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Article

A study on the design of residential areas incorporating physical education functions - enhancing community health education

Peng Chen [1,*]

[1] Physical Education Department, Anyang University, Anyang, Henan, 455000, China
* Correspondence author: PengChen1032@163.com

Abstract: Traditional residential area design lacks the integration of physical education functions, making it difficult to meet the health needs of residents. With the enhancement of national health awareness, the integration of physical education functions into residential area design has become an important way to improve community health education. This paper proposes a residential layout optimization design method that integrates physical education functions, which aims to improve the level of community health education. The study extracts the spatial distribution characteristics of the main functional areas of residential areas through deep neural networks, establishes a residential area layout optimization design model, and solves the problem by using the improved adaptive variational particle swarm algorithm (IAMPSO). The experiments are carried out in nine areas of a city and verified under five planning scenarios, and the spatial compactness of urban residential land planned by the research method reaches more than 0.92, which is much higher than that of the planning method based on geospatial information system (0.73) and the planning method based on big data (0.77). Based on the data from the China Household Tracking Survey, the current status of the health level of Chinese residents was analyzed, and it was found that the health score of residents in the eastern region (5.52) was higher than that in the central (5.44) and western regions (5.26), and the health level of urban residents (5.6859) was significantly higher than that of rural residents (5.3143). The study shows that optimizing the layout of residential areas through the IAMPSO algorithm can effectively improve the land space utilization rate, and the integration of physical education functions can improve the level of health education in the community, which provides new ideas for the design of residential areas.

Keywords: physical education function; residential area design; spatial distribution characteristics; IAMPSO algorithm; community health education; layout optimization

1. Introduction

With the strategy of a strong sports nation proposed, China has further strengthened its emphasis on physical exercise and physical education, and promoted the effective combination of physical education teaching resources and community sports facilities [1]. In general, community sports development often faces a variety of conditions and resource deficiencies, which seriously impedes the effective implementation of the national fitness movement [2]. By promoting the synergistic development of physical education teaching function and community sports resources, different levels of people can be integrated together, and the fitness concepts and exercise methods of schools can be used to cultivate people's good exercise awareness and habits, so as to realize the goal of lifelong sports and promote the rapid development of the national fitness movement [3-6].

At the same time, through the construction and cultivation of various types of stadiums, sports facilities and professional coaching team and other sports teaching resources in the community, it can provide more opportunities for community residents to engage in sports activities and provide sports guidance for community residents [7-9]. These community infrastructures and resources with sports teaching functions will be conducive to promoting the popularization of social sports and the promotion of healthy lifestyles, popularizing the knowledge and skills of healthy lifestyles to community residents, and increasing the awareness and participation in social sports [10-13]. Therefore, it is necessary to increase the process of community design that combines the functions of physical education and accelerate the pace of realizing the synergistic development of the functions of physical education and community resources, so as to fully reflect the value of community health education and realize the goal of a strong sports nation.

As the main place of daily life for urban residents, the design quality of residential areas directly affects the quality of life and health of residents. At present, the acceleration of urbanization has led to the increasing density of urban population and the growing tension of urban land resources, so how to meet the diversified needs of residents' lives within the limited space has become an important issue in urban planning and construction. In China, the design of residential areas has long been focused on the residential function itself, and insufficient attention has been paid to the integration of education, health and other functions, especially the research on the application of physical education functions in the design of residential areas is still in the exploratory stage. The implementation of the Healthy China strategy requires the integration of health concepts into all aspects of urban planning and construction, and residential areas, as an important part of urban construction, must assume the important mission of promoting residents' health.

In recent years, scholars at home and abroad have conducted in-depth research on the relationship between residential area design and residents' health. Overseas studies have shown that a community environment with good sports facilities can significantly improve the physical activity level of residents and reduce the incidence of chronic diseases. Domestic studies have also confirmed that the improvement of community sports environment has a positive effect on enhancing residents' health literacy. However, existing studies have mostly focused on the layout and configuration of sports facilities, with less attention paid to the systematic integration of sports teaching functions in the overall planning of residential areas. The function of physical education in residential areas not only includes the configuration of hardware facilities, but also the provision of software services, such as sports instruction and health education, to form a complete community health education system.

In terms of planning and design methods for residential areas, traditional methods mostly rely on empirical judgments and simple mathematical models, making it difficult to meet the needs of complex system optimization. With the development of artificial intelligence technology, optimization design methods based on intelligent algorithms provide new ideas for residential area planning. Among them, particle swarm algorithm is widely used in space layout optimization due to its simple and efficient characteristics. However, the standard particle swarm algorithm has the problem of easy to fall into local optimization, which needs to be further improved to enhance the performance of the algorithm.

