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Application of Machine Learning Algorithms in Bone Mineral Density Risk Stratification in Patients with Type 2 Diabetes and Obesity

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Abstract: *As the number of individuals with diabetes who are also overweight continues to rise, the risks associated with abnormal bone mineral density (BMD) and osteoporosis are gradually emerging. Existing studies mostly rely on single obesity indicators to assess BMD, which fails to reflect the comprehensive impact of differences in fat distribution on bone metabolism and lacks stratified analysis methods for different obesity types. Therefore, this study, based on the construction of BMD risk stratification and determination rules, combined with multidimensional obesity indicators to systematically analyze the relationship between different types of obesity and BMD in patients with type 2 diabetes. A BMD risk label and differentiation determination rule that mapped ongoing BMD indicators to stratified risk levels were developed based on BMD measurements findings. Waist circumference, width-to-hip ratio, and body fat % were all adversely connected with BMD (r=−0.17 to −0.29, all P<0.05), although BMI had a significant correlation with BMD (r=0.28–0.31). Obesity at the abdomen (OR=1.64, 95%CI: 1.08–2.50) and mixed obesity (OR=2.12, 95%CI: 1.36–3.29) were found to be distinct risk variables for abnormal density of bone by a multivariate analysis.*

Keywords: *Type 2 Diabetes; Different Types of Obesity; Bone Mineral Density; Risk Stratification; Multivariate Statistical Analysis*

1. Introduction

Globally, the prevalence of type 2 diabetes mellitus (T2DM), a metabolic disease characterized by reduced digestive β-cell function and insulin resistance, is rising. Obesity, particularly related to the abdomen, is thought to play a significant role in the development and progression of type 2 diabetes. With the increasing survival of T2DM patients, related chronic complications have received growing attention, among which decreased bone mineral density and osteoporosis-related fractures have become important public health issues affecting patients' quality of life and prognosis.

Based on this background, this study investigated type 2 diabetes patients, grouping them according to different obesity types. The study compared the variations in levels of the density of bone minerals among the groups and further explored the relationship between obesity-related indicators and the number of bones and the likelihood of anomalous levels of bone minerals, aiming to provide a more refined basis for the clinical assessment and risk identification of bone health in T2DM patients.

2. Related Work

In recent years, with the continuous rise in the prevalence of obesity and metabolic diseases, the influencing factors of bone mineral density changes and osteoporosis risk have gradually attracted attention, especially in people with metabolic abnormalities such as type 2 diabetes. The complex relationship between obesity-related indicators, fat distribution characteristics and bone metabolism status has become a research hotspot. Deng et al. explored the relationship between obesity-related indicators and bone mineral density in patients with type 2 diabetes. The results showed that Waist-to-body weight ratio (WWR) and Weight-corrected waist circumference index (WWI) were significantly increased in patients with osteopenia and osteoporosis, and were negatively correlated with bone mineral density T-values [1]. Agarwal et al. assessed the impact of changes in body composition on prognosis in patients with cirrhosis within one year. The findings demonstrated that

