RESEARCH ARTICLE

Using artificial intelligence to study the effects of combined impact load and resistance exercise on bone mineral density and muscle mass in elderly patients with osteosarcopenia

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Osteosarcopenia characterized by the concurrent decline in bone mineral density (BMD) and skeletal muscle mass is a major geriatric syndrome that exponentially raises the risks of falls and fragility fractures. Although combined impact and resistance training is empirically recommended, the precise dose–response relationship and potential synergy between these two exercise modalities remain poorly understood due to complex biological interactions. This study constructed an artificial intelligence model to quantify the improvement effect of combined impact load and resistance exercise on bone mineral density and muscle mass in the elderly with osteosarcopenia. Sixty-nine (69) elderly patients aged 65 – 80 years with sarcopenia were enrolled in the research. Thirty-five (35) patients underwent a 24-week combined exercise training program, which included dropping to the ground from a height of 15 cm for 90 repetitions per week during the adaptation phase and 8 sets of 12 repetitions at an intensity of 40% of the one-repetition maximum (1RM) in resistance training. In the intensive period, 144 times a week with 30 cm jumping to the ground + 16 groups of 8 repetitions at 75% 1RM resistance training were employed. 34 cases were set in the control group. The impact load cumulative effect index (CILI) was extracted from the data of wearable accelerometer and dynamometer. XGBoost model was established to predict the change of lumbar bone mineral density. Time series convolution network (TCN) was used to predict the change track of skeletal muscle mass index (ASMI) of limbs. The results showed that the mean absolute error (MAE) of ΔBMD predicted by XGBoost was 0.021 g/cm² with R^2 = 0.67. TCN predicted that MAE of δ ΔASMI was 0.12 kg/m² with R^2 = 0.71. A CILI threshold of 3.2 × 10^5 N·log(ms) effectively improved the outcomes. The coefficient of the interaction term was 0.052 (*P* = 0.012), which proved the synergistic effect. AI model could accurately predict the effect of joint exercise. CILI and resistance training could promote the improvement of BMD and muscle mass.

Keywords: osteosarcopenia; impact load; resistance training; artificial intelligence; bone density.

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Introduction

Osteosarcopenia refers to the coexistence of osteoporosis and sarcopenia, and its prevalence increases with age. This geriatric syndrome is diagnosed when bone mineral density T score falls below 1.0 and the appendicular skeletal muscle mass index (ASMI) is below 7.0 kg/m² for men or 5.4 kg/m² for women [1, 2]. In China, the prevalence among people over 60 years old is approximately 12.3%. The clinical significance of this condition is substantial that every standard deviation reduction in bone mineral density is associated with a 2.6 fold increase in hip fracture

risk, while a 10% decline in muscle mass raises the fall risk by 30%. These parallel deteriorations create a vicious cycle that severely compromises mobility, independence, and quality of life in the aging population [3].

Impact loading exercise stimulates bone formation through mechanical strain, while resistance training promotes muscle hypertrophy *via* mechanical tension and metabolic stress. The combination of these two exercise modalities is hypothesized to produce synergistic effects on both bone and muscle tissues. Recent advances have elucidated key training variables. Mcleod *et al*. demonstrated that resistance training at 70 – 80% of one repetition maximum (1RM), performed 2 – 3 times per week with 8 – 12 repetitions per set, yielded the most robust hypertrophic response [4]. Zhang *et al*. emphasized that velocity-based resistance training was superior to percentage-based training for explosive power adaptations and highlighted the importance of individualized load adjustments [5]. Kircher *et al*. reported that high intensity intermittent training reduced paraspinal muscle fat infiltration by 5.7% over 24 weeks, significantly outperforming moderate intensity continuous training [6]. Meanwhile, plyometric and jump training studies have confirmed the osteogenic potential of impact loads, though the cumulative dose response relationship remains inadequately characterized. In parallel, artificial intelligence (AI) techniques are emerging in sports medicine. Liu *et al*. explored the mediating role of cognitive load in AI assisted learning systems [7], while Yao *et al*. developed a cognitive load scale for human computer interaction, providing methodological foundations for AI applications in exercise adherence monitoring and personalized prescription generation [8]. Despite these advances, several critical gaps persist. The optimal dose combination of impact loading and resistance training for osteosarcopenia has not been established, largely because traditional statistical methods cannot adequately handle the nonlinear, multidimensional interactions between exercise parameters and physiological outcomes. Further, no validated quantitative index exists to capture the cumulative biological effect of repetitive impact loads over time. Furthermore, there is a lack of predictive tools that can estimate individualized changes in bone mineral density and muscle mass in response to combined exercise, hindering the translation of research findings into clinical practice. These gaps limit the ability of clinicians and rehabilitation specialists to prescribe precise, evidence based exercise regimens for elderly patients with osteosarcopenia.

This study constructed an AI driven analytical system to develop a cumulative impact load effect index (CILI) derived from wearable accelerometer and dynamometer data, to establish an XGBoost model for predicting lumbar bone mineral density changes following a 24 week combined exercise intervention, and to employ a temporal convolutional network (TCN) for forecasting the trajectory of ASMI over time. The input features encompassed demographic characteristics, baseline bone and muscle parameters, and real time exercise execution data, enabling the model to capture both inter individual variability and temporal dynamics. This research proposed an AI framework by quantifying the synergistic interaction between impact loading and resistance training to provide a mechanistic understanding of combined exercise effects that transcended the simple additive model. The identification of an optimal CILI threshold offered a tangible target for exercise prescription, while the predictive accuracy of the models supported individualized decision making. Ultimately, this work bridged the gap between exercise physiology and AI, paving the way for data driven, personalized rehabilitation strategies in the growing elderly population affected by osteosarcopenia.