In this context, this study proposes a residential area layout optimization design method that combines the function of physical education, extracts the spatial distribution characteristics of the main functional area of the residential area through deep neural networks, establishes a layout optimization design model of the main functional area of the residential area, and solves the problem by using the improved Adaptive Adaptive Mutating Particle Swarm Algorithm (IAMPSO). In this study, the IAMPSO algorithm is first designed to adopt different adaptive mutation operations for the particles in the three cases of non-optimal position, zero velocity, and optimal position; then the algorithm is applied to solve the layout optimization model of the residential area to verify the validity of the algorithm; and finally, the health level of the residents of communities in different regions of China is analyzed, which provides references to the incorporation of physical education functions into the design of the residential area.

2. IAMPSO-based design method for optimizing the layout of residential areas

Based on the IAMPSO algorithm, this chapter proposes a design method for optimizing the layout of residential areas combined with physical education and teaching functions to achieve community health improvement.

2.1. Extraction of the spatial distribution characteristics of the main functional areas of residential areas

Before carrying out the layout optimization of the main functional area of the residential area, the layout space distribution characteristics are extracted based on the collected and processed functional area spatial data. In this paper, we mainly obtain the distribution structure and distribution pattern from two aspects of the layout space. Due to the more complex nature of the land in the main functional area of the residential area, the information entropy is selected as the spatial distribution structure feature of the main functional area, and the information entropy value of the spatial feature is:

$$\delta = -\sum\left(\frac{S_n}{S_0}\right)\ln\left(\frac{S_n}{S_0}\right) \tag{1}$$

Where: S_0 is the total area of each functional area; S_n is the area of the n th functional area. In general, when the information entropy obtained from equation (1) is 0, it indicates that the functional area site is not developed. On the contrary, if the information entropy is the maximum value, it indicates that the development of the functional area has stabilized. Therefore, when optimizing the layout of the main functional area of the residential area, it is necessary to combine the information entropy to determine the development of various functional areas. In this paper, in order to determine the degree of disposability of land types in the main functional area of the residential district, the degree of equilibrium is chosen as the second feature of the spatial structure. The expression for the degree of equilibrium of the land in each functional area of the residential district is:

$$\eta = \frac{\delta}{\ln(N)} \tag{2}$$

Where: N is the number of types of land in each functional area of the residential area. Usually the equilibrium degree of equation (2) is [0,1], if the equilibrium degree is 0, it indicates that the land in the functional area is in an unbalanced state. On the contrary, if the equilibrium degree is 1, it indicates that the land use of the functional area has reached the ideal equilibrium state.

In this paper, shape rate and compactness are taken as the spatial distribution characteristics of the main functional areas in residential areas. The shape rate feature can measure the number of shapes in the functional area. The shape rate expression of each functional area is:

$$\lambda = \frac{S_1}{L^2} \tag{3}$$

Where: S_1 is the area of the region and L is the length of the region. If the value of the shape rate obtained from equation (3) is small, it indicates that the region is more distinctly banded. On the contrary, if the value of shape rate is large, it indicates that the region is block-like distribution.

Compactness is mainly used to measure the shape characteristics of functional area regions. The expression for the layout compactness of each functional area region is:

$$\mu = \frac{S_1}{S_1'} \tag{4}$$

Where: S_1' is the minimum external circle area of the functional area. The deep neural network is utilized to extract the spatial distribution characteristics of the main functional area of the residential area, and the established deep neural network is shown in Figure 1.

The deep neural network is used to collect relevant feature points, calculate the corresponding measurement function index parameters, and determine whether it is suitable for layout optimization design. The formula for calculating the feature index parameters is:

$$A = b + \frac{w}{r(s-w)} \tag{5}$$

Where: b is the upper limit of eigenvalue, r is the optimization coefficient of eigenparameter, s is the distribution range, and w is the lower limit of eigenvalue. After the operation, the corresponding eigenvalue index parameters are determined. Using the calculated feature index parameters, the layout feature extraction results of the functional area are evaluated, once exceeding this value range, it indicates that there is anomaly in feature extraction and needs to be re-extracted, otherwise, it indicates that the layout feature extraction results are suitable for the layout optimization design, and the subsequent operations can be carried out.

