RESEARCH ARTICLE

Comprehensive evaluation of intrinsic capacity and early exercise intervention in the elderly based on biomechanical parameters

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Received: August 19, 2025; **accepted:** December 27, 2025.

The intrinsic abilities of the elderly include their physical functions, motor coordination, and balance control, which are the basic abilities for maintaining daily activities. This intrinsic capacity can directly affect the quality of life and health level of elderly people. Evaluating this ability can help elderly people better understand their own level and provide data support for exercise interventions for the elderly. At present, assessment methods for evaluating the intrinsic abilities of the elderly still suffer from significant errors in evaluation and exhibit subpar effectiveness. This study utilized a motion capture system to collect biomechanical data from elderly individuals, processed the collected data using backpropagation neural networks and support vector machines, and evaluated the intrinsic abilities of the elderly using a weighted scoring method. Based on the evaluation results, a series of exercise intervention methods were proposed including balance training, lower limb strength training, and joint flexibility training. The analysis of the data processing effect showed that the accuracy of the data processing method in extracting biomechanical parameters of balance force, muscle strength, and joint flexibility could all reach over 95%. In addition, the evaluation errors of the three biomechanical parameters by this evaluation method were 0.98%, 0.87%, and 0.91%, respectively, and the comprehensive evaluation error of intrinsic capacity was only 0.72%. Following three months of training with the proposed exercise intervention approach, the elderly participants experienced an average of 8.3 ± 0.4-point increase in their internal ability scores. The proposed biomechanical parameter-based internal ability assessment method for elderly people could accurately evaluate their internal abilities, and the proposed exercise intervention method could improve their internal abilities and ensure their physical health.

Keywords: biomechanics; sports intervention; internal ability; elderly; support vector machine.

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Introduction

The intrinsic abilities of the elderly encompass a diverse range of capabilities including self-care, cognitive functioning, emotional regulation, and social engagement, which manifest at the physical, psychological, and social dimensions [1]. As society experiences a growing aging population, there is a persistent and intensifying focus on the intrinsic abilities of the elderly [2]. A comprehensive evaluation of the intrinsic abilities of the elderly can provide scientific basis for the identification of early functional failure and theoretical support for physical exercise intervention in the elderly.

With the development of artificial intelligence (AI), deep learning algorithms and other intelligent algorithms are broadly applied in various evaluation models [3]. Many scholars have employed evaluation models to assess the intrinsic abilities of elderly people. Blažič *et al*. designed a simulation and digital challenge-based elderly adaptability assessment method and applied it to practical situations to evaluate the adaptability of elderly people to modern digital environments. The results showed that the accuracy of this assessment method for the adaptability of elderly people reached 90.4% [4]. Zhang *et al*. proposed a machine learning model-based evaluation method to assess the risk of falls in elderly people and used this evaluation method to evaluate the elderly. The results showed that the error of this evaluation method was 8.9% [5]. Ashraf *et al*. evaluated various functions in the skeletal joints of elderly people in remote healthcare and designed a skeletal joint function evaluation method based on dynamic time-frequency features. The evaluation method was compared with previous machine learning based evaluation methods, and the outcomes revealed that the evaluation method could improve the accuracy by 12.8% [6]. In addition, Pramod *et al*. designed a cognitive ability assessment method based on hedonic motivation and process models to evaluate the cognitive abilities of the elderly [7]. Analysis of current evaluation methods showed that various methods for assessing the intrinsic abilities of the elderly still had shortcomings such as poor evaluation effectiveness and low accuracy, and further optimization of these evaluation methods is needed [8].

