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Construction of an Exercise Health Assessment Model and Precision Intervention for the Elderly Based on Health Big Data

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SUMMARY: *Based on the data of elderly body morphology, biochemical indexes, mental indexes, diet and other data for, and based on big data analysis, this study constructs the structure of the intelligent human body system, which contains the information entry area and the data collection area and so on, in order to realize the precise intervention. Through the wearable sensor technology, physiological indicators such as heart rate, pulse, blood oxygen, blood pressure, blood glucose, etc. are monitored, and the Qt5.9.3 platform is adopted to realize the hierarchical, componentized, generalized, extensible and cross-platform development of the software platform. The mathematical model of association rules and parameter estimation equations are established, and the association rules are designed by combining the nodes of Apriori algorithm to realize the monitoring and evaluation of sports health status. The study selected a total of 1,000 older adults in two communities in a first-tier city as the object, and the reliability test showed that the structural validity coefficients were greater than 0.7 and 0.8, and the average reliability of the intra-survey group and functional scores were 0.956 and 0.979. After the test, the intervention group test lung capacity (1.73±0.15)L/min, and the respiratory system was improved. In addition, a sound elderly exercise health precision intervention system is proposed, which provides a theoretical and practical reference for the intelligent and precise health management of the elderly.*

KEYWORDS: *big data analysis; intelligent human body; wearable sensors; association rules; exercise health status*

1 Introduction

Since the 1990s, the overall aging trend has become more and more obvious, and the problem of aging in China has become more and more prominent, and now for the Chinese people, the whole has entered the old age type, because of the different occupations engaged in, so the development of a comprehensive health evaluation of the elderly is imminent [1]. Comprehensive geriatric health evaluation is not only the evaluation of the health status of the individual elderly population, but also the evaluation of the whole elderly social group, and is related to the allocation of resources to the entire population, the adjustment of social policy [2]. The essence of health management is to comprehensively monitor and manage the health risk factors of individuals and groups, with the aim of mobilizing the enthusiasm of individuals and groups, and effectively utilizing limited resources to achieve maximum health effects. The health management based on big data focuses on combining the advantages of both, in order to give full play to its preventive health care [3]. Health assessment model construction and

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precise intervention is a shift from the traditional health evaluation indexes that focus only on life extension and local somatic function improvement, which can reflect not only physical health, but also psychological, social and emotional health [4, 5]. With the accelerated pace of population aging, health management for the elderly is not only limited to life extension and local improvement of “headache and footache”, but also focuses on their physiological, psychological, social functions and self-perception of health, and improves their quality of life in multiple ways [6].

Zhang X et al. suggested that aging is a global challenge and that there is a need to comprehensively promote the establishment of a big data infrastructure for older adults, to develop across biology and medicine, to establish technologies for intelligent monitoring and management, and also to focus on the psychological characteristics and behaviors of older adults [7]. Guo Q et al. in gerontology research proposed to define old age mainly from age and physical function decline as the definition, as well as the integration of various mental problems as a measure of indicators, these factors as a way of old age in the real life manifestation, to understand the differences of the elderly individual. A better perception of the level of risk can lead to a deeper understanding of coping mechanisms and pathways [8]. Wu X, et al. used big data analytics to enable older adults to scientifically go about managing the field of exercise health assessment and intervention, many healthcare organizations are unstructured health data. Data-driven decision making in geriatric exercise health assessment and exercise direction development to transition to a precise model of exercise health management for older adults [9]. Zhang L et al. conducted research on issues such as the quality of geriatric services, through experiments with traditional geriatric services compared to smarter, the gradual increase in population aging, the establishment of a platform for the intelligent elderly, to meet the basic movement requirements of the elderly, and the use of a variety of advantages to enhance effective and accurate interventions for the elderly to create a happy and healthy later life [10]. Shandhi M M H et al. found that with the popularity of smart portable devices, it provides an opportunity to collect physiological, behavioral and activity data for health research, monitoring. A survey was conducted by studying patients in a large academic healthcare system in the southeastern United States, and it was found that younger age groups were more likely to have wearable devices. A portion of older adults are willing to go ahead and share their devices, and also many respondents use their devices to monitor their activities on weekdays and weekends, and a small portion of older adults only use them during the day and do not use them at night, limiting the development of digital health technology [11]. Chen M et al. suggested that falls during outside exercise have been recognized as an important factor leading to accidental disability and death in older adults, and in order to predict the risk of falls sensors can be worn, and big data analytics can be used to develop accurate, easy-to-use wearable sensors. In practice, sensor data is usually noisy and contains a lot of inaccurate vibration information, the data collection may be more complex to develop a set of models for the risk of falling during normal exercise [12]. Hager A G M et al. conducted a 12-month experiment with older adults over the age of 65 as the subjects to study different exercise programs on the low incidence of falls in older adults. Through big data to analyze the phenomenon of self-exercise at home falls lowest, the results of the study and big data analysis of the effect is consistent with the results of the experimental results to establish a big data model can make more older people to prevent falls appear their own safety [13]. Javed A R et al. conducted an in-depth study on the uncertainty of today's health assessment systems, utilizing artificial intelligence and machine learning to experiment with the automation of health systems, and moreover revealed the current challenges in improving the accuracy of prediction and diagnosis, thus enabling future researchers to better identify the gaps in the research [14].

In order to experiment with accurate assessment and intervention of exercise health in the elderly, this paper designs a smart human system architecture that contains an information entry area, a data collection area, a comprehensive data processing area, and a health smart doctor assessment area to realize the management from data collection and intervention. Through wearable sensors, based on platform hierarchical, componentization, generalization, scalability, and cross-platform performance, it realizes all-around monitoring of the elderly's sports and health, and collects health data such as heart rate, blood pressure, and so on. Association rule mining is applied to identify potential associations between exercise behavior and health status. The research object is to select two communities in a first-tier city with long-term persistent exercise of the elderly, divided into the intervention group and the control group for controlled experiments. The structural validity and reliability of the research questionnaire, as well as the actual intervention effect of health big data, were verified by adopting the Liker5 rating scale and SPSS software for testing and statistics, in order to accurately assess the exercise health of the elderly, and to provide a basis for the development of precise intervention measures.