Materials and methods

Data sources and collection methods

The data originated from a multicenter randomized controlled trial conducted at the

Department of Rehabilitation Medicine of West China Hospital of Sichuan University, Sichuan Provincial People's Hospital, and the General Hospital of Western Theater Command in Chengdu, Sichuan, China from March 2022 to August 2024. Participants were recruited through the community physical examination system for the elderly. A total of 69 elderly individuals aged 65 – 80 years old were included based on the inclusion criteria of lumbar bone mineral density T-score between −2.5 and −1.0, ASMI below 7.0 kg/m² for men or 5.4 kg/m² for women, and irregular exercise participation over the past 6 months. The exclusion criteria included prior hip or knee replacement, severe cardiovascular disease (New York Heart Association class III or above), and cognitive impairment (Mini-Mental State Examination score below 24). All 69 participants were randomly assigned to the combined exercise group (35) and the control group (34). Data was collected in three stages including baseline (week 0), mid-point of intervention (week 12), and study end point (week 24). Bone mineral densities of lumbar (L1 – L4) and femoral neck bone were measured using Hologic Horizon Wi dual-energy x-ray absorptiometry (DEXA) (Hologic Inc., Danbury, CT, USA). Muscle mass and body fat percentage were assessed *via* InBody 770 bioelectrical impedance analyzer (InBody Co., Ltd., Seoul, South Korea). Vertical ground reaction forces during 30 cm drop jump landings were recorded using Kistler 9286BA portable force platform (Kistler Group, Winterthur, Switzerland). Physical activity and impact steps were monitored using ActiGraph wGT3X-BT triaxial accelerometer (ActiGraph LLC, Pensacola, FL, USA) worn on the right anterior iliac crest at a sampling rate of 30 Hz for 7 consecutive days. All measurements were conducted by trained technicians following standardized protocols. The research procedures were approved by the Ethics Committee of West China Hospital (Chengdu, Sichuan, China) with the approval number of 2022-0389. All participants signed written informed consent forms and were informed of the study objectives, the duration of the intervention, and potential risks. The study was registered with the Chinese Clinical Trial Registry on March 1, 2022, under the registration number ChiCTR2200061234. All 69 participants completed the 24-week intervention, yielding 69 complete datasets. Baseline characteristics were well balanced between groups with no significant statistical difference. The mean age was 71.3 ± 4.2 years in the exercise group and 72.1 ± 3.9 years in the control group. The baseline BMDs of exercise group and control group were 0.82 ± 0.09 g/cm² and 0.83 ± 0.08 g/cm² for lumbar, 0.68 ± 0.07 and 0.67 ± 0.08 g/cm² for femoral neck, respectively, while ASMIs were 6.2 ± 0.5 and 6.1 ± 0.6 kg/m², grip strengths were 24.3 ± 5.1 and 23.9 ± 5.4 kg, and serum 25(OH)Ds were 22.4 ± 6.2 and 21.8 ± 5.9 ng/mL, respectively. Both groups received vitamin D supplementation at 800 IU daily due to the baseline levels below 30 ng/mL [9, 10].

Data preprocessing

The original data included BMD (g/cm^2), ASMI (kg/m^2), impact force of dynamometer (Newton, N) and counts per minute. There were dimensional differences in bone mineral density at different measurement sites of lumbar vertebrae and femoral neck, and direct input into the model would introduce bias. Z-score standardization was used to eliminate dimensional influence and obtain normalized BMD as follows [11].

$$\mathrm{BMD}_{\mathrm{norm}} = \frac{\mathrm{BMD}_{\mathrm{raw}} - \mu_{\mathrm{BMD}}}{\sigma_{\mathrm{BMD}}} \quad (1)$$

where $\mathrm{BMD}_{\mathrm{raw}}$ was the original bone density value of a certain part. μ_{BMD} was the average value of this part measured in all subjects. $\mathrm{BMD}_{\mathrm{norm}}$ was dimensionless and followed the standard normal distribution. Standardization was carried out independently for lumbar vertebrae as the average of four vertebral bodies, left femoral neck, and right femoral neck. The unit of resistance training variable ($\mathrm{RT}_{\mathrm{volume}}$) was not uniform and was compressed to [0, 1] by maximum-minimum normalization as below.

$$\mathrm{x}_{\mathrm{norm}} = (\mathrm{x} - \mathrm{x}_{\mathrm{min}})/(\mathrm{x}_{\mathrm{max}} - \mathrm{x}_{\mathrm{min}}) \quad (2)$$

where x_{min} was taken from the lowest value in the training set (120 per week).

Data cleaning

The original data set consisted of 69 subjects, 3 time points of 0, 12, and 24 weeks, and 3 repeated measurements of each index. The proportion of missing values was 2.3%, which were concentrated in the accelerometer data in the 12th week and the dynamometer data in the 24th week [12]. The missing pattern was determined to be missing completely at random (MCAR) by Little's MCAR test with *P* value of 0.23. Continuous variables were imputed using mean values stratified by time point, sex, and 5-year age groups. Dynamometer missing values were imputed by linear interpolation between week 0 and week 24. The complete datasets were used for modeling [13].