Gait analysis, joint mobility, muscle strength, and balance control, among other biomechanical parameters, can quantify the motor ability, body coordination, and stability of the elderly [9]. Motion capture system (MCS) is a technology that converts the motion of a person or object into digital data by tracking and recording it [10]. Support vector machines (SVM) can extract features from signals [11]. The back propagation neural network (BP) can establish a prediction model based on the extracted features [12]. The above methods have been widely used in various fields. Moniruzzaman *et al*. used MCS technology to collect various motion data of pedestrians to collect behavioral posture data of patients with movement disorders and found that the data collection accuracy of this technology was 94.5% [13]. Lai *et al*. proposed a feature extraction method based on SVM algorithm to optimize the performance of data feature extraction in the field of pattern recognition. The method was tested in practical situations and demonstrated that the feature extraction accuracy of the method could reach 94.3% [14]. In addition, Pan *et al*. used the BP algorithm to design a wind power prediction model to make short-term predictions for wind and electricity. The results showed that the accuracy of the prediction model could reach 92.1% [15].

There are still shortcomings in the current comprehensive evaluation methods for the intrinsic abilities of the elderly such as poor evaluation results and large evaluation errors, which can easily lead to incorrect exercise intervention effects. This study aimed to address the aforementioned issues by developing an assessment method for the intrinsic abilities of elderly individuals based on biomechanical parameters. Based on the evaluation results of this method, an exercise intervention approach for the elderly was proposed to ensure their physical health. This study was the first time using MCS technology to collect biomechanical data on elderly people, then using BP-SVM algorithm to preprocess the collected data and finally constructing an elderly evaluation model based on the processed motion mechanics parameters. Based on the evaluation results, exercise intervention was carried out on the elderly. This study provided technical support for a comprehensive understanding of the intrinsic abilities of the elderly, laying the foundation for future attention to areas such as elderly health and exercise physiology. Moreover, personalized intervention could improve the physical function of the elderly and ensure their physical health.

Materials and methods

Collection of biomechanical data based on MCS technology

A total of 100 people aged between 50 and 60 years old with a male to female ratio of 1:1 from Beijing, China were involved in this research. All participants were divided into an average of 10 groups with 10 people in each group. The test lasted for 2 weeks. All procedures of this study were approved by the Ethics Committee of the Harbin Sport University (Harbin, Heilongjiang, China). This study applied MCS technology to collect various biomechanical data of elderly people during exercise [16]. The study symmetrically distributed 12 ACE 2 acA1920-150uc high-speed infrared camera (Basler AG, Ahrensburg, Germany) in a room free of reflection interference around the subjects to avoid missing or obstructing marker points and multiple sensors on the subjects to record exercise data. Data from various exercise processes such as static standing, sitting standing transition, turning, and climbing up and down stairs of the subjects were collected. During data collection, the experimental environment was properly controlled by covering doors and windows with blackout cloth to prevent light interference, setting the indoor temperature at 20 - 25℃ to ensure the stability of the sensor's physical performance, controlling the relative humidity between 40 - 60% to reduce the impact of static electricity on electronic devices. Multiple sensors were installed at 19 points of the subject including head, left and right shoulders, left and right upper arms, left and right anterior spines, left and right radius, left and right ulna, left and right thighs, left and right knees, left and right ankles, and left and right toes using ADXL345 accelerometer (Analog Devices, Wilmington, MA, USA), MPU-6050 angular velocity sensor (TDK InvenSense, San Jose, CA, USA), and the S2M force sensor (Hottinger Baldwin Messtechnik GmbH, Darmstadt, Germany). All collected data were processed in an Intel Xeon Gold 6248R processor with 128 GB of memory and an NVIDIA Tesla V100 graphics card under Windows 10 operating system and Python 3.12.0 software (https://www.python.org/). The learning rate of the algorithm was set to 0.001, and the iteration coefficient was set to 100.