2 Construction of health assessment model for the elderly based on big data analysis

2.1 Intelligent human system structure

Intelligent human health management system should be based on the elderly body morphology indicators, biochemical indicators, mental indicators, diet and other data, real-time monitoring of blood pressure, body temperature, heart rate and other changes in the exercise data, through the big data comprehensive assessment of the elderly state of the body is suitable for what kind of intensity and way of exercise between. The state of the elderly can not be maintained every day full of energy, and can not be suitable for every day exercise or high intensity exercise. So when do you need to exercise a little more intensively, when do you need to exercise a little less intensively, this is a systematic project, which requires big data analysis and intelligent evaluation, and the comprehensiveness of the intelligent human health management system is particularly important.

Intelligent human system structure is shown in Figure 1, intelligent human health management system is divided into information entry area, data collection area, comprehensive data processing area, and health intelligent doctor assessment area, medical warning function, prescribing exercise prescription, etc. [15].

The information entry area is divided into body index entry, exercise-related information entry, body index is generally half a year to a year of data, to keep the data up-to-date, such as gender, age, body shape height, weight, limb defects, etc., physiological indicators of routine blood, urine routine examination data, etc., their own medical history or family history of hereditary diseases. Exercise-related information can be entered into the exercise program that you are good at, and the place where you often exercise. Data collection is divided into exercise collection and non-exercise collection. Exercise collection is to collect blood pressure, body temperature, respiration, blood oxygen, heart rate, step frequency and step length in normal times, and step frequency and step length in running times, etc. During exercise, the data can be collected in the course of exercise, such as blood pressure, body temperature, respiration, blood oxygen, heart rate, step frequency and step length. Non-exercise time collection is to collect some data in the usual time and sleeping. The data in the entry area and collection area are summarized to the big data comprehensive processing area, which processes all the data. The system will summarize the results based on scientific calculations and comparisons to the intelligent doctor area, where the intelligent doctor conducts a comprehensive assessment based on the data results, and gives appropriate exercise recommendations and dietary combinations through the relevant theories of kinesiology, exercise rehabilitation, and nutrition, etc. If the data is abnormal or has a certain risk to the life of the system, the system will send out an alarm, informing the elderly of the need to carry out medical interventions. After recovery from medical intervention, the data is again entered into the entry area for data updating [16]. The older adult will then proceed to the next round of exercise workout based on the daily exercise prescription and diet pairing in order to achieve exercise precision intervention.

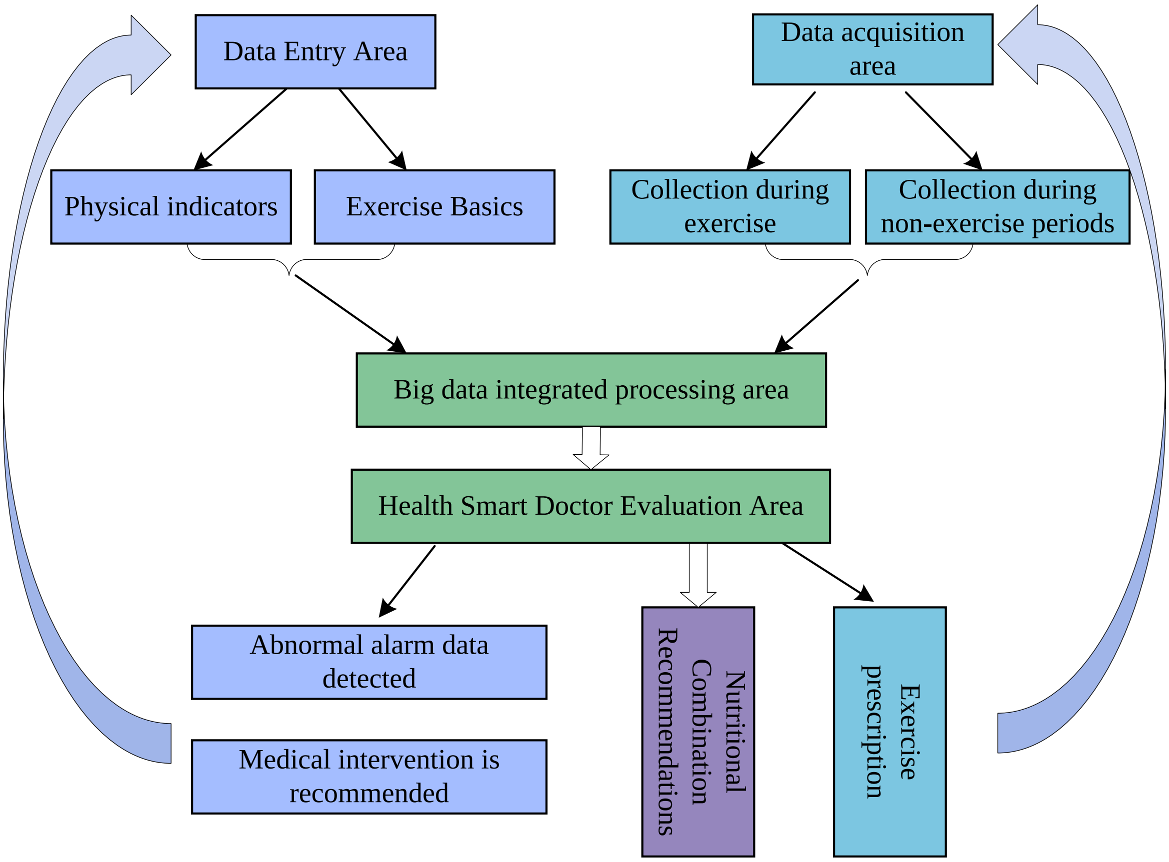

Figure 1: Intelligent human body system structure

2.2 Indicators for monitoring big data on health

The main observation indicators of health big data are shown in Figure 2, the health data of the guardianship object should be all-round, the data elements will be multifaceted, and should be the more the better under the existing technical conditions. From the current technical means of sensors that can be used for wearable, it is possible to do the perception and digitization of physiological indicators such as heart rate, pulse, blood oxygen, blood pressure, blood glucose and so on. Geographic location information can be obtained by Beidou, GPS cell phone base station and other positioning methods, for air quality can be obtained through the geographic location of the region's public services, for the required data can be provided directly by the health big data platform.