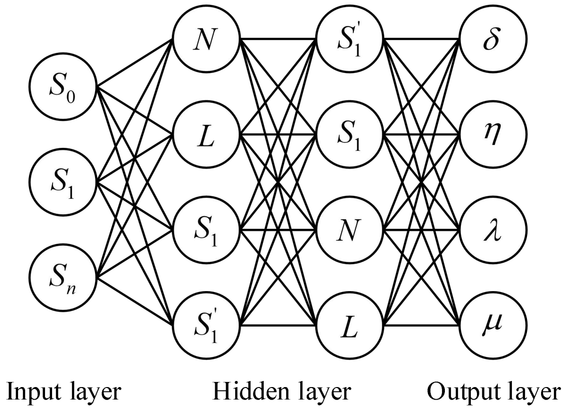

Figure 1. Deep neural networks with spatial distribution of main functional areas

2.3. Design model for optimizing the layout of the main functional areas in residential areas

Based on the spatial distribution characteristics of the main functional area of the residential area, the layout optimization design model of the main functional area of the residential area is established. The complex layout problem is converted into a composite model form. Before the model is established, the main functional area of the residential area is divided into m-row and n-column units. There are a total of K primary functional area types that need to be laid out in the region, and k_1 and k_2 describe the land types (ij) and $(i^{'}j^{'})$ $(i=1,\cdots,n:j=1,\cdots,m)$ of the unit. $U_{ij,i^{'}j^{'}}$ is a binary variable that equals 1 if (ij) and $(i^{'}j^{'})$ are neighbors, and 0 if the opposite is true. V_{k_1,k_2} describes the degree of coordination between units (ij) of type k_1 and units $(i^{'}j^{'})$ of type k_2, i.e., the degree of comfort that develops when the two types of functional zones are in close proximity. Using X_{k_i} to represent the footprint of the main functional area of type k_1, X_{ijk_i} is also a binary variable that equals to 1 if the type of functional area in the cell (ij) is k_1 and 0 otherwise. $S_{ij,i^{'}j^{'}}$ is the total number of times a unit (ij) is adjacent to $(i^{'}j^{'})$, and P_{ijk_i} is the cost of laying out the k_1 functional zones within the (ij) unit.

To simplify the model structure, only two factors, the coordination of layout design and the design cost, are considered, and the objective function expression is:

$$MaxD=\sum_{i=1}^{m}\sum_{j=1}^{n}U_{ij,i^{'}j^{'}}V_{k_1,k_2} \tag{6}$$

$$MinP=\sum_{i=1}^{m}\sum_{j=1}^{n}P_{ijk_i}X_{ijk_i} \tag{7}$$

The objective function should also satisfy constraints:

(1) A cell needs to be neighboring one or more cells:

$$S_{ij,i^{'}j^{'}}\geq 1,\quad \forall k_1 \tag{8}$$

(2) Use $d_{i_1j_1k_1\ i_2j_2k_2k_2}$ to describe the distance between k_1 and k_2 cells, which has to be greater than D, then the expression of the distance constraint is :

$$d_{i_1j_1k_1\ i_2j_2k_2}\geq D \tag{9}$$

By restraining the use of as much land as possible in residential areas, the utilization rate of land resources in each functional area will be effectively improved, and waste of land resources will be avoided.

2.3. Solving layout optimization model based on IAMPSO algorithm

This paper takes the optimization idea of elementary particle swarm (PSO) algorithm as the basic framework, and adopts different adaptive mutation operations for the different characteristics of the particles in the three cases of non-optimal position, zero velocity, and optimal position, respectively, to differentiate and improve their positions and velocities, and builds the improved adaptive mutation particle swarm algorithm (IAMPSO), which is used for the solution of the layout optimization design model.

2.3.1. Standard Particle Swarm Algorithm

Birds always adopt the strategy of clustering towards the closest bird to the food when feeding, exploring the space around it to increase the efficiency and accuracy of the flock.PSO algorithm [14] as an emerging intelligent optimization algorithm thus a natural phenomenon emerged, which compares the process of exploring the optimal solution of an optimization problem to the process of a bird searching for food. All the particles update their own speed and position based on the individual and global extremes and their own experience, and the degree of positional superiority is examined by the algorithm's fitness value function.

The definition of each unknown quantity of the algorithm is shown below:

$X=(X_1,X_2,\cdots,X_n)$ denotes a population of n particles.

$X_i=(x_{i1},x_{i2},\cdots,x_{iD})^T$ denotes the position vector of particle i.

$V_i=(v_{i1},v_{i2},\cdots,v_{iD})^T$ denotes the velocity vector of particle i.

$P_i=(P_{i1},P_{i2},\cdots,P_{iD})^T$ denotes the individual poles.

$P_G=(P_{G1},P_{G2},\cdots,P_{GD})^T$ denotes the global extreme value.

The updating equations of velocity vector and position vector during population exploration are as follows:

$$V_i^{k+1}=wV_i^k+c_1r_1(P_i^k-X_i^k)+c_2r_2(P_G^k-X_i^k) \tag{10}$$

$$X_i^{k+1}=X_i^k+V_i^{k+1},\quad i=1,2,\cdots,n \tag{11}$$

where n is the number of population particles, w is the inertia weight, c_1,c_2 is called the learning factor, and r_1 and r_2 are random values distributed in the interval [0,1].