Analysis of biomechanical parameter signals based on BP-SVM

After the acquisition of biomechanical data from elderly individuals *via* sensors integrated within MCS technology, the BP algorithm was applied to remove abnormal data, while the SVM algorithm was applied to classify the data through the optimal hyperplane [17]. The BP-SVM algorithm first preprocessed the data for feature extraction and classification by normalizing data using Z scores as below.

$$Z = \frac{x - \mu}{\sigma} \tag{1}$$

where *x* was the input data. *Z* was the normalized data. μ and σ were the mean and standard deviation of the data, respectively. After preprocessing, the data were input into the BP algorithm to determine the number of nodes, activation function, and loss function in the input layer (IL), hidden layer (HL), and output layer (OL) of the network in order. The output result of the HL was calculated below.

$$H' = \sigma'(W'X + b) \tag{2}$$

where *H'* was the output of the HL. *W'* was the weight matrix. *X* was the input data of HL. *b* was the bias vector. σ' was the activation function. The data was then transmitted to OL to calculate the final output as follows.

$$Z' = W''H' + b'' \tag{3}$$

where *Z'* was the extracted features. *W''* was the weight of the OL. *b''* was the bias vector of the HL. After feature extraction, the mean square error was calculated for loss function determination as below.

$$L = \frac{1}{n}\sum_{i=1}^{n}\left\| Y_i - \hat{Y}_i \right\|^2 \tag{4}$$

where Y_i was the reconstructed data, i was the sequence number of the i-th data. n was the total number of data. $\hat{Y}_i$ was the predicted value. BP was then performed to calculate the gradient of the loss function on the OL weights, and the HL weights and biases were updated based on the propagation gradient using the calculation below.

$$W^{(j)} \leftarrow W^{(j)} \leftarrow \eta \frac{\partial L}{\partial W^{(j)}} \tag{5}$$

where η was the learning rate. $W^{(j)}$ was the weight matrix of the j-th layer in BP. $\frac{\partial L}{\partial W^{(j)}}$ was the partial derivative of the loss function L with respect to the weight $W^{(j)}$, i.e., the gradient. Forward propagation and backward propagation were repeated until the max iteration count was reached. The trained BP neural network was eventually used for feature extraction while removing irrelevant data before data classification that the SVM algorithm needed to select an appropriate kernel function based on the extracted feature data, usually using Gaussian kernel function with strong nonlinear modeling ability as shown below.

$$K(x_p, x_q) = \exp(-\gamma \|x_p - x_q\|^2) \tag{6}$$

where $K(x_p, x_q)$ was the Gaussian kernel function, which measured the similarity between x_p and x_q. $\exp$ was the exponential function. γ was a hyperparameter. After selecting the kernel function, the SVM algorithm mapped the feature data to a high-dimensional space through the kernel function, making the data more linearly separable, and then adjusted other parameters of the SVM algorithm. After all parameters were determined, the data were input into SVM for training and adjustment. SVM would find an optimal hyperplane that maximized the distance between data points of different categories and the hyperplane and then use this hyperplane to classify the data as the expression below.

$$\omega^T \phi(x) + B = 0 \tag{7}$$

where ω was a weight vector. $\phi(x)$ was a mapping function. *B* was a bias term. The formula for calculating the distance between various data points and the optimal hyperplane was shown below.

$$d = \frac{|\omega^T \phi(x) + B|}{\|\omega\|} \tag{8}$$

where $\|\omega\|$ was the norm of weight vector ω. After calculating the distance between the point and the hyperplane, the data were classified based on the calculated distance and symbol.

Assessment of inner abilities and exercise intervention in the elderly

After processing and classifying biomechanical data using the BP-SVM algorithm, the intrinsic capabilities of the elderly were evaluated based on the extracted biomechanical parameters. Multiple biomechanical parameters including balance ability, muscle strength, and joint flexibility were utilized as evaluation indicators. The weighted scoring method was employed to assign corresponding weights to each evaluation indicator. The weights for each biomechanical parameter were determined through importance scoring based on expert experience, and the final weights were established by synthesizing expert opinions. Briefly, the internal ability assessment model tailored for the elderly initially received a diverse array of biomechanical parameter data that had been extracted and categorized by the BP-SVM algorithm. The model enlisted the expertise of 10 rehabilitation physicians specializing in geriatric care, 10 geriatric medical researchers, and 10 senior nursing staff to evaluate the significance of each biomechanical parameter. The final weights for these parameters were computed by averaging the scores provided by these 30 experts. The mean values of all parameters were then normalized to guarantee that the cumulative sum of the weights equaled 1. Upon completion of the weight allocation process, the weights were verified by aligning them with clinical expectations to remove outliers through reconvening expert discussions or adjusting the scoring accordingly. Ultimately, by using the measured values of each biomechanical parameter and their corresponding weights, the intrinsic capacity score for the elderly was calculated as follows.