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variations in the density of bone minerals of the femoral head and lumbar spinal column could significantly predict survival, while changes in Body Mass Index (BMI), mass of lean muscle, and volume of fat had no predictive value [2]. Gruneisen et al. Reviewed the connection involving hunger and its metabolic phenotype and bone metabolism and fracture risk, concentrating on examining bone turnover markers and immunological components of metabolism benign overweight individuals. The study pointed out that obesity does not necessarily increase the risk of fractures, and that obese people with healthy metabolism have relatively favorable bone metabolism and lower risk of fractures[3]. Using data from the US NHANES (National Health and Nutrition Examination Survey) from 1999 to 2018, Zhang et al. examined the long-term evolution of peak lumbar bone mineral density in youth. The findings revealed that while various patterns in obesity stratification were noted, there was no discernible difference in peak bone mineral density between men and women or across races [4]. Based on the Chinese community osteoporosis cohort, Xu et al. analyzed the relationship between malnutrition in different developmental stages in childhood and fracture and fracture risk in adulthood. The results showed that malnutrition in the fetal and childhood periods significantly elevated adult-related probability of osteosarcoma[5]. Mu et al. investigated the connection between menopause females actual strength of their bones and bone mineral density tests. By using the balloon expansion pressure during vertebroplasty to reflect bone strength, the results showed that lumbar BMD was moderately correlated with bone strength. After age and BMI correction, the explanatory power of DXA (Dual-Energy X-ray Absorptiometry) for bone strength was significantly improved[6]. Brandt et al. reviewed the latest evidence on the relationship between T-score and fracture risk in diabetic patients based on the T-score adjustment recommendations proposed in the 2024 ADA (American Diabetes Association) guidelines. The study pointed out that although patients with type 2 diabetes had higher T-scores, their fracture risk was actually increased[7]. Using a sizable database, Leslie et al. investigated the causes of the decline in TBS (Trabecular Bone Score) in individuals with type 2 diabetes. The findings demonstrated that TBS was significantly influenced by abdominal tissue thickness, and that the direction of the difference in TBS between individuals with and without diabetes was reversed after adjustment [8]. Smith et al. used the Manitoba Bone Mineral Registry database to analyze the risk of adverse cardiovascular events by using vertebral fracture assessment images in bone mineral density examinations and machine learning to automatically identify abdominal aortic calcification. The results showed that the higher the degree of abdominal aortic calcification, the significantly higher the incidence of MACE (Major Adverse Cardiovascular Events), suggesting that osteoporosis screening can assist in cardiovascular risk stratification[9]. In order to carefully assess the decline in bone mineral density, osteoporosis, and fracture risk in patients with ankylosing spondylitis, Yan et al. incorporated 39 articles in a meta-analysis. The findings demonstrated that bone mineral density (BMD) in the lumbar spine, femoral neck, and other regions was markedly reduced in patients with ankylosing spondylitis (AS) [10]. Li et al. used cardiac CT to quantitatively measure thoracic vertebral cancellous bone mineral density based on the MESA (Multi-Ethnic Study of Atherosclerosis) multi-ethnic cohort to assess its predictive value for fractures. The results showed that low thoracic BMD significantly increased the risk of hip and vertebral fractures, and was independent of age, sex, and race, confirming that CT-derived BMD can effectively predict future fractures [11]. Existing studies mostly rely on single obesity indicators or cross-sectional analyses, which make it difficult to simultaneously characterize the complex relationship between differences in fat distribution, metabolic status, and changes in bone mineral density, thus limiting the accurate assessment of the risk of abnormal bone mineral density in people with type 2 diabetes.

3. Method

3.1 Construction and Stratification Rules of Bone Mineral Density Risk Labels

3.1.1 Algorithmic Definition of Bone Mineral Demand Risk Level

In individuals with type 2 diabetes and obesity, bone mineral density (BMD) serves as a core indicator of individual bone health. To facilitate processing by machine learning models, this study maps continuous BMD values (BMD_i) to discrete risk level labels (y_i), forming a target variable suitable for classification. Assuming there are (K) risk levels, the mapping function can be expressed as:

$$y_i=f(BMD_i)=\begin{cases}0, \text{if } BMD_i\geq\theta_1 \text{(Low risk)}\\ 1, \text{if } \theta_2\leq BMD_i<\theta_1 \text{(Medium risk)}\\ 2, \text{if } BMD_i<\theta_2 \text{(High risk)}\end{cases} \quad (1)$$

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Here, (θ_1) and (θ_2) are the threshold parameters for low and high risk, respectively, typically set by the data distribution or professional reference standards. This mapping not only discretizes continuous variables but also ensures the order of multi-level risks, making it suitable for classification or ranking models to learn.

For multi-indicator bone mineral density combinations (such as the femoral bones neck, posterior spinal column, and total body mineral makeup density), a comprehensive risk score (S_i) can be constructed:

$$S_i = \sum_{j=1}^{M} w_j \cdot BMD_{ij} \tag{2}$$

Where (M) represents the number of bone mineral density indicators, (w_j) represents the weight of each indicator, and (BMD_{ij}) shows the (j)th mineral density of bones indicator's number obtained from the (i)th collection.. The comprehensive score (S_i) can also be converted into a multi-level risk label using the same mapping function ($f(S_i)$), achieving risk stratification after multi-indicator fusion.

3.1.2 Risk Stratification Threshold Setting Method

The key to risk stratification lies in determining the threshold (θ_k), which directly affects the rationality of the classification label and the training effect of the machine learning model. To ensure the stability and reproducibility of the threshold, this study adopts a strategy combining distribution quantization and probability mapping.

Distribution Quantization Method

Based on the cumulative distribution function (CDF) ($F_{BMD}(x)$) of sample bone mineral density, different quantiles are set as thresholds:

$$\theta_1 = F_{BMD}^{-1}(q_1), \theta_2 = F_{BMD}^{-1}(q_2) \tag{3}$$

Where (q_1) and (q_2) correspond to the low-risk and high-risk quantiles, respectively, for example, (q_1=0.67) and (q_2=0.33), ensuring that each risk level contains a relatively balanced number of samples.