Characteristic engineering and quantitative model of impact load

Twenty-two (22) input features were extracted from the original measurement data and were divided into four groups including demographic features covering age (65 – 80 years), gender (0 for female and 1 for male), BMI (18.5 – 32.0 kg/m²); bone mineral density features consisting standardized BMD of lumbar vertebrae L1-L4 and bilateral femoral necks with z-score ranging from −2.5 to 1.5; muscle mass features including ASMI from 4.5 – 8.0 kg/m², grip strength from 15 – 40 kg, gait speed from 0.6 – 1.4 m/s, ultrasonic value of quadriceps thickness from 1.2 – 2.5 cm; and exercise parameters of impact load accumulation index CILI from 0 – 8.5×10^5 N·log(ms), normalized resistance training volume RT_{volume} from 0 - 1, weekly impact exercise frequency ranging from 0 – 150 impacts/week, and session duration from 30 – 60 min/session. The quantification of impact load integrated the peak force and duration of each landing as follows.

$$CILI=\sum_{t=1}^{T}\left(F_t \times \log\left(duration_t+1\right)\right) \quad (3)$$

where CILI was the cumulative impact load index in N·log(ms). T was the total number of impact landings over the 24-week intervention period. F_t was the peak vertical ground reaction force in Newtons (N) during the t-the landing with the actual measured value ranging from 1,500 N to 2,800 N. $duration_t$ was the rise time from initial ground contact to the peak force in milliseconds (ms) for the t-the landing with ranging from 15 ms to 40 ms. The logarithmic transformation log ($duration_t$ + 1) compressed the long-tail distribution of duration and added 1 to avoid logarithm being zero. The greater the CILI value, the stronger the cumulative bone stimulation effect [14]. Biochemical indicators included serum 25-hydroxyvitamin D (25(OH)D) (15 – 45 ng/mL), parathyroid hormone (PTH) (15 – 65 pg/mL), and albumin (3.5 – 5.0 g/dL).

Prediction model of bone mineral density improvement based on XGBoost

The final BMD results was determined as lumbar BMD minus baseline BMD at week 24 with the unit of g/cm². XGBoost regression model (https://xgboost.ai) was used to capture nonlinear relationships and feature interactions. The input of the model was 22 features, while the continuous value ΔBMD was used as output. The model training parameters were 300 trees, 0.05 learning rate, 4 maximum tree depth, 0.8 column sampling ratio, and 0.8 sub-sampling ratio. The objective function was calculated as follows.

$$\mathcal{L}(\phi)=\sum_i l\left(y_i,\hat{y}_i\right)+\sum_k \Omega\left(f_k\right)$$
$$\Omega(f)=\gamma T+\frac{1}{2}\lambda \parallel w \parallel^2 \quad (4)$$

where $\sum_i l\left(y_i,\hat{y}_i\right)$ was the loss function. l was mean square error (MSE) loss function. y_i was the true ΔBMD value of the i-the sample. $\hat{y}_i$ was the predicted value. $\sum_k \Omega\left(f_k\right)$ was a regularization term to control the model complexity. $\Omega(f)=\gamma T+\frac{1}{2}\lambda \parallel w \parallel^2$ and T were the numbers of leaf nodes of a single tree with values ranging from 1 to 16. Ω(f) was tree complexity penalty. γ was leaf penalty coefficient. λ was L2 regularization coefficient. w was the leaf node weight vector (regression

score). $\| w \|^2$ was L2 norm square. γ and λ were hyperparameters, which were set to 0.1 and 1.0, respectively. The regularization term punished excessive tree structure and weight to prevent over-fitting [15].

Prediction model of muscle mass change

Muscle mass changes were measured every 4 weeks with ASMI as an index with 7 time points of 0, 4, 8, 12, 16, 20, and 24 weeks. Time series convolutional network (TCN) implemented with TensorFlow 2.9.1 (https://www.tensorflow.org) was used for the task of variable-length sequence prediction. The input was ASMI, grip strength, pace, and muscle thickness with window length of 3, step length of 1 at the past three time points. The output was ASMI at the next time point [16]. The TCN model employed four layers of dilated causal convolutions with dilation factors d as 1, 2, 4, and 8, respectively, each with a kernel size of 3 and 64 filters. Each convolutional layer was followed by ReLU activation and Dropout (rate 0.2), and residual connections were applied after each layer to ensure gradient flow. The total receptive field covered 28 time points and calculated as 2 × (3 − 1) × (1 + 2 + 4 + 8), which was sufficient to span the entire 24-week sequence. A fully connected output layer with 64-to-1 dimension produced the predicted ASMI value. Causal convolution ensured that predictions at each time point depended only on past data, preventing future information leakage.

Analysis model of joint movement effect

Both impact load and resistance training alone had effects on bone mineral density and muscle mass, and combined exercise might have synergistic or antagonistic effects. Multiple linear regression model was adopted, and interaction term was added based on main effect term as below.

$$E_{joint} = \beta_1 \cdot CILI + \beta_2 \cdot RT_{volume} + \beta_3 \cdot (CILI \times RT_{volume}) \quad (5)$$

where E_{joint} was the comprehensive effect of combined exercise on bone mineral density or muscle mass. β_1 was the main effect coefficient of CILI, which reflected the change of bone mineral density caused by increasing the impact load index by $10^5 \mathrm{N} \cdot \log(\mathrm{ms})$. β_2 was the main effect coefficient of RT_{volume}. After normalization, the corresponding change of bone mineral density was increased by 0.1 unit. β_3 was the coefficient of interaction term. If it was positive, it meant synergistic effect, otherwise, it meant antagonism. Interactive items reduced multicollinearity through centralization as $(CILI - \overline{CILI}) \times (RT_{volume} - \overline{RT_{volume}})$, where $\overline{CILI} = 2.3 \times 10^5$. The model was fitted by least square method with all 69 samples being used [17].