$$Score = \sum_{l=1}^{l} (Q_l \times P_l) \quad (9)$$

where l was the total number of biomechanical parameters. Q_l was the measured value of the l-th biomechanical parameter. P_l was the weight of the l-th biomechanical parameter. After multiplying each parameter measurement value with its weight, the original score was obtained and converted into a standard interval score from 0 to 100 points based on the data distribution and clinical needs, which was used as the evaluation result of the intrinsic capacity of the elderly. The priority of exercise interventions for the elderly was established based on their comprehensive intrinsic capacity scores. A higher overall score in intrinsic abilities corresponded to a lower intervention priority. Specifically, when the intrinsic capacity score fell below 40 points, the intervention priority was deemed the highest, necessitating urgent action. Once the intervention sequence was determined, tailored intervention strategies were formulated based on the elderly individuals' scores across various biomechanical parameters. Following a short-term intervention period of three months, the intrinsic abilities of the elderly were reassessed, and the resulting changes were analyzed to gauge the effectiveness of the interventions.

Statistical analysis

SPSS 26.0 (IBM, Armonk, New York, USA) and Excel 2013 (Microsoft, Redmond, Washington, USA) were employed for statistical analysis of this research. The data were presented as mean ± standard error. Multiple comparison analysis was performed to evaluate the significant differences between different concentration treatment groups with *P* values less than 0.05 as statistically significant and less than 0.01 as very significant.

Results

Collection effect of biomechanical parameters

To verify the accuracy of the internal ability assessment of elderly people proposed in this study and the effectiveness of exercise intervention, the collection effect of biomechanical data based on MCS technology was analyzed to determine whether all the biomechanical data related to the human body were accurately collected. The collection accuracy of MCS technology was assessed by comparing the biomechanical data collected using MCS technology with the actual data of the center of gravity position, arm endurance, and shoulder flexion range of motion of elderly people during normal walking. Arm endurance was represented by the number of times an elderly person completed elbow lifts within 30 seconds. When MCS technology was employed to collect the center of gravity position of elderly people during normal walking, the difference between the measured value and the actual value was relatively low, and the accuracy of data collection reached 93.8% (Figure 1a). The difference between the measured data of arm endurance and shoulder joint flexion range of motion in elderly people and the actual data was also relatively low with the measurement accuracy reaching over 90% (Figures 1b and 1c). The results confirmed that the proposed method based on MCS technology was able to accurately collect biomechanical data of the elderly, providing accurate data support for the subsequent assessment of their intrinsic abilities.

Analysis of data processing effectiveness of BP-SVM algorithm

After verifying the accuracy of data collection, the effectiveness of data processing was evaluated. The feature extraction and classification capabilities of the BP-SVM algorithm for various biomechanical data were