The inertia weight w is the effect of the previous search when a particle performs a search, and thus can be interpreted as the inertia of the particle when it performs an update. Depending on the different levels of particle probing ability required at different stages of the population exploration process, the appropriate w is then set. A larger w enables the particles to maintain a higher velocity and position updating tendency, so that the spatial exploration ability of the particles is not weakened, and the particles are still able to search in a larger space. And a smaller w enables the particle to explore in the small neighborhood it is in, improving the accuracy of exploring potential solutions. Therefore, this paper adopts the linear decreasing weight method to select w, which can improve the exploration ability of the particle in the early stage and also ensure the accuracy in the late stage of convergence. Namely:

$$w=w_{\max}-\frac{t(w_{\max}-w_{\min})}{M},\quad t=1,2,\cdots,M \tag{12}$$

where t is the current number of iterations and M is the maximum possible number of iterations for the population.

2.3.2. Improved adaptive variational particle swarm algorithm

Existing PSO algorithms are prone to premature convergence and low population diversity due to the low exploration performance at the later stage of the algorithm, which makes it difficult to obtain the global optimal solution in problem solving. Therefore, in this paper, we enhance the possibility of the algorithm to approach the global optimal solution through the adaptive operation of the particle swarm to enhance the activity and diversity of the population in the exploration process. In this paper, according to the similarity and difference of the functions of the particles in the non-optimal position and the optimal position to the whole population, different mutation strategies are adopted to enhance the activity and diversity of the population. The technical flow of the improved adaptive mutation particle swarm algorithm [15] is shown in Fig. 2.

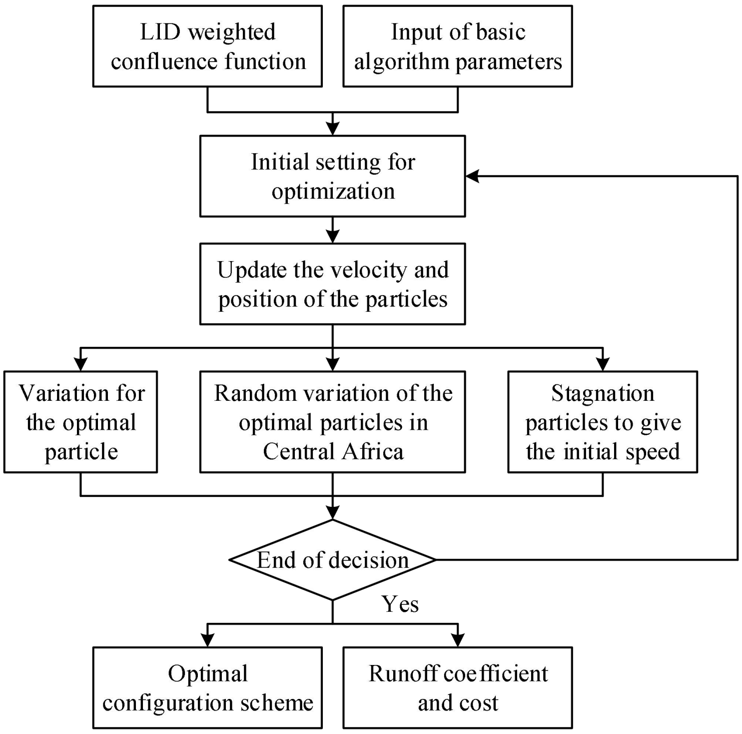

Figure 2. The technical process of IAMPSO algorithm

(1) Randomized mutation strategy for non-optimally located particles

The following randomized mutation strategy is adopted for non-optimal location particles:

$$\text{if}(P_t > P_0)$$

$$\begin{cases} \mu(t) = 1 - \alpha(1 - \dfrac{t}{M})^2 \\ X_i^{k+1} = X_i^k + \mu(t) X_i^k R, \quad r \geq 0.5 \\ X_i^{k+1} = X_i^k - \mu(t) X_i^k R, \quad r < 0.5 \end{cases} \tag{13}$$

where P_t is the probability of generating a random mutation, $P_0 \in [0,1]$, if $P_t \geq P_0$ the population particles undergo a mutation, and if $P_t < P_0$ the population particles do not undergo a mutation. $\alpha \in (0,1)$, R, r are random numbers. $\mu(t)$ is the variation factor in the t th population exploration. It can be seen from Eq. In the early stage of the population exploration process, $\mu(t)$ is larger, which can make the particle swarm have stronger search ability, while in the later stage, $\mu(t)$ will gradually decrease, so as to improve the accuracy of the local convergence of the population.

The standard deviation of the fitness of all the particles in the population at the current moment is introduced as the population diversity operator, and the "aggregation" level of the particles in the population can be described by the standard deviation of the fitness:

$$\sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(f_i - f_a)^2} \tag{14}$$

$$f_a = \frac{1}{n}\sum_{i=1}^{n} f_i \tag{15}$$

where n is the total number of individuals in the population, and f_i is the fitness value of the i th particle in the current state.