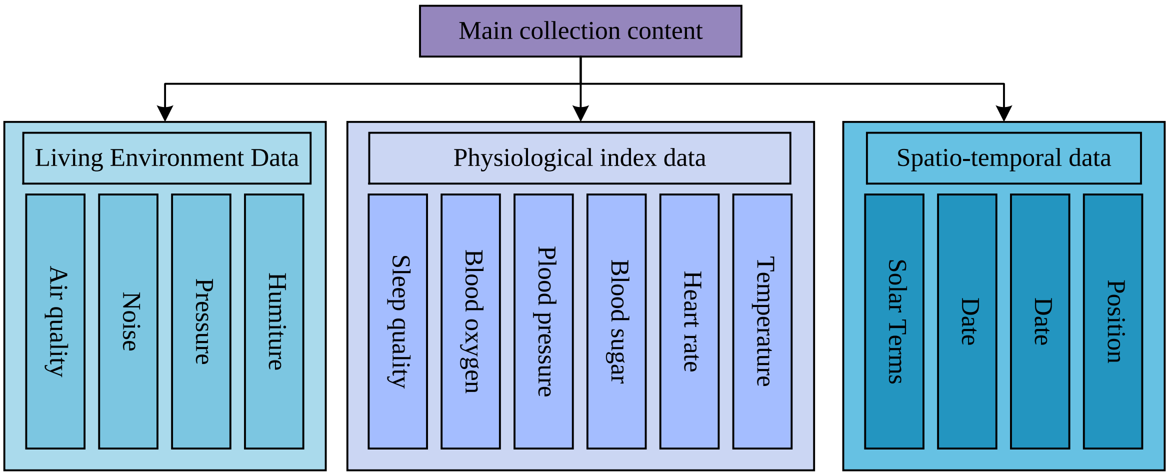

Figure 2: Key Observables for Big Data in Health

2.3 Software Architecture Design and Functionality

Figure 3 shows the design and function of the software structure. The health assessment and health management system based on big data analysis adopts the microkernel architecture design to realize the hierarchical, componentized, generalized, scalable and cross-platform development of the software platform. The user interface is beautiful, operable, easy to expand, and highly versatile, and can be applied in other electronic systems including health assessment systems other than health assessment systems. The software platform is developed using Qt5.9.3 to complete the online assessment of the health status of the elderly. In addition to completing the local intelligent diagnosis and health assessment functions, the system software platform has added a remote control module, which realizes the testing of health assessment with a large amount of data and high reliability requirements, big data storage, mining and analysis, remote status monitoring, intelligent diagnosis and rapid positioning, remote guidance and health status assessment capabilities.

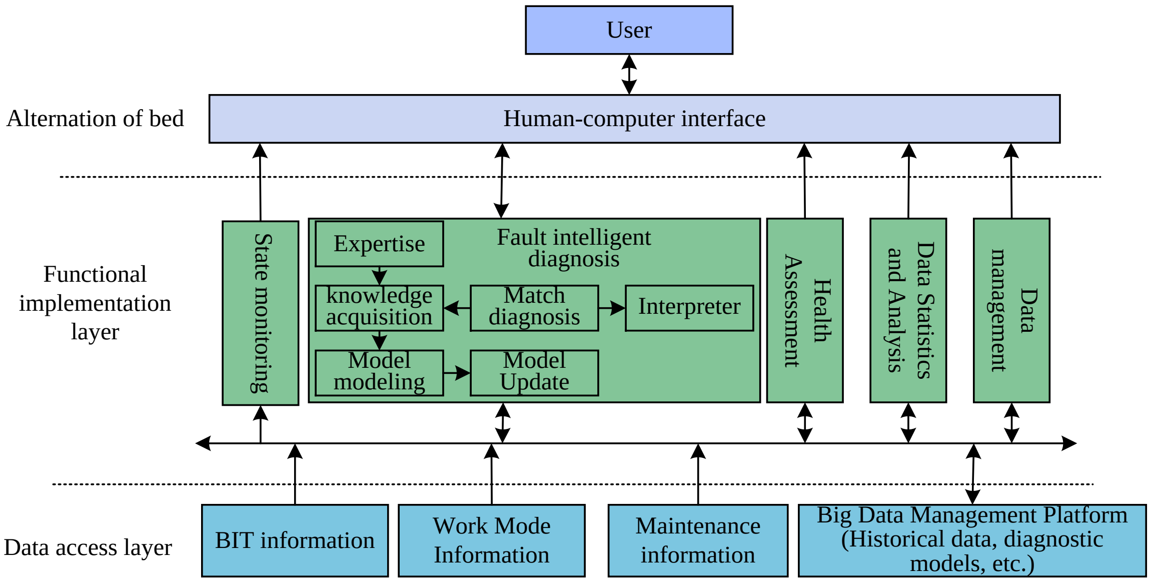

Figure 3: Software Architecture Design and Functions

2.4 Application of association rule mining in health management

2.4.1 Mathematical modeling

The problem of mining association rules from databases has become the most mature, active, and important research in health management, attracting a great deal of attention from the research community of mining algorithms and their applications.