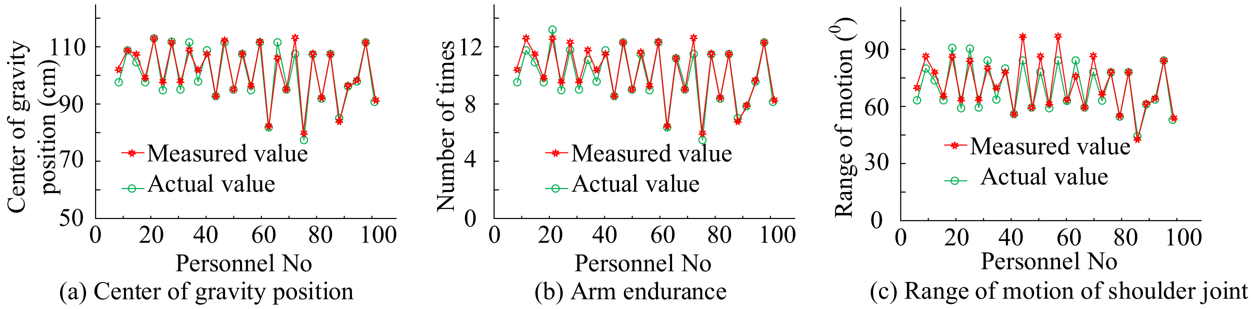


Figure 1. Accuracy of data collection.

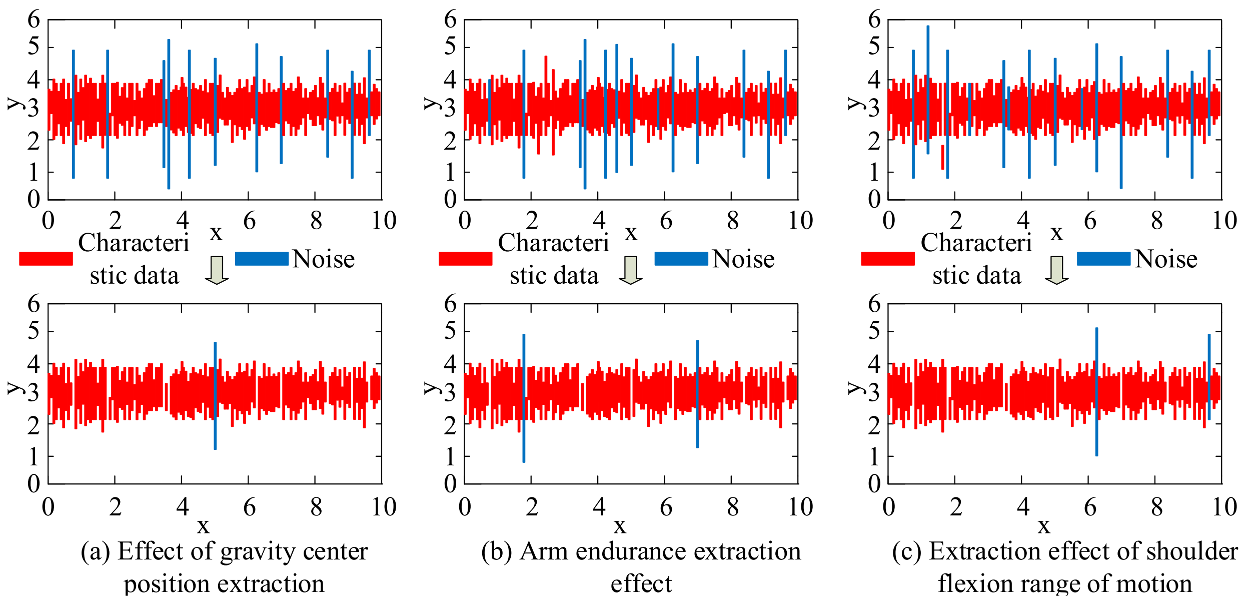
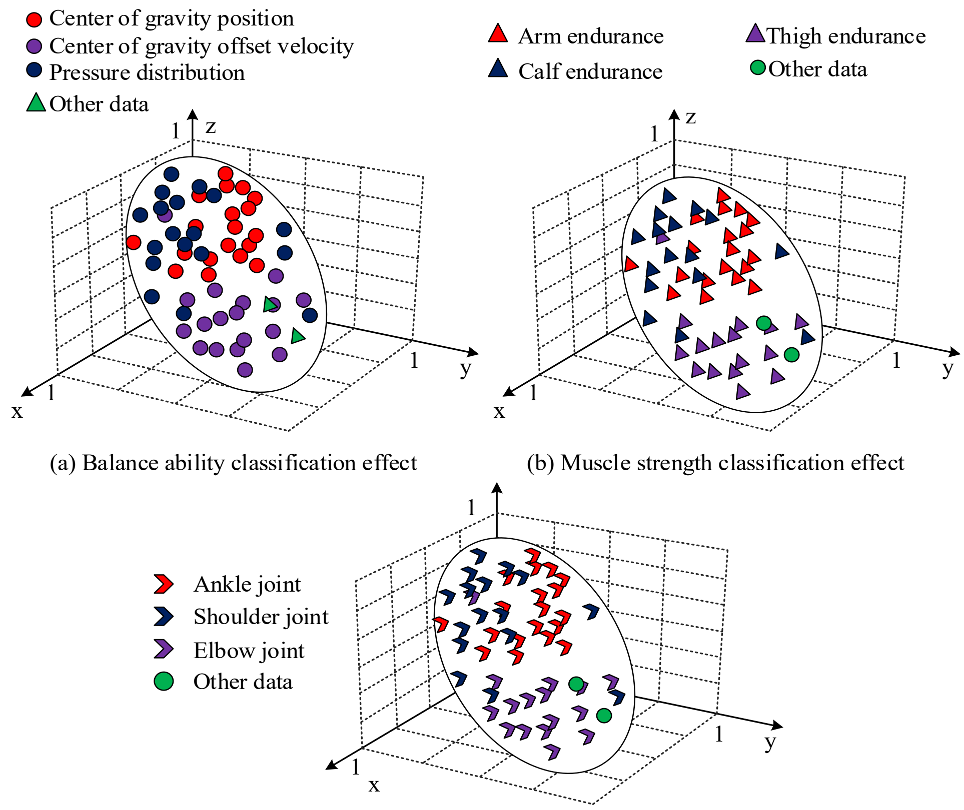