Evaluation indicators

The prediction task of BMD improvement adopted three indexes including mean absolute error (MAE), root mean square error (RMSE), and determining coefficient (R^2). The prediction task of muscle mass changed TCN additionally increased the mean absolute percentage error (MAPE). The MAE unit was g/cm² for ΔBMD or kg/m² for $\Delta ASMI$, which reflected the average deviation between the predicted value and the real value. RMSE was sensitive to large errors and punished outliers. The range of R^2 was set as 0 - 1, and the closer to 1, the higher the variance ratio of model interpretation. The performance of the joint model needed to synthesize two tasks, and the cross-task comprehensive evaluation score (CS) was constructed as follows.

$$CS = \frac{1}{2}\left(\frac{MAE_{BMD}}{MAE_{baseline,BMD}} + \frac{MAE_{SMI}}{MAE_{baseline,SMI}}\right) \quad (6)$$

where CS was comprehensive evaluation score. MAE_{BMD} was the average absolute error of bone mineral density prediction. $MAE_{baseline,BMD}$ was bone mineral density of benchmark model MAE (0.042 g/cm²). MAE_{SMI} was the average absolute error of muscle mass prediction, which predicted the MAE of $\Delta ASMI$ for TCN model. $MAE_{baseline,SMI}$ was muscle mass of benchmark model MAE (0.31 kg/m²). The smaller the CS value, the greater the relative benchmark improvement. In actual calculation, if

the MAE of XGBoost was 0.021 g/cm², the ratio of the first term was 0.5, the MAE of TCN was 0.12 kg/m², the second ratio was about 0.387, and CS was 0.4435. In the training process, CS was calculated by cross-validation in each round, and a group of hyperparameters with the smallest CS was selected [18].

Cross-validation strategy

Cross-validation with 50% discount in layers was adopted. The complete data of 69 cases were stratified according to two dimensions of gender and baseline BMD grade with each layer being randomly assigned to five compromises. Each fold contained 13 - 14 samples, of which the ratio of the joint exercise group to the control group was 2:1. Each round of training set accounted for 40% discount (about 55 - 56 cases) and verification set accounted for 1% discount (13 - 14 cases). The processes cycled 5 times with changing the verification set each time. The report index was the mean standard deviation of the results of 5 verification sets. To avoid time-dependent leakage, all time points of the same subject appeared in the same compromise at the same time. When dividing, the subjects' ID was taken as the unit, and the time points were not divided. 80%/20% of the training set was divided for early stop (patience = 10 rounds). The model was retrained with all 69 cases' data, and the super parameter was the configuration with the lowest mean value of CS in the validation set.

Model comparison and ablation experiment

Five models were compared including XGBoost, random forest with the number of trees as 500, the maximum depth of 10), Light Gradient Boosting Machine (LightGBM) (https://lightgbm.readthedocs.io) with the number of leaves as 31, the learning rate of 0.05, support vector regression (SVR) with RBF kernel and C = 1.0, TCN and long short-term memory (LSTM) with hidden unit of 64. Ablation experiment removed three feature sets of demographic features only including age, gender, BMI, exercise parameters only with CILI, RT_{volume}, and biochemical indicators only with 25OHD, PTH, albumin.

Feature importance analysis

Shapley Additional Explanations (SHAP) 0.41.0 (https://shap.readthedocs.io) is used to explain the predicted output of XGBoost model. 22 characteristic SHAP values of all 69 samples were calculated to determine the marginal contribution of each feature of the SHAP value to the predicted value of a single sample in ΔBMD (g/cm²). Global importance was then obtained by sorting the absolute value and average value.

Sports intervention program

The joint exercise group performed 24 weeks of structured training, which was divided into adaptation period from weeks 1 - 8 and strengthening period from weeks 9 - 24. Training was conducted three times a week with an interval of at least 48 hours. Each training sequence included warm-up for 5 minutes using slow walking and joint activities, impact load training for 15 minutes, resistance training for 25 minutes, and finishing activities by cooling down for 5 minutes. During the adaptation period, impact loading involved box jumps from a 15 cm height, performed as 10 repetitions × 3 sets with 30 impacts per session, 90 impacts per week. Resistance training included leg press, seated leg extension, prone leg curl, and standing calf raise at 40% of 1RM with 12 repetitions × 2 sets per exercise as 8 sets per session, 24 sets per week. During the strengthening period, box jump height increased to 30 cm with 12 repetitions × 4 sets as 48 impacts per session, 144 impacts per week. Resistance training intensity increased to 75% of 1RM with 8 repetitions × 4 sets per exercise as 16 sets per session, 48 sets per week. Rest intervals were 45 seconds between impact sets and 90 seconds between resistance sets. The control group performed low intensity stretching three times per week for 30 minutes per session with heart rate (HR) maintained within resting HR + 10 beats/min without impact or resistance components.

Data acquisition

For BMD measurements, the accuracy error (CV%) was 0.8% for lumbar spine and 1.2% for femoral neck. For muscle mass evaluation,

subjects were fasting for 2 hours, emptying urinary bladder, and standing barefoot for 3 minutes. The skeletal muscle mass (kg) and ASMI (kg/m^2) of limbs were measured. The vertical ground reaction force was recorded by the time of ground reaching that the subjects conducted box jumps. Muscle thickness was evaluated using a portable GE Logiqe ultrasound system (GE Healthcare, Chicago, IL, USA) worn on the right anterior superior iliac crest with a sampling rate of 30 Hz. The daily impact steps with the threshold ≥ 2.5 g vertical acceleration were recorded for 7 consecutive days. The dominant hand was measured by a grip dynamometer with the elbow flexed 90 degrees in sitting position and the maximum isometric contraction being averaged for 3 times. Pace test included 6 meters walking with 4 meters in the middle as normal speed.

