Educ. Inst. 1993, 35, 29–31.
24. Xian, C. The Cognition and Comparison of Squatting Downwards, Lifting up wards and Arrow Pace Lifting. J. Nanjing Inst. Phys. Educ. 2002, 25, 27–28.
25. Zhaoxin, C.; Guiping, S. Discussion on Advantages and Disadvantages of Drop Jerk in Clean and Jerk. J. Beijing Univ. Phys. Educ. 2000, 52, 408–410.