According to the size of the population adaptation standard deviation σ, the size of the variation probability P_k can be determined, and the update formula for P_k is as follows:

$$P_k = (P_{\max} - P_{\min})\left(\frac{\sigma_k^2}{n}\right)^2 + (P_{\max} - P_{\min})\left(\frac{2\sigma_k^2}{n}\right) + P_{\max} \tag{16}$$

where $P_{\max}$ and $P_{\min}$ represent the maximum and minimum values of the mutation probability, respectively.

(2) Re-initialize the mutation strategy

When the velocity of the particle at the non-optimal position stagnates to zero, stops moving, and no longer explores the space, the following operation is taken on the particle's:

$$\begin{cases} \mu(t) = 1 - \alpha^{\left(1-\frac{t}{M}\right)2} \\ V_i^{k+1} = \mu(t)Rv \\ X_i^{k+1} = \mu(t)RX_i^k, \quad r \geq 0.5 \end{cases} \tag{17}$$

where v is the reinitialized velocity.

This strategy enables the particle with zero velocity to regain the search ability and mutate the position of the particle with a certain probability.

(3) Optimal position particle mutation strategy

When a particle in the population explores the current optimal position, the particles in its vicinity will quickly move to the position of the current optimal particle, which will lead to a decrease in the activity and diversity of the population. The following is the strategy implemented in this paper for the speed and position of the optimal particle in the population:

$$\begin{cases} V_i^{k+1} = \rho^k(1-2r) \\ X_i^{k+1} = P_{Gi} + wV_i^{k+1}, r \geq 0.5 \end{cases} \tag{18}$$

where r is a random number; ρ is a scaling factor, which affects the size of the neighborhood explored by the optimally located particles, and it varies according to the following rules:

$$\rho^{k+1} = \begin{cases} 2\rho^k, & s > s_c \\ 0.5\rho^k, & f > f_c \\ \rho^k, & otherwise \end{cases} \tag{19}$$

where s and f are the number of consecutive successes and consecutive failures, with failure defined as the unchanged particle fitness before and after the update, and success defined in the opposite way. s_c, f_c and ρ^0 are constants.

3. Experimental validation of the design methodology

3.1. Subjects and environment

In order to verify the feasibility and reliability of the designed design method for optimizing the layout of the main functional areas of residential areas based on the IAMPSO algorithm, a city with nine districts, a total area of 3462.83 km², a total population of 845,000, of which the urban population is 192,000, and the population density is 244 people/km² is taken as an experimental object. Comparative experiments are carried out on the spatial planning of residential land in this city using the design method of this paper, and the planning method based on geospatial information system and the planning method based on big data are used as the control group to compare with the method of this paper. The experiment was carried out from the following environment: Windows 11 operating system, configured with Inter Core I9 CPU, 2TB SSD and 64GB RAM, and Python version 3.11.8 was used to edit the IAMPSO algorithm.

3.2. Experimental parameters and evaluation indexes

Comparison experiment of the three methods in the above environment, collect the spatial planning data information of residential land in the city, substitute it into the layout optimization model, and use the IAMPSO algorithm to solve the calculation of the model, and the parameter settings of the IAMPSO algorithm are shown in Table 1.

Table 1. Parameters of IAMPSO algorithm

Serial number	Parameter	Set value
1	Group size N	800
2	Parametric coefficient c_1	1.5264
3	Parametric coefficient c_2	1.5264
4	Maximum iteration number M	800
5	The upper limit of the particle's flight speed $T_{\max}$	0.5
6	The lower limit of the particle's flight speed $T_{\min}$	-0.5
7	The upper limit of the particle search range $pop_{\max}$	1
8	The upper limit of the particle search range $pop_{\min}$	0
9	The probability of adaptive random variation P_0	0.5

The IAMPSO algorithm is used to solve the layout optimization model and output the optimal planning scheme. Five planning scenarios are set up in the experiment, which are 15%, 20%, 25%, 30% and 35% of the total area of the city, and the spatial planning of urban residential land under the scenario of occupying 20% of the land is shown in Fig. 3, in which the spatial planning of the urban residential land is four residential districts, which are distributed in the center of the city. In order to evaluate the effect of urban residential land space planning, the spatial compactness is chosen as the evaluation index, and the higher the spatial compactness of urban residential land, the higher the spatial utilization rate of urban residential land, and the higher the applicability and feasibility of the planning scheme. Therefore, by comparing the spatial compactness of the three methods of planning, the application effect of this paper's method is evaluated.