AI system deployment environment

The AI analysis system was deployed in the local server with Intel Xeon Gold 6248 (20 cores, 2.5 GHz) CPU, 256 GB RAM, NVIDIA Tesla V100 (32 GB) GPU, and 2 TB NVMe SSD. Ubuntu 20.04 LTS (https://ubuntu.com/20-04) was adopted as operating system. Python 3.8.12 (https://www.python.org), XGBoost 1.6.2, TensorFlow 2.9.1 (for TCN), scikit-learn 1.1.2 (https://scikit-learn.org), SHAP 0.41.0 were implemented for model development. Data management used PostgreSQL 14 database (https://www.postgresql.org) to store the original measured values and intermediate features. Data pipeline included the original data of DEXA, BIA, and dynamometer being imported through comma-separated values (CSV). The accelerometer data were exported to ActiGraph data forma (AGD) format through ActiLife software (https://www.actigraphcorp.com) and analyzed by Python. The model training was encapsulated by Docker container (https://www.docker.com) with the image sized 4.2 GB. The inference interface provided RESTful API based on Flask 2.1 framework (https://flask.palletsprojects.com) to input JSON format (22 eigenvalues) and return the predicted value of δ ΔBMD and SHAP explanation. When deploying, four concurrent working processes were set up, and the average time for a single reasoning was 120 ms (GPU acceleration). The system log recorded the time of each request, input characteristics, and output results] with the retention period of 90 days.

Statistical analysis

Python 3.8.12 with scikit-learn 1.1.2 and SciPy 1.8.0 (https://pypi.org/project/scipy/ 1.8.0/) were employed for statistical analyses. Continuous variables were presented as mean ± standard deviation (SD). Baseline comparisons between groups were conducted using independent samples t-tests for normally distributed variables and Mann-Whitney U tests for non-normal distributions. Categorical variables were compared using chi-square tests. Repeated measures ANOVA was used to evaluate group-by-time interaction effects for ASMI trajectories. Multiple linear regression was applied to quantify the main effects and interaction between CILI and RT_{volume} on ΔASMI, with model fit assessed by adjusted R^2 and residual standard error. The Bland-Altman method was used to evaluate agreement between predicted and measured values. A two-sided *P* value less than 0.05 was considered statistically significant. All model evaluation metrics (MAE, RMSE, R^2, MAPE) were computed using standard scikit-learn functions with 5-fold stratified cross-validation.

Results and discussion

Feature importance analysis

The global feature importance ranking revealed CILI as the most influential predictor with a mean absolute SHAP value of 0.0092 g/cm², contributing approximately 31% of the total prediction magnitude. RT_{volume} ranked second as 0.0058 g/cm², followed by baseline lumbar BMD's 0.0045 g/cm², the interaction term CILI × RT_{volume} (0.0031 g/cm²), and age (0.0028 g/cm²). Vitamin D level ranked sixth with negative SHAP values observed when concentrations fell below 25 ng/mL. Gender ranked seventh with males

Table 1. Changes in outcome indicators before and after intervention (mean ± SD and percent change).

Indicator	Joint exercise group (n = 35)	Control group (n = 34)
Lumbar BMD (g/cm²)	0.83 ± 0.08 → 0.89 ± 0.07 (+7.2%)	0.82 ± 0.09 → 0.81 ± 0.09 (−1.2%)
Femoral neck BMD (g/cm²)	0.67 ± 0.07 → 0.72 ± 0.06 (+7.5%)	0.68 ± 0.08 → 0.67 ± 0.08 (−1.5%)
ASMI (kg/m²)	6.21 ± 0.48 → 6.63 ± 0.51 (+6.8%)	6.16 ± 0.52 → 6.09 ± 0.53 (−1.1%)
Grip strength (kg)	24.3 ± 5.1 → 28.4 ± 5.3 (+17.2%)	23.9 ± 5.4 → 23.6 ± 5.2 (−1.3%)
CILI (×10^5 N·log(ms))	0 → 4.52 ± 0.67	0 → 0.08 ± 0.12
RT_{volume} (normalized)	0 → 0.64 ± 0.08	0 → 0

showing a 0.002 g/cm² greater benefit than females. This ranking confirmed that exercise parameters (CILI and RT_{volume}) contributed more to BMD improvement predictions than biochemical or demographic features.

Baseline data and grouping balance of subjects

Among 69 participants, 35 cases (17 males and 18 females) were involved in the combined exercise group and 34 cases (16 males and 18 females) in the control group. The mean baseline ages of the two groups were 71.4 ± 4.1 years and 71.9 ± 4.3 years, respectively. The baseline lumbar bone mineral density was 0.83 ± 0.08 g/cm² in the combined exercise group and 0.82 ± 0.09 g/cm^2 in the control group. The baseline ASMI in combined exercise group was 6.21 ± 0.48 kg/m^2, and that in the control group was 6.16 ± 0.52 kg/m^2. The changes of various indicators before and after intervention demonstrated that the BMD of lumbar spine in the combined exercise group increased from 0.83 ± 0.08 to 0.89 ± 0.07 g/cm² with change rate of +7.2%, while that in the control group increased from 0.82 ± 0.09 to 0.81 ± 0.09 g/cm² with change rate of -1.2%. ASMI combined exercise group increased from 6.21 ± 0.48 to 6.63 ± 0.51 kg/m^2 (+6.8%), while the control group decreased from 6.16 ± 0.52 to 6.09 ± 0.53 kg/m^2 (-1.1%). CILI reached (4.52 ± 0.67) × 10^5 N·log(ms) in the combined exercise group, while it was close to 0 in the control group. Grip strength increased by 4.1 kg (+17.2%) in the combined exercise group and decreased by 0.3 kg in the control group (Table 1).