X_{ij} is the state of the elderly j movement i, then:

$$P\left(X_{ij}\middle|\ \theta_j\right)=p_{ij}^{X_{ij}}q_{ij}^{1-X_g} \tag{1}$$

where $X_{ij}=0,1$ is the response of the elderly, θ is the potential characteristics of the elderly j, P is the probability that the subject elderly is healthy i, and $q_{ij}=1-p_{ij}$. Then there are:

$$p_{ij}=P\left(X_{ij}=1\middle|\ \theta_j\right)=c_i+\left(1-c_i\right)\frac{\exp\left(D\alpha_i\left(\theta_j-\beta_i\right)\right)}{1+\exp\left(D\alpha_i\left(\theta_j-\beta_i\right)\right)} \tag{2}$$

where α,β,c are the degree of health, coefficient of movement and physical function, respectively. D is a constant, 1 or 1.7. When $\alpha_j=\alpha$ for all items, Equation (2) is the Rasch model. When $D=1.7$, Eq. (2) is a normal ovoid model. When $c=0$, $D=1$, Eq. (2) is a two-parameter IRT model, see Eq. (3):

$$P\left(X_{ij}=1\middle|\ \theta_j\right)=\frac{\exp\left(\alpha_i\left(\theta_j-\beta_i\right)\right)}{1+\exp\left(\alpha_i\left(\theta_j-\beta_i\right)\right)} \tag{3}$$

2.4.2 Parameter estimation

Assuming that there are a total of N subjects, M items, then it is necessary to estimate N potential characteristic parameters and $3M$ item parameters, α,β,c each M. Assuming that the items are scored as 0 and 1, the response matrix X has a total of N rows M columns. The response matrix consists of rows and columns:

$$X=\left(x_{ij}\right)_{N\times M}=\begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1M} \\ x_{21} & x_{22} & \cdots & x_{1M} \\ \cdots & \cdots & \cdots & \cdots \\ x_{N1} & x_{N2} & \cdots & x_{NM} \end{bmatrix} \tag{4}$$

Under the assumption that subjects are independent of each other and the same subject's responses to each item are independent of each other, the likelihood function of the response matrix X is:

$$L\left(\theta_1,\cdots\theta_N,\alpha_1,\cdots\alpha_M,\beta_1,\cdots\beta_M,c_1,\cdots c_M\middle|\ x_{11},\cdots x_{NM}\right)=\prod_{i=1}^{N}\prod_{j=1}^{M}P_{ij}^{x_{ij}}Q_{ij}^{1-x_{ij}} \tag{5}$$

It can be abbreviated as:

$$L = \prod_{i=1}^{N}\prod_{j=1}^{M} P_{ij}^{x_{ij}} Q_{ij}^{1-x_{ij}} \tag{6}$$

Bringing Eq. (2) into Eq. (4), then the likelihood function contains $N+3M$ unknown parameters. For parameter estimation, find the log-likelihood function of Eq. (4):

$$\ln(L) = \ln\left(\prod_{i=1}^{N}\prod_{j=1}^{M} P_{ij}^{x_{ij}} Q_{ij}^{1-x_{ij}}\right) = \sum_{i=1}^{N}\sum_{j=1}^{M}\Big(x_{ij}\ln\left(P_{ij}\right) + \left(1-x_{ij}\ln\left(Q_{ij}\right)\right)\Big) \tag{7}$$

The following system of equations can be obtained by taking the log-likelihood function and making it equal to 0 by taking the partial derivatives of the log-likelihood function for N θ and each X α,β,c separately, so that it equals 0:

$$\begin{cases} \sum_{i=1}^{N}\left[\left(x_{ij}-P_{ij}\right)/P_{ij}Q_{ij}\right]\left(\partial P_{ij}/\partial\theta_i\right)=0 \quad (i=1,\cdots,N) \\ \sum_{j=1}^{M}\left[\left(x_{ij}-P_{ij}\right)/P_{ij}Q_{ij}\right]\left(\partial P_{ij}/\partial\alpha_j\right)=0 \quad (j=1,\cdots,M) \\ \sum_{j=1}^{M}\left[\left(x_{ij}-P_{ij}\right)/P_{ij}Q_{ij}\right]\left(\partial P_{ij}/\partial\beta_j\right)=0 \quad (j=1,\cdots,M) \\ \sum_{j=1}^{M}\left[\left(x_{ij}-P_{ij}\right)/P_{ij}Q_{ij}\right]\left(\partial P_{ij}/\partial c_j\right)=0 \quad (j=1,\cdots,M) \end{cases} \tag{8}$$

The above system of equations can be divided into two parts, N equations that are derived for potential characterization parameters θ and $3M$ equations that are derived for project parameters.

2.4.3 Association rules

The Apriori algorithm node in SPSS Clementine 12.0 is used for association rule mining of the preprocessed data, with the number of rule antecedents set to 4, and the minimum support $\min\_\sup$ and minimum confidence $\min\_conf$ set to 10% and 25%, respectively. However, the confidence level ignores the probability of occurrence of the latter term, and when the probability of occurrence of the latter term is larger, a higher confidence level will be generated. For this reason, the degree of action $lift$ is defined as the ratio of the probability of the occurrence of the posterior term Y under the condition of the occurrence of the rule antecedent term X to the probability of the occurrence of the posterior term Y under the condition of disregarding the antecedent term X and is calculated by the following formula:

$$lift(X \Rightarrow Y) = \frac{P(Y|\ X)}{P(Y)} \tag{9}$$

The value of $lift$ ranges from $\left[0,\infty\right)$, when $lift > I$, it means that compared with the probability of the occurrence of the latter item Y under the condition that the former item X is not taken into account, the occurrence of the former item X reduces the possibility of the occurrence of the latter item Y, which is known as the negative correlation rule. When $lift < I$, it means that the occurrence of the antecedent X increases the likelihood of the occurrence of the consequent Y compared to the probability of the occurrence of the consequent Y under the condition that the antecedent X is not taken into account, which is called the positive correlation rule. When $lift = I$, it means that the antecedent X and the consequent Y are independent events, and the rule is called an irrelevant rule.

3 Research Objects and Methods

3.1 Objects of study

The pre-survey selected 500 elderly people in two communities of a first-tier city who persisted in exercising for a long time, and 476 valid questionnaires were recovered, with a recovery rate of 95.2%. The formal survey selected 1,000 fitness elderly people in two communities of a first-tier city who insisted on exercising for a long time, and 976 valid questionnaires were recovered, with a recovery rate of 97.6%. Among them, there were 620 males and 380 females, and the average age of the subjects was 69.5 years old with a standard deviation of 3.6 years old.