Figure 2. Effect of feature extraction.

examined with the feature extraction effect being tested by comparing biomechanical data related to center of gravity position, arm endurance, and shoulder joint flexion range of motion. The results demonstrated that, when the BP-SVM algorithm was used to process the center of gravity position data of elderly people, it could almost entirely remove noise information while preserving the feature information, achieving a feature extraction accuracy of 98.9% (Figure 2a). When this algorithm was applied to extract features from the dataset related to arm endurance and shoulder joint flexion range of motion in elderly people, it was also capable of completely preserving the feature information and eliminating most of the irrelevant information with a feature extraction accuracy of over 95% (Figures 2b and 2c). The analysis results of the classification performance of the algorithm for various biomechanical parameters showed that, when the BP-SVM algorithm classified the biomechanical parameters related to the elderly's center of gravity position, center of gravity offset velocity, and pressure distribution peak for balance ability assessment, almost all balance ability data were correctly classified with only a very small portion of data being misclassified (Figure 3a). When classifying the collected data into muscle strength and joint flexibility categories, only a negligible fraction of the data was misclassified, resulting in biomechanical data classification accuracy rates



(a) Balance ability classification effect (b) Muscle strength classification effect

(c) Classification effect of joint flexibility

Figure 3. Classification effect of BP-SVM algorithm.

exceeding 97% (Figures 3b and 3c). The results suggested that the feature extraction and classification method based on the BP-SVM algorithm proposed in the study were capable of accurately extracting the features of biomechanical data of elderly people and classifying the biomechanical data effectively.

Evaluation of inner abilities in the elderly and analysis of the effectiveness of exercise intervention

The intrinsic abilities of elderly people were assessed by 30 experts based on the extracted biomechanical dataset and compared with the actual values of the elderly's intrinsic abilities. When proposed method was used to assess the balance ability of elderly people, the disparity between the evaluation results and the actual results was relatively minor with an evaluation error of merely 0.98% (Figure 4a). Furthermore, the proposed method exhibited a relatively low difference between the outcomes of muscle strength assessment and joint flexibility assessment in elderly people and the actual results with errors of only 0.87% and 0.91%, respectively (Figures 4b and 4c). The results showed that, when conducting a comprehensive evaluation of the intrinsic abilities of the elderly, the variance between the evaluation results and the actual results was also small with an error rate of only 0.72%, which almost perfectly aligned with the actual values. Additionally, the comprehensive scores of the intrinsic abilities of the elderly were all below 70 points, indicating that most elderly individuals needed to engage in physical exercise to enhance their intrinsic abilities (Figure 4d). The effect of exercise intervention on elderly people based on the evaluation results was then analyzed. After continuous training for 3 months, the changes in the comprehensive scores of balance ability, muscle strength, joint flexibility, and intrinsic