Improvement effect of BMD

The dose-response curve showed a clear threshold effect at CILI = 3.2 × 10^5 N·log(ms). Below this threshold, each 1 × 10^5 increase in CILI yielded 0.021 g/cm² BMD gain. Above it, the gain diminished to 0.005 g/cm² per unit increase, suggesting that the biological response to mechanical loading plateaus was beyond a cumulative dose. This threshold corresponded to approximately 144 impacts per week from a 30 cm drop height, providing a quantifiable target for exercise prescription, which was consistent with the mechanostat theory, where bone formation was maximally stimulated once the strain magnitude exceeded a certain threshold, beyond which additional loading yielded diminishing returns. The distribution of lumbar bone mineral density before and after the intervention of combined exercise group and control group demonstrated that, in the joint exercise group, the baseline median was 0.83 g/cm², while the 24th week median was 0.89 g/cm². The interquartile range was reduced from 0.78 - 0.88 to 0.85 - 0.92. In the control group, the baseline median was 0.82 g/cm², and the 24th week median was 0.81 g/cm². The distribution basically overlapped. The difference between the two groups was 0.07 g/cm^2 with 95% CI of 0.05 - 0.09 and Cohen's effect of 1.24 (Figure 1). The bone mineral density gain at different CILI levels showed that the horizontal CILI was divided into five equal parts (about 14 cases each) as Q1 (0 - 1.2 × 10^5), Q2 (1.2 -2.5 × 10^5), Q3 (2.5 - 3.8 × 10^5), Q4 (3.8 - 5.1 × 10^5) and Q5 (> 5.1 × 10^5). The δ ΔBMD of Q1 group was only 0.008 ± 0.011 g/cm², and that of Q5 group was 0.074 ± 0.012 g/cm². The dose-response curve entered a plateau after CILI exceeded 3.0 × 10^5 (the change slope

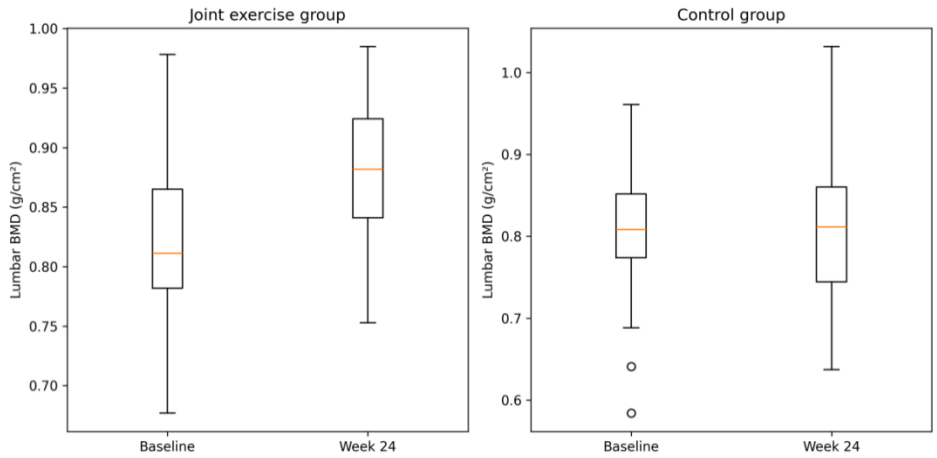


Figure 1. Bone mineral density changes between combined exercise group and control group.

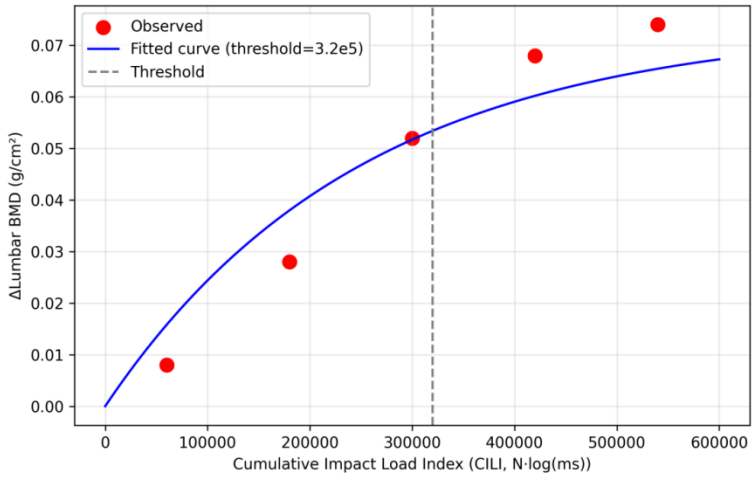


Figure 2. Dose-response curve of bone mineral density gains under different impact load levels.

decreased from 0.028 to 0.009). The optimal threshold CILI = 3.2 × 10^5 N·log(ms) was obtained by nonlinear regression fitting, below which the gain was 0.021 g/cm² for every 1 × 10^5 increase in bone mineral density, and above which the gain was reduced to 0.005 g/cm² (Figure 2).

Effect of muscle quality improvement

The trajectory of ASMI changes with time between the combined exercise group and the control group at three measuring points of 0, 12, and 24 weeks showed that, in the combined exercise group, the ASMI increased from 6.21 ± 0.48 to 6.44 ± 0.49 kg/m^2 in the 12^{th} week, and then to 6.63 ± 0.51 kg/m^2 in the 24^{th} week with a linear growth slope of 0.0175 kg/m^2/week. In the control group, the ASMI decreased from 6.16 ± 0.52 to 6.11 ± 0.53 kg/m^2 in the 12^{th} week and 6.09 ± 0.53 kg/m^2 in the 24^{th} week with a slight decrease (Figure 3). The analysis of variance of repeated measurement showed that the interaction effect of group × time was significant with F of 18.6 (P < 0.001). Multiple linear regression analysis for ΔASMI (week 24 minus baseline) revealed that CILI had a main effect coefficient of 0.087 per 10^5 N·log(ms) (95% CI: 0.060 – 0.114, P < 0.001), indicating that each 10^5 increase in CILI was associated with a 0.087 kg/m² increase in ASMI. RT_{volume} showed a main effect coefficient of 0.340 (95% CI: 0.122 – 0.558, P <

Table 2. Performance comparison of different AI models.