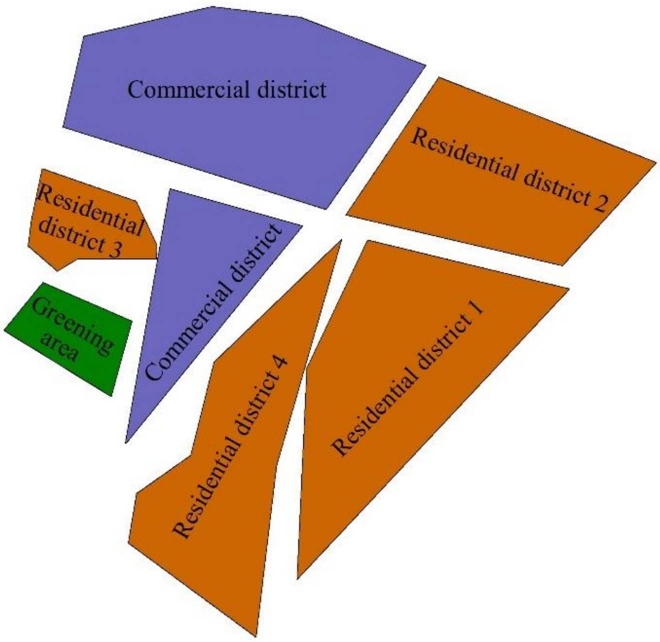

Figure 3. Spatial planning map of urban residential land

3.3. Examination of planning effects

Comparison of the spatial compactness of urban residential land planned by this paper's method with control group 1 and control group 2 under different planning situations is shown in Figure 4. It can be seen that among the three methods, this paper's method has the highest spatial compactness of urban residential land, which is above 0.92, and the highest spatial compactness of control group 1 and control group 2 is 0.73 and 0.77 respectively, which is lower than this paper's method. Therefore, the above comparison proves that the design method of this paper is more suitable for the urban residential land space planning combined with the function of physical education, which can effectively ensure a high urban residential land space utilization rate and avoid the waste of land resources.

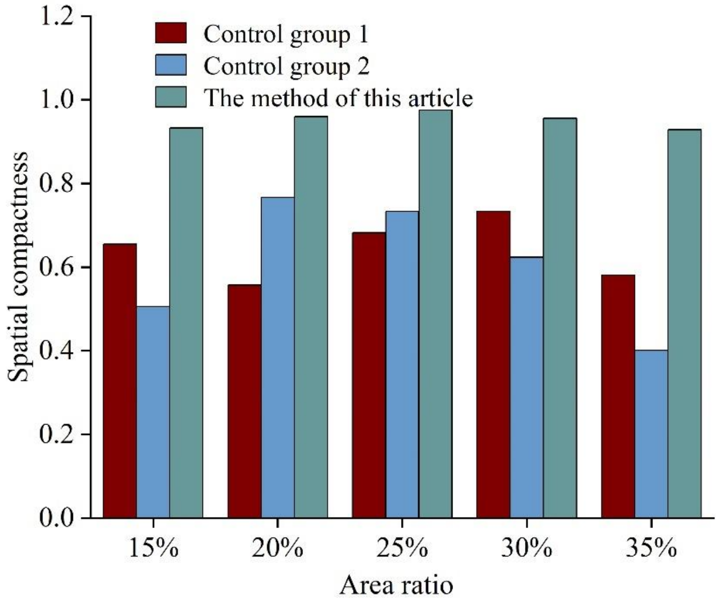

Figure 4. Comparison of spatial compactness

4. Analysis of the current state of health of the population in the community

This chapter analyzes the current situation of the health level of community residents in different regions of China, and provides a reference for the integration of physical education functions in the design of residential areas, so as to enhance the level of community health education.

4.1. Descriptive analysis of the population's health level

The data for this study came from the China Family Tracking Survey (CFPS), and after excluding samples containing outliers and missing values, the five-year survey data for 10,823 individuals were retained, totaling 54,115 data items. The demographic structure of the sample is shown in Table 2, which shows that the age of the interviewed individuals is distributed in the range of 18-93 years old, centered on the age of 55 years old, and there are slightly more individuals under the age of 55 years old. The age structure data shows that the sample has a more balanced male-female structure.

Table 2. Sample population structure

Division basis	Category	Number	Proportion /%
Age	[18,23]	637	1.18
	(23,28]	1699	3.14
	(28,33]	2763	5.10
	(33,38]	3643	6.73
	(38,43]	5255	9.71
	(43,48]	7308	13.50
	(48,53]	7639	14.12
	(53,58]	6649	12.29
	(58,63]	6319	11.68
	(63,68]	5697	10.53
	(68,73]	3607	6.66
	(73,78]	1921	3.55
	(78,83]	784	1.45
	(83,88]	109	0.20
	(88,93]	85	0.16
Total		54115	100.00
Gender	Female	5627	51.99
	Male	5196	48.01
Total		10823	100.00

4.1.1. Regional comparison of health levels

The analysis of variance of the health level of the sample interprovince is shown in Table 3, and the analysis of variance of the health level between regions is shown in Table 4. From the results of the ANOVA, it can be seen that the hypothesis test F statistic for the hypothesis that there is a significant gap in the health level of residents between provinces and regions is much larger than the critical value, and it can be assumed that there is a significant gap in the health level between provinces and between regions.