3.2 Research procedures

3.2.1 Initial questionnaire development

The initial exercise health questionnaire was developed with reference to relevant research and in consultation with relevant exercise experts and qualified health assessors. After the initial questionnaire was developed, five qualified sports experts with more than 10 years of experience and three health assessors were asked to review the specific content of the entries. They were asked to make changes to the improperly expressed content of the entries, and were asked to add or delete some of the entries, and the initial questionnaire was formed with a total of 20 entries after analyzing, processing, and screening based on the principle of concise language and clear meaning.

The theoretical construction was based on the main observational indicators of health big data, and the two dimensions of the exercise dependence questionnaire were initially constructed after discussion by the expert group. The size of lung capacity and the robustness of gait are also important indicators reflecting the health status of the elderly. Large lung capacity indicates that the respiratory system is functioning well and can provide sufficient oxygen to the body. A steady gait means good balance and muscle strength. These are the cornerstones of healthy living for the elderly. Joint mobility (ROM), muscle strength, and balance and coordination are all important indicators of an older person's ability to move. Higher joint mobility means greater flexibility. Strong muscle strength allows for greater freedom of movement in daily life. Good balance and coordination greatly reduces the risk of falling.

3.2.2 Questionnaire testing

The questionnaire took the form of a Liker 5-point scale, ranging from 1 for strongly disagree to 5 for strongly agree, and was preliminarily pretested on 500 older adults, with 476 valid questionnaires returned. The returned questionnaires were item-analyzed, and 20 entries were retained after deleting some of them to form the Exercise Dependence Formal Questionnaire. The questionnaire was utilized to test 1,000 older adults who have been adhering to fitness and exercise for a long period of time, and 976 valid questionnaires were returned, and the returned questionnaires were tested for reliability and validity.

3.2.3 Statistical processing

The raw data were entered using EpiData, items were analyzed using SPSS 13.0 for the pretest questionnaire, and validation factor analysis was performed using LISREL 8.53 software, after which the formal questionnaire formed was tested for reliability and validity.

4 Results and analysis

4.1 Reliability test

4.1.1 Structural validity

In the evaluation of scale validity, structural validity is considered to be the strongest evaluator and is used to analyze the stability of the scale structure. Content validity, on the other hand, helps the measurer to make a judgment on whether the variables and entries to be measured, as well as the proportion of their content distribution, are appropriately reflected. Factor loadings reflect the degree of correlation between an entry and a dimension, and the closer the absolute value of the factor loading is to 1, the more closely the entry is related to the dimension to which it belongs. The sum of the squares of the factor loadings of all the entries of the dimension is the variance contribution of the dimension, and the higher the value, the higher the importance of the corresponding dimension. Before factor analysis, the Kaiser-Meyer-Olkin (KMO) test was used to determine whether the factor analysis was suitable or not. the closer the KMO value was to 1, the more it indicated that the sum of the squares of the simple correlation coefficients among all variables was much larger than the sum of the squares of the partial correlation coefficients, which meant that the stronger correlation coefficients among variables were, and the more suitable the original variables were for the factor analysis. More than 0.6 was suitable for the factor analysis, and the results of the questionnaire validity test in this study are shown in Table 1. The results of the questionnaire validity test, this study used the association rule statistics to select the common factors with eigenvalues greater than 1, and finally extracted five common factors, which were consistent with the five dimensions of sports knowledge, sports willingness, sports behavior, professional support, and social support. Orthogonal rotation by the maximum variance method was performed on all variables to obtain named interpretations for each dimension. Variables with correlation coefficients >0.7 with Common Factor 1 included the five entries of motor knowledge, with each entry loading 0.826-0.875 on this common factor. Variables with correlation coefficients >0.7 with Common Factor 2 included the five entries for exercise intentions, with each entry loading 0.747-0.846 on this common factor. Variables with correlation coefficients >0.8 with Common Factor 3 included five entries for motor behavior, with each entry loading 0.816-0.853 on this common factor. Variables with correlation coefficients >0.7 with Common Factor 4 included 3 entries for Professional Support, with each entry loading on this common factor with values of 0.795-0.841. Variables with correlation coefficients >0.8 with Common Factor 5 included 2 entries for Social Support, with each entry loading on this common factor with values of 0.802 and 0.815.

Table 1: Results of questionnaire validity test

Entry	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
Appropriate exercise helps blood glucose control (Q_1)	0.875	-	-	-	-
Exercise 30min to 1h after meals (Q_2)	0.826	-	-	-	-
Exercise at least 150min per week (Q_3)	0.864	-	-	-	-
Each exercise lasts more than 30min on average (Q_4)	0.855	-	-	-	-
Exercise for the elderly should be at low or medium intensity (Q_5)	0.843	-	-	-	-
Happy to do exercise (Q_6)	-	0.747	-	-	-
Can do exercise according to the exercise program set by my doctor (Q_7)	-	0.751	-	-	-
Overcome the difficulty of Do exercise (Q_8)	-	0.802	-	-	-
Exercise is risky for the elderly (Q_9)	-	0.846	-	-	-
Regularly carried out an exercise program according to my doctor's requirements (Q_{10})	-	0.841	-	-	-
Each exercise session lasts more than 30min on average (Q_{11})	-	-	0.816	-	-
Exercise 30min-1h after meals (Q_{12})	-	-	0.842	-	-
Exercise for at least 150min per week (Q_{13})	-	-	0.853	-	-
Conducted a big-data monitoring program prior to exercise (Q_{14})	-	-	0.824	-	-
Conducted exercise based on the results of the analysis of the big-data (Q_{15})	-	-	0.819	-	-
Conveniently get information support about exercise (Q_{16})	-	-	-	0.841	-
Provide demonstration facilities for exercise (Q_{17})	-	-	-	0.795	-
My family often encourages me to exercise regularly (Q_{18})	-	-	-	0.802	-
The community where I live is equipped with a wide range of exercise equipment and venues (Q_{19})	-	-	-	-	0.802
The community where I live creates a good atmosphere for exercise (Q_{20})	-	-	-	-	0.815

4.1.2 Questionnaire Reliability Test

The results of the questionnaire reliability test are shown in Figure 4, where the upper and lower horizontal lines are the maximum and minimum values of reliability, the center dot is the mean value, and the vertical line is the mean interval. The mean reliability within the survey group was 0.956, within the 0.90-0.99 interval, and the mean reliability of the functional scores was 0.979, within the 0.94-0.99 interval. The reliability of all entries within the survey group and between the functional scores was high, indicating that the designed research methodology has high reliability and internal consistency.