Model	Task	MAE	RMSE	R^2
XGBoost	ΔBMD (g/cm^2)	0.021 ± 0.003	0.028 ± 0.004	0.67 ± 0.05
Random Forest	ΔBMD (g/cm^2)	0.025 ± 0.004	0.033 ± 0.005	0.58 ± 0.06
LightGBM	ΔBMD (g/cm^2)	0.023 ± 0.003	0.031 ± 0.004	0.62 ± 0.05
SVR	ΔBMD (g/cm^2)	0.032 ± 0.005	0.041 ± 0.006	0.45 ± 0.07
TCN	ΔASMI (kg/m^2)	0.12 ± 0.02	0.16 ± 0.03	0.71 ± 0.06
LSTM	ΔASMI (kg/m^2)	0.18 ± 0.03	0.24 ± 0.04	0.55 ± 0.07
XGBoost (no exercise features)	ΔBMD	0.036 ± 0.005	0.047 ± 0.006	0.38 ± 0.08
TCN (no temporal info)	ΔASMI	0.23 ± 0.04	0.31 ± 0.05	0.31 ± 0.09

0.01), corresponding to a 0.34 kg/m² ASMI increase when RT_{volume} increased from 0 to 1. The interaction term coefficient was 0.052 (95% CI: 0.012 – 0.092, $P < 0.05$), demonstrating a synergistic effect that, when high CILI ($> 3.5 \times 10^5$) and high RT_{volume} (> 0.6) coexisted, ΔASMI increased by an additional 0.052 kg/m² beyond the additive main effects. The model had an adjusted R^2 of 0.74 and a residual standard error of 0.11 kg/m².

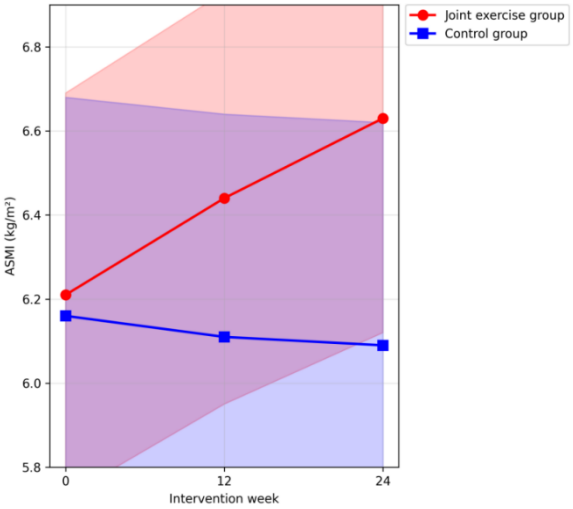


Figure 3. Skeletal muscle mass index (ASMI) of limbs changing with time.

AI model prediction performance evaluation

The Bland-Altman analysis confirmed that the prediction error was stable across the entire measurement range with no trend in the difference as a function of the mean value (Pearson r = 0.12, P > 0.05). The mean bias was 0.002 g/cm² with 95% limits of agreement from −0.045 to 0.049 g/cm², and 13 of 14 test points fell within the limits. On the independent test set (14 cases), the XGBoost model achieved a mean absolute error (MAE) of 0.021 g/cm² (95% CI: 0.018 – 0.024) for ΔBMD prediction with a root mean square error (RMSE) of 0.028 g/cm² (95% CI: 0.024 – 0.032) and an R^2 of 0.67 (95% CI: 0.60 – 0.74), substantially outperforming the baseline benchmark that MAE was 0.042 g/cm². The TCN model for ΔASMI prediction yielded an MAE of 0.12 kg/m² (95% CI: 0.10 – 0.14), RMSE of 0.16 kg/m² (95% CI: 0.13 – 0.19), and R^2 of 0.71 (95% CI: 0.64 – 0.78), compared to a baseline MAE of 0.31 kg/m². Bland-Altman analysis showed a mean bias of 0.002 g/cm² between predicted and measured BMD values with 95% limits of agreement ranging from −0.045 to 0.049 g/cm², indicating no systematic over- or under-prediction across the measurement range. The performance comparison of each model on the test set showed that, in the task of muscle mass prediction, the MAE of TCN was 0.12 kg/m², which was better than the 0.18 kg/m^2 of LSTM. The r of XGBoost in predicting bone mineral density was 0.67, which was higher than 0.58 in random forest. MAE_BMD increased from 0.021 to 0.036 after removing the motion parameters in the ablation experiment with a decrease of 29% [19] (Table 2).

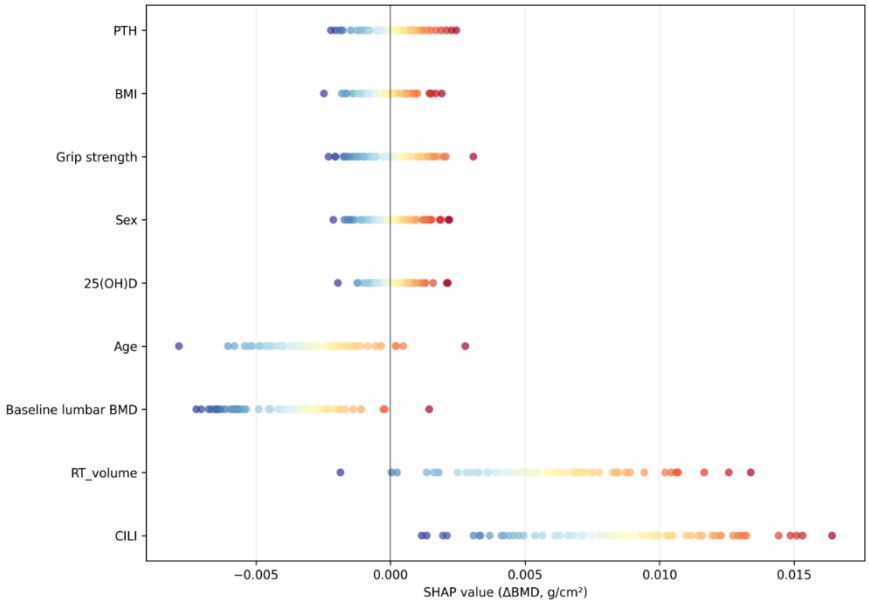


Figure 4. The distribution and direction of feature effects on ΔBMD predictions.