Table 3. Analysis of variance for inter-provincial health levels

Source of difference	SS	df	MS	F	P-value	F crit
Between groups	6975.634	25	296.1534	221.715	0	1.6052
Within the group	62143.46	69213	1.423041			
Total	69119.09	69238				

Table 4. Analysis of variance for health levels among regions

Source of difference	SS	df	MS	F	P-value	F crit
Between groups	4135.815	6	812.6914	585.2764	0	2.325143
Within the group	95243.07	69233	1.442816			
Total	99378.885	69239				

The mean values of the health scores of residents in each province are shown in Figure 5, and the mean values of the health scores of residents in each region are shown in Table 5. From a regional perspective, eastern region > central region > western region. Specifically, Tianjin > Beijing > Hunan > Liaoning > Zhejiang > Jiangsu > Hubei > Shanghai > Shanxi > Jilin > Guangdong > Guangxi Zhuang Autonomous Region > Anhui > Henan > Shandong > Helongjiang > Shanxi > Yunnan > Hebei > Guizhou > Gansu > Sichuan > Chongqing > Fujian > Jiangxi. It is reasonable to assume that there is a positive correlation between the health level of the population and the level of economic development of the geographic area.

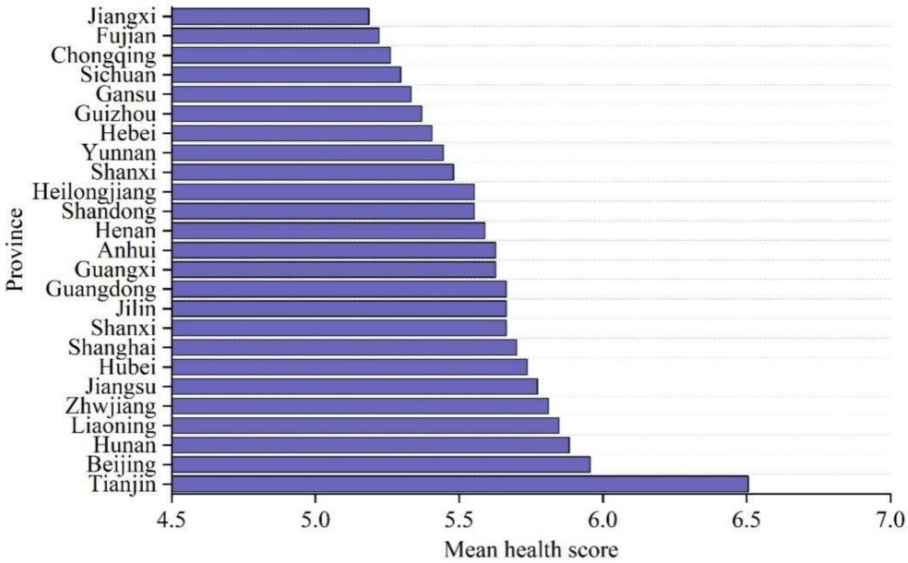

Figure 5. Mean health scores of residents in each province

Table 5. The average health scores of residents in each region

Region	Mean health scores
The eastern region	5.52
The central region	5.44
The western region	5.26

Further comparing the health level of residents in each region from 2016-2024, the results of health level comparison are shown in Table 6.

In terms of the time dimension, the health level of residents within the three major economic regions showed an increasing trend in the successive surveys from 2016-2024. Among them, in the four surveys from 2016-2022, the indicator of the average value of health scores continued to rise, and there was a certain drop in 2024. In terms of the regional dimension, the western region > central region > eastern region, the phenomenon is also consistent with the economic development of each region, the economically developed regions will have better medical service conditions, nutrition and health conditions, and the health level of local residents will be higher.

Table 6. Comparison of the health levels of residents in various regions

	The eastern region	The central region	The western region	Nationwide
2016	5.32	5.27	4.94	5.21
2018	5.54	5.46	5.07	5.44
2020	5.68	5.75	5.43	5.62
2022	5.81	5.67	5.56	5.73
2024	5.59	5.45	5.42	5.47

4.1.2. Gender Comparison of Health Levels

The results of the comparison of the health status of men and women in urban and rural areas are shown in Table 7. From a gender perspective, the health level of China's male residents is higher than that of its female residents. From the urban and rural perspectives, the health level of urban residents is significantly higher than that of rural residents.