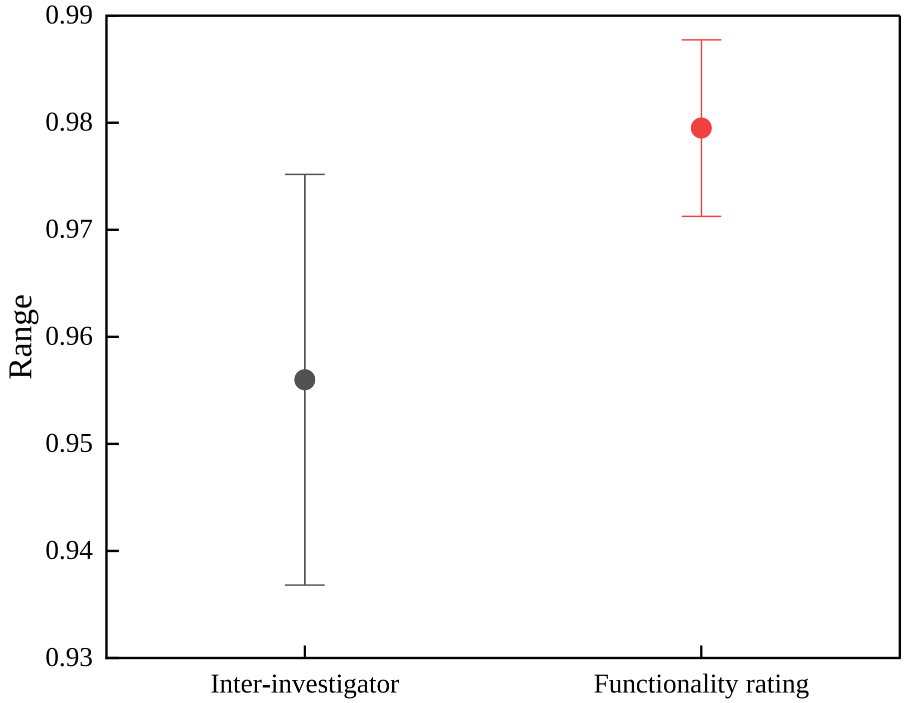

Figure 4: Results of questionnaire reliability test

4.2 Association rule analysis

Figure 5 shows the results of the association rule analysis, and it can be seen that the maximum difference of confidence and support is 0.013, and the confidence and support of questions 1, 11, 19 and 20 are 0, indicating that there is an interconnected relationship between the common factor 1, common factor 3 and common factor 5. That is to say, there is a great correlation between the health big data and the exercise health of the elderly, which verifies that the intelligent human system structure proposed in this paper plays a positive role in the exercise health of the elderly.

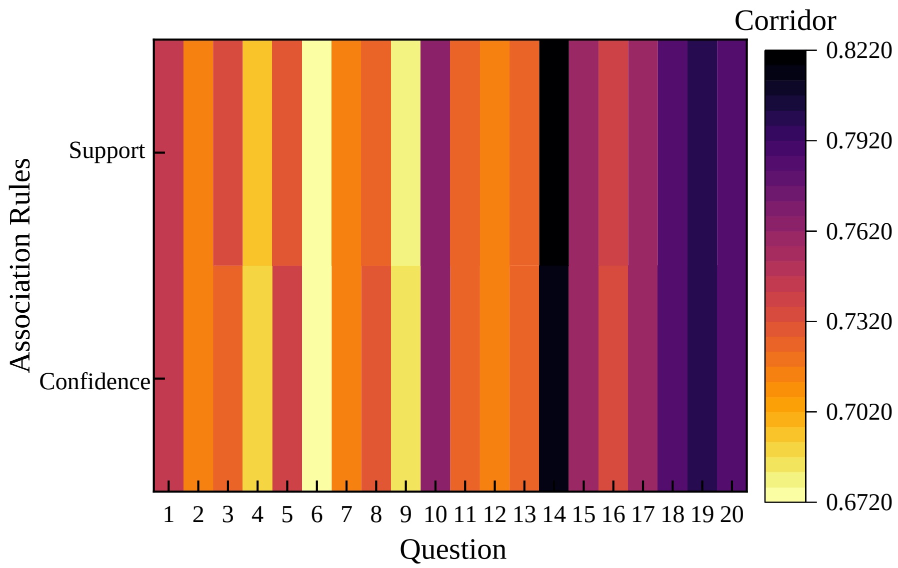

Figure 5: Results of association rule analysis

4.3 Health assessment of the elderly

The 1,000 older adults who participated in the survey were randomly divided into an intervention group and a control group, and both groups underwent a one-month exercise health intervention. The intervention group of 500 used an exercise health assessment model based on big data analytics to assess and intervene in the health of older adults, while the control group of 500 did not take any approach.

4.3.1 Lung function indicators

Table 2 shows the comparison of lung function indexes between the two groups, before the test, the difference between the two groups was not statistically significant (P>0.05). After the test, the intervention group was significantly higher than the control group, and the difference was statistically significant (P<0.01). For example, after the test, the lung capacity of the intervention group (1.73±0.15)L/min was better than that of the control group (1.72±0.13)L/min, and the respiratory system function was better.