Identification of key prediction features

SHAP profile demonstrated the direction and magnitude of influence of each feature on bone mineral density prediction with each point representing a sample (69 cases ×22 features). The results showed that CILI was the most important feature concentrated in the range of 0.005 - 0.015. The high CILI value (> 3.5 × 10^5) corresponded to a positive contribution. RT_{volume} also gathered on the positive side. Baseline BMD of lumbar spine showed an inverse relationship as high baseline BMD corresponded to negative SHAP value. Age characteristics showed that low age was positive, while high age was negative. Gender demonstrated that males were concentrated in the positive area (Figure 4). The subgroup analysis of top 5 characteristics (CILI, RT_{volume}, baseline lumbar BMD, age, 25OHD) were performed by age (65 - 72 years old and 73 - 80 years old), gender, and baseline bone mineral density (T score between -2.5 to -1.5 and < -2.5). CILI showed a stronger effect in the low bone mass group with coefficient of 0.094 *vs*. 0.065. In age stratification, 65 - 72 years old was more sensitive to RT_{volume} with coefficient of 0.41 *vs*. 0.28. In gender stratification, males benefited more from interaction (0.068 *vs*. 0.039) (Table 3).

Practical significance of the results

CILI threshold of 3.2 × 10^5 N·log(ms) corresponded to 144 times of 30 cm jumping to the ground every week, which was the lowest cumulative impact load to distinguish the effective improvement of bone mineral density. Below this threshold, every increase of 1×10^5 CILI would bring 0.021 g/cm² bone density gain, while above it, it would drop to 0.005 g/cm². CILI of 3.2 × 10^5 could be used as the target dose when designing exercise prescription. The cross-term coefficient of 0.052 proved that there was a synergistic effect between impact load and resistance training, and the combined exercise produced 0.052 g/cm² more bone mineral density gain (about 12% of the total gain) than the two types of exercise alone. The combination of CILI main effect of 0.087 and RT_{volume} main effect of 0.34 in the regression model provided quantitative basis for individualized adjustment of the two types of motion proportions. If the subject's baseline bone mineral density was lower than 0.75 g/cm², CILI should be given priority. If ASMI was lower than 5.5 kg/m^2, RT_{volume} should be increased first. SHAP analysis showed that baseline bone mineral density contributed negatively, suggesting that the

Table 3. Subgroup analysis of top 5 important features (coefficient of ΔBMD, g/cm²).

Feature	Age 65-72 years (n=38)	Age 73-80 years (n=31)	Male (n=33)	Female (n=36)	Low bone mass (n=42)	Osteoporosis (n=27)
CILI (per 10^5 N·log(ms))	0.088	0.079	0.092	0.076	0.094	0.065
RT_volume (normalized)	0.41	0.28	0.38	0.32	0.36	0.33
Baseline lumbar BMD (g/cm²)	-0.31	-0.28	-0.33	-0.27	-0.29	-0.35
Age (per 5 years)	-0.022	-0.018	-0.024	-0.017	-0.021	-0.019
25(OH)D (per 5 ng/mL)	0.019	0.021	0.018	0.022	0.020	0.020

elderly with high bone mineral density had limited room for improvement before intervention, and resources could be allocated to high-risk groups with low bone mineral density.

The application scenario

The community elderly sports rehabilitation center may use the wearable accelerometer to collect the daily steps for 7 days, identify the impact steps with vertical acceleration ≥ 2.5 g through the algorithm, and estimate the weekly cumulative impact load. If the weekly CILI is lower than 2.5×10^5, it is suggested to increase the jumping box training 60 times a week from 15 cm height. If the CILI is higher than 4.0×10^5 and the BMD gain enters the plateau period, the system prompts to reduce the impact load to 120 times per week and increase the number of resistance training groups to 16 groups. When the orthopedic outpatient department of the hospital prescribes exercise for patients with osteosarcopenia, the patient's age, gender, baseline BMD, ASMI, and 25(OH)D are input, and the AI model predicts δ BMD and δ ASMI after 24 weeks of joint exercise. It is suggested to strengthen the impact load by increasing the height of jumping box to 45 cm or landing on one leg for patients with predicted δ ΔBMD below 0.03 g/cm². It is also suggested that the resistance strength should be increased to 85% 1RM for patients whose predicted δ ΔASMI is less than 0.25 kg/m^2. Drugstores or physical examination centers can deploy lightweight reasoning terminals, input rapid detection indicators such as ultrasonic bone mineral density, bioelectrical impedance measurement ASMI, and output individualized exercise programs.

Conclusion

This study demonstrated that an AI-driven analytical system could effectively quantify the dose-response relationship and synergy between impact loading and resistance training in elderly patients with osteosarcopenia. The CILI threshold of 3.2×10^5 N·log(ms) provided a practical target for exercise prescription, while the synergistic interaction coefficient of 0.052 confirmed that combined exercise yielded superior benefits over single-modality training. The XGBoost and TCN models offered accurate, individualized predictions of bone mineral density and muscle mass improvements, supporting their use in personalized rehabilitation. Future work should focus on external validation, lightweight system deployment, and integration of long-term follow-up data to assess fracture risk reduction.

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