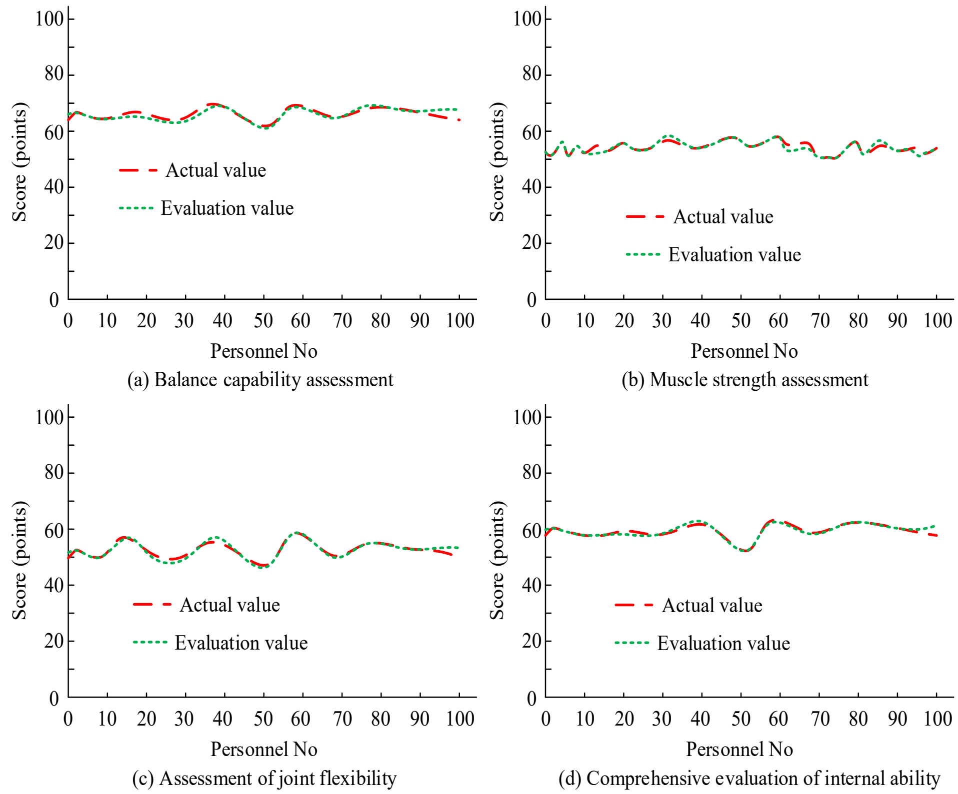


Figure 4. Comparison of evaluation results.

Table 1. Changes in intrinsic abilities of the elderly.

Time	Balance capacity	Muscle strength	Joint flexibility	Comprehensive assessment
Before training	62.4 ± 3.2	51.2 ± 2.8	49.8 ± 2.5	61.8 ± 3.0
1 month	69.2 ± 1.9*	56.2 ± 1.6**	53.2 ± 2.7*	66.1 ± 3.2**
2 months	70.2 ± 1.7**	57.9 ± 2.5**	58.1 ± 2.9*	67.8 ± 3.1**
3 months	73.7 ± 4.1**	62.4 ± 1.7**	60.2 ± 2.9**	70.1 ± 3.4**

Note: *: $P < 0.05$. **: $P < 0.01$ (compared with before training).

abilities demonstrated that the balance ability of the elderly significantly improved from 62.4 ± 3.2 points to 73.7 ± 4.1 points ($P < 0.01$), while the muscle strength and joint flexibility of the elderly were also significantly improved ($P < 0.01$). The comprehensive score of the elderly's intrinsic abilities significantly improved with an increase of 8.3 ± 0.4 points compared to that before training ($P < 0.01$) (Table 1). The results confirmed that implementing targeted sports intervention strategies for the elderly had the potential to elevate their biomechanical parameter scores, which in turn could further augment the comprehensive internal ability scores and safeguard the physical health status.