Table 2: Comparison of lung function indexes between the two groups (L/min,x±s)

Group	Spirometry		Expiratory volume at 1st second		Maximum ventilation per minute	
	Pre-test	Pro-test	Pre-test	Pro-test	Pre-test	Pro-test
Intervention group	1.17±0.28	1.73±0.15	2.31±0.29	2.55±0.41	78.65±4.83	89.42±2.69
Control group	1.02±0.16	1.72±0.13	2.13±0.22	2.60±0.37	76.16±4.25	89.70±2.58
t value	2.185	0.661	4.125	0.769	4.985	1.103
P value	0.545	0.002	0.389	<0.001	0.187	<0.001

4.3.2 Comparison of joint mobility

Table 3 shows the comparison of joint mobility between the two groups. Before the test, there was no statistically significant difference between the two groups of patients in terms of shoulder joint mobility such as supination (P>0.05). After the test, the angles of supination, posterior extension and external rotation of the two groups were significantly greater than before the intervention, and the maximum angles of supination (187.52±9.14)°, posterior extension (79.86±9.16)° and external rotation (172.65±9.65)° of the patients in the intervention group were significantly greater than those of the control group, and the difference was statistically significant (P<0.05 or P<0.01).

Table 3: Comparison of joint mobility between the two groups (°x±s)

Group	Supination		Back Extension		External Rotation	
	Pre-test	Pro-test	Pre-test	Pro-test	Pre-test	Pro-test
Intervention group	178.19±9.02	187.52±9.14	73.25±7.77	79.86±9.16	168.41±8.26	172.65±9.65
Control group	179.11±9.13	180.25±9.12	75.26±8.11	78.32±8.54	170.23±7.66	171.54±8.67
t value	3.578	0.325	4.332	0.701	2.185	1.002
P value	0.621	<0.001	0.401	<0.001	0.214	0.006

4.3.3 Satisfaction evaluation

The satisfaction ratings of the two groups are shown in Table 4, with 1 being less satisfied and 5 being very satisfied. The system function, convenience and usage feeling of the intervention group were (4.65±3.87), (4.71±4.04), (4.95±4.21), and the control group evaluated (3.57±3.21), (4.02±3.85), (3.95±3.62), with the P-value of less than 0.001, which is statistically significant. It shows that the application of the intervention group based on health big data can be widely promoted and applied with universal applicability.

Table 4: Satisfaction evaluation of the two groups

Group	System Features	Convenience	Usage Experience
Intervention group	4.65±3.87	4.71±4.04	4.95±4.21
Control group	3.57±3.21	4.02±3.85	3.95±3.62
t value	0.662	0.214	0.321
P value	<0.001	<0.001	<0.001

5 Discussion

Based on the results of the survey and analysis, the precision intervention program of exercise health for the elderly is shown in Figure 6. Strengthen the cognition of the elderly population on exercise for health promotion, improve the health literacy of the elderly, community medical and sports organizations to provide sports medical services for the elderly, pay attention to the physiological and psychological health of the elderly [17]. According to the demand of the elderly health market, the demand for elderly sports services and the demand for the development of the sports industry for the elderly, the construction of elderly sports service organizations and community health services as the main body of the professional and skilled personnel training system, to provide protection for the elderly active health promotion sports professionals. The community is the most basic unit that makes up the development of society, and the promotion of active health promotion action programs for the elderly population should effectively solve the problems of health intervention models, mechanisms and paths for the elderly in the community. On the basis of actively promoting health big data, build an active health promotion system for the elderly that is compatible with it. Explore the basic content of physical health promotion for the elderly, the types of indicators and their weighting ratios, and the evaluation system of mental health promotion for the elderly, which should objectively, comprehensively and accurately reflect the health status of the elderly population. To establish the evaluation system of health performance, scientifically and comprehensively evaluate the effect of active exercise to promote health, and accurately construct the evaluation system through closed-loop experimental research tests [18].