Table 7. Comparison of health conditions between men and women in urban and rural areas

	Rural area	Town	Mean value
Male	5.4561	5.7485	5.6023
Female	5.1724	5.6232	5.3978
Mean value	5.3143	5.6859	5.5001

4.1.3. Age Comparison of Health Levels

The health scores for each age group are shown in Figure 6. The “age<20” line in the figure is missing from 2018 because the sample used in this paper is a continuous survey data of 10,823 samples, and some of the survey respondents who were born before 2000 have entered the age range of 20-40 years old in 2020, so the data are blank after 2018.

Judging from the trend of change, the health level of Chinese residents of all ages basically shows an upward trend. At the same time, the health level of residents of different age groups shows obvious stratification, and it can be clearly seen that as the age group gets higher, the health level of residents gets lower.

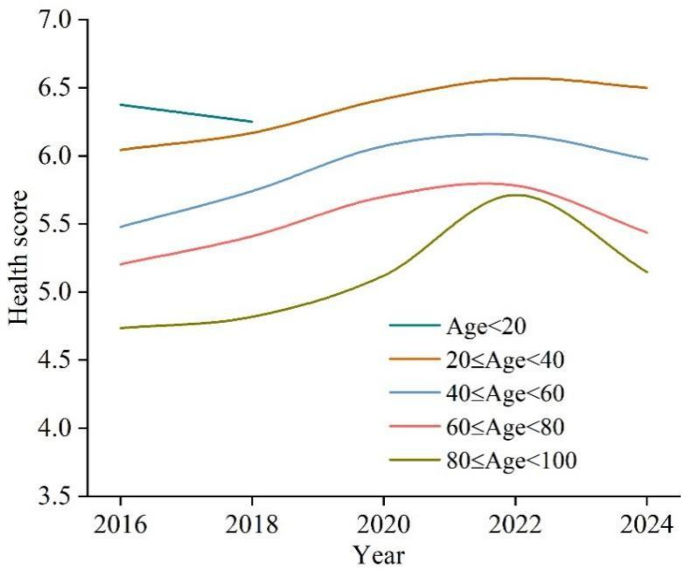

Figure 6. Health scores of each age group

4.2. Convergence analysis of population health disparities

σ Convergence refers to the process by which the degree of dispersion in the health levels of different regions continues to decline as time moves on. Measurement methods often used in this convergence test generally include Theil index, standard deviation, coefficient of variation and other statistical indicators that can represent the degree of dispersion, this paper here uses the coefficient of variation method of measurement, to get the health differences in each region as shown in Table 8.

From the time dimension, the differences in the health level of residents within the three major economic regions basically show a flat state with a slight decrease in the successive surveys from 2016 to 2024. From the regional dimension, western region > central region > eastern region. The health level of residents is affected by the level of regional economic development, and the degree of difference in the health level of residents is also affected by the level of economic development of each region. Because the health level of the population and the level of economic development is not a simple linear relationship and there is a threshold effect, when the economic development to a certain extent, its effect on individual health promotion will be reduced. The higher the level of economic development of the region, the overall health of the living environment of its residents, medical services more inclusive, to achieve the basic health protection of low-income people, but can not infinitely improve the health of high-income people, thus reducing the health disparities. Overall, the health disparities of residents in central and eastern China are divergent, while those in western China are convergent.

Table 8. The health differences in various regions

	The eastern region	The central region	The western region
2016	0.3024	0.2625	0.2349
2018	0.3022	0.2596	0.2328
2020	0.3013	0.2593	0.2314
2022	0.3018	0.2595	0.2315
2024	0.3057	0.2623	0.2328

5. Conclusion

The following conclusions are drawn from the study of the layout optimization design method for residential areas incorporating physical education and teaching functions:

The IAMPSO algorithm performs well in the layout optimization of the main functional area of the residential district and achieves efficient spatial planning. Experimental data show that the spatial compactness of urban residential land planned by this method exceeds 0.92, which is significantly higher than that of the traditional method, effectively avoiding the waste of land resources. There are obvious regional differences in the health level of Chinese residents, and the health score of residents in the eastern region is 5.52, which is higher than that of 5.44 in the central region and 5.26 in the western region, reflecting the positive correlation between the level of economic development and the health of the residents. From the urban and rural dimensions, the health level of urban residents was 5.6859, significantly higher than that of rural residents, which was 5.3143, suggesting that the urbanization process has a positive effect on improving residents' health. From the gender perspective, the health level of male residents (5.6023) is higher than that of female residents (5.3978), suggesting the need to pay more attention to female groups in community health education.

The integration of physical education into the design of residential areas can effectively improve the level of community health education and meet the health needs of residents of different ages and genders. The optimized layout of the residential area not only ensures the efficiency of space utilization, but also provides residents with convenient places for physical activities and health education, which promotes the overall improvement of community health. The future design of the residential area should further strengthen the systematic integration of physical education functions and build an all-age friendly, diversified and inclusive healthy community environment.

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