Discussion

The internal abilities of elderly people such as muscle strength, balance, and joint flexibility could directly affect their mobility. Decreased mobility could change their daily habits and lower their psychological and physiological health. Evaluating the intrinsic abilities of the elderly could identify their mental and physical health status and thus develop reasonable plans for intervention. In response to the issues of inaccuracy and significant errors in the existing assessment methods for the intrinsic abilities of the elderly, this study initially employed MCS technology to collect biomechanical data from elderly individuals and then combined the BP algorithm and SVM algorithm to process the biomechanical data, extract their features, and classify them. The weighted scoring method was used to evaluate the intrinsic abilities of the elderly based on the classification results, and targeted early exercise intervention methods were developed for the elderly based on the evaluation results of the intrinsic capacity score. The evaluation results reflected the balance ability, muscle strength, and joint flexibility information of the elderly to develop targeted training plans for the elderly based on various data. The study analyzed the effectiveness of the MCS biomechanical data collection method. The results showed that the data collection integrity of this method was strong, and the accuracy of collecting various data for the elderly reached over 90%. This result was similar to the research findings of Peng *et al*. with their average data collection accuracy of 87.5%, slightly lower than the MCS technique used in this study [18]. The reason for this minor difference might be that Peng *et al*. only used fiber optic sensors for data collection, while this study used both infrared cameras and sensors for data collection, which could avoid data loss and other situations. Further analysis of the data processing performance of the BP-SVM algorithm showed that, when extracting features from biomechanical data, the algorithm achieved an accuracy of over 95% in extracting various biomechanical parameters. Furthermore, when using this algorithm to classify biomechanical parameters, its accuracies in classifying balance force, muscle strength, and joint flexibility biomechanical parameters were all over 97%. Those results were roughly consistent with that of Cahyo *et al*., but when they used convolutional neural networks and SVM algorithms for feature extraction and classification of data, the feature extraction accuracy was 92.1%, which was lower than the BP-SVM algorithm proposed in this study [19]. The reason might be that the BP neural network used in this study could perform forward and backward propagation, enhancing the feature extraction effect of the neural network. The evaluation effect of the internal abilities of the elderly and the effectiveness of exercise intervention measures showed that the evaluation method had evaluation errors of 0.98%, 0.87%, and 0.91% for balance ability, muscle strength, and joint flexibility, respectively, while the comprehensive evaluation error for the internal abilities of the elderly was only 0.72%. These results were consistent with the research findings of Huang *et al*. [20]. The exercise intervention method developed based on the evaluation results increased the internal ability score of the elderly from 61.8 ± 3.0 points to 70.1 ± 3.4 points, which had a significant impact on the internal ability of the elderly. In real life, community service centers could regularly organize internal ability assessments for elderly people, establish health records for each elderly person, record assessment results and trends, and develop appropriate sports interventions based on the assessment results. The proposed evaluation approach was capable of accurately assessing the intrinsic abilities of the elderly, while the formulated exercise intervention method demonstrated a notable capacity to significantly enhance these abilities. However, the weighted scoring method employed in this study was inherently subjective and might exert an influence on the evaluation outcomes. Future study may adopt techniques such as the entropy weight method or principal component analysis to allocate weights to various biomechanical parameters, thereby minimizing the interference of human factors and enhancing the precision and dependability of the evaluation results.

Acknowledgement

This work was supported by Social Science Foundation of Heilongjiang Province (Grant No. 22RKC306).

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