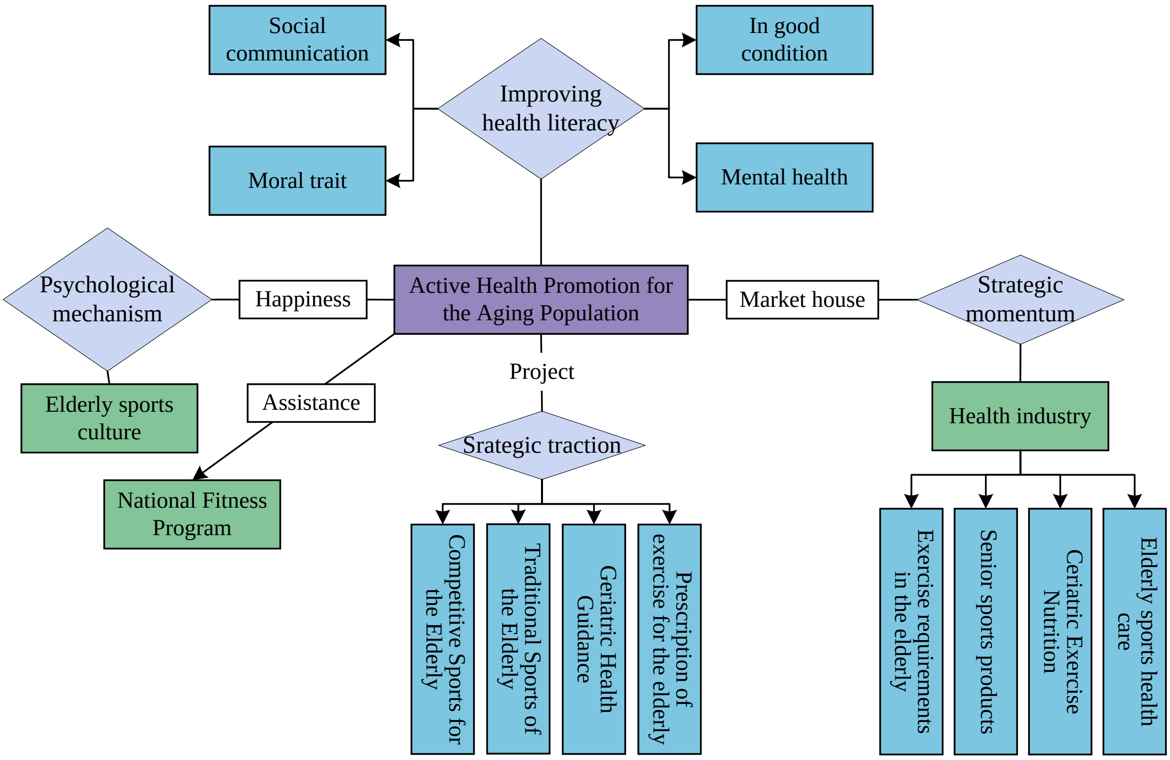

Figure 6: Exercise Health Precision Intervention Program for the Elderly

6 Conclusion

In this study, an exercise health assessment model for the elderly based on health big data was established, and the validity of the constructed model was verified by questionnaire research. The lung function indexes showed that the intervention group was significantly better than the control group, such as lung capacity was improved to (1.73±0.15)L/min (P<0.0), and the joint mobility showed significant improvement in supination, posterior extension and external rotation (P<0.05). In addition, the association rule analysis found that the association rows between the male factor 1, male factor 3 and male factor 5 were significant, which further verified the reasonableness of the model construction. In the satisfaction evaluation, the scores of the intervention group were significantly higher than those of the control group in terms of system function, convenience and experience of use (P<0.001), with system function, convenience and experience of use being (4.65±3.87), (4.71±4.04), and (4.95±4.21), respectively, which indicates that the model has a large potential for promotion. The findings suggest that the health assessment and intervention model based on health big data can accurately assess the exercise health status of the elderly, and improve the exercise health level and quality of life of the elderly population through personalized suggestions such as strengthening their knowledge of exercise for health, in order to realize the practical application of smart health management in the elderly population.

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References

[1] Luo, Y., Su, B., & Zheng, X. (2021). Trends and challenges for population and health during population aging—China, 2015–2050. *China CDC weekly*, 3(28), 593.

[2] Nord, M., Lyth, J., Alwin, J., & Marcusson, J. (2021). Costs and effects of comprehensive geriatric assessment in primary care for older adults with high risk for hospitalisation. B*MC geriatrics*, 21(1), 263.

[3] Ye, Y., Shi, J., Zhu, D., Su, L., Huang, J., & Huang, Y. (2021). Management of medical and health big data based on integrated learning-based health care system: A review and comparative analysis. *Computer Methods and Programs in Biomedicine*, 209, 106293.

[4] Schork, N. J., & Goetz, L. H. (2025). From precision interventions to precision health. *Nature Communications*, 16(1), 5024.

[5] Hussain, M. S., Silvera-Tawil, D., & Farr-Wharton, G. (2021). Technology assessment framework for precision health applications. *International Journal of Technology Assessment in Health Care*, 37(1), e67.

[6] Migliorini, F., Giorgino, R., Hildebrand, F., Spiezia, F., Peretti, G. M., Alessandri-Bonetti, M., ... & Maffulli, N. (2021). Fragility fractures: risk factors and management in the elderly. *Medicina*, 57(10), 1119.

[7] Zhang, X., Gao, X., Wu, D., Xu, Z., & Wang, H. (2021). The role of big data in aging and older people's health research: A systematic review and ecological framework. *Sustainability*, 13(21), 11587.

[8] Guo, Q., & Chen, P. (2024). Construction and optimization of health behavior prediction model for the older adult in smart older adult care. *Frontiers in Public Health*, 12, 1486930.

[9] Wu, X., Duan, J., Pan, Y., & Li, M. (2023). Medical knowledge graph: Data sources, construction, reasoning, and applications. *Big data mining and analytics*, 6(2), 201-217.

[10] Zhang, L., & Xu, X. (2023). Construction of smart older adults care service model driven by primary health care. *Frontiers in public health*, 11, 1157758.

[11] Shandhi, M. M. H., Singh, K., Janson, N., Ashar, P., Singh, G., Lu, B., ... & Dunn, J. P. (2024). Assessment of ownership of smart devices and the acceptability of digital health data sharing. *NPJ digital medicine*, 7(1), 44.

[12] Chen, M., Wang, H., Yu, L., Yeung, E. H. K., Luo, J., Tsui, K. L., & Zhao, Y. (2022). A systematic review of wearable sensor-based technologies for fall risk assessment in older adults. *Sensors*, 22(18), 6752.

[13] Javed, A. R., Saadia, A., Mughal, H., Gadekallu, T. R., Rizwan, M., Maddikunta, P. K. R., ... & Hussain, A. (2023). Artificial intelligence for cognitive health assessment: state-of-the-art, open challenges and future directions. *Cognitive Computation*, 15(6), 1767-1812.

[14] Hager, A. G. M., Mathieu, N., Carrard, S., Bridel, A., Wapp, C., & Hilfiker, R. (2024). Partially supervised exercise programmes for fall prevention improve physical performance of older people at risk of falling: a three-armed multi-centre randomised controlled trial. *BMC geriatrics*, 24(1), 311.

[15] Zhu, Y., Yang, Q., & Mao, X. (2023). Global trends in the study of smart healthcare systems for the elderly: artificial intelligence solutions. *International Journal of Computational Intelligence Systems*, 16(1), 105.

[16] Khan, M. F., Ghazal, T. M., Said, R. A., Fatima, A., Abbas, S., Khan, M. A., ... & Khan, M. A. (2021). An iomt-enabled smart healthcare model to monitor elderly people using machine learning technique. *Computational Intelligence and Neuroscience*, 2021(1), 2487759.

[17] Sun, T., Xu, Y., Xie, H., Ma, Z., & Wang, Y. (2021). Intelligent personalized exercise prescription based on an ehealth promotion system to improve health outcomes of middle-aged and older adult community dwellers: pretest–posttest study. *Journal of Medical Internet Research*, 23(5), e28221.

[18] Chen, L. K. (2024). Integrating precision health with multidomain interventions to

advance strategies for healthy aging. *The Journal of nutrition, health and aging*, 28(10), 100354.