Probability Mapping Method:

For the continuous risk probability ($\hat{p}_i$) predicted by the machine learning model (e.g., based on regression output or probability prediction values), a mapping can be defined as a risk level:

$$y_i = \begin{cases} 0, \hat{p}_i \le \phi_1 \\ 1, \phi_1 < \hat{p}_i \le \phi_2 \\ 2, \hat{p}_i > \phi_2 \end{cases} \tag{4}$$

Where (ϕ_1) and (ϕ_2) are mapping thresholds, which can be fine-tuned through cross-validation or expert opinions to ensure a stable distribution of different risk levels in the model output.

3.2 Machine Learning Model Construction and Training Mechanism

3.2.1 Risk Stratification Baseline Model Construction Method

To achieve multi-level classification of bone mineral density risk, this study first establishes a baseline discriminant model, including a linear discriminant model and a nonlinear discriminant model.

Linear Discriminant Model:

The linear discriminant model assumes that the feature vector of each risk level follows an identical coefficient matrix for a multichannel Gaussian model. For the feature vector of the (i)th sample ($\mathbf{x}_i \in R^M$), the risk level prediction is:

$$\hat{y}i = \arg\max k \in 0,1,2\ \delta_k(x_i) \tag{5}$$

The discriminant function ($\delta_k(\mathbf{x}_i)$) is defined as:

$$\delta_k(x_i) = x_i^T \Sigma^{-1} \mu_k - \frac{1}{2} \mu_k^T \Sigma^{-1} \mu_k + \log \pi_k \tag{6}$$

The (k)th risk grade's standard deviation column is denoted by (μ_k), the standardized covariance

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matrix is represented by (Σ), and the (k)th risk level's preceding likelihood by (π_k) .

This method can effectively handle multi-class problems and is suitable for preliminary risk stratification modeling.

Nonlinear Discriminant Model

For cases where there is a nonlinear relationship between features and risk labels, a kernel-based discriminant method can be used to map a space with many dimensions to the given input attributes (H):

$$\phi: x \mapsto H, \quad \hat{y}_i = \arg\max_k \delta_k(\phi(x_i)) \tag{7}$$

By selecting an appropriate kernel function $(K(\mathbf{x}_i,\mathbf{x}_j)=\langle\phi(\mathbf{x}_i),\ \phi(\mathbf{x}_j)\rangle)$, nonlinear relationships can be captured in high-dimensional space by linear discriminant analysis, thereby improving classification accuracy.

3.2.2 Risk Stratification Implementation of Ensemble Learning Models

To enhance the stability and accuracy of risk stratification, this study employs ensemble learning methods, primarily including Random Forest and Gradient Boosting Trees.

Random Forest (RF)

Random Forest implements a multi-model voting mechanism by constructing (T) decision trees. Each tree $(h_t(\mathbf{x}))$ generates a predicted class for the input sample (x), and the final risk stratification prediction is the majority vote result:

$$\hat{y}_i = \arg\max_K \sum_{t=1}^{T} I(h_t(x_i)=k) \tag{8}$$

Where $(I(\cdot))$ is an indicator function, representing whether the tree predicts class (k).

Random Forest uses random sampling of a subset of features for feature selection, which can reduce the impact of feature correlation on model performance.

Gradient Boosting (GBM)

Gradient Boosting builds a model by iteratively optimizing the loss function $(L(y,F(\mathbf{x})))$. For multi-class classification problems, cross-entropy loss can be used:

$$L(y,F(x)) = -\sum_{k=0}^{K-1} I(y=k) \log p_k(x) \tag{9}$$

Where $(p_k(\mathbf{x})=\frac{\exp(F_k(\mathbf{x}))}{\sum_{j=0}^{K-1}\exp(F_j(\mathbf{x}))})$ is the predicted probability of class (k), and $(F_k(\mathbf{x}))$ is the score output by the model iteration.

Each iteration optimizes the model by fitting the residuals:

$$r_{ik}^{(m)} = -\left[\frac{\partial L(y_i,F(x_i))}{\partial F_k(xi)}\right] F=F^{(m-1)} \tag{10}$$

In this way, gradient boosting trees gradually improve the stratification accuracy for difficult-to-classify samples.

3.2.3 Model Complexity Control and Generalization Constraints

To prevent overfitting and improve the model's generalization ability on new samples, this study strictly controls model complexity:

Regularization and Pruning

For the baseline model, ridge regression or Lasso regularization terms can be introduced:

$$\min_\beta \sum_{i=1}^{N} l(y_i, x_i^T\beta) + \lambda|\beta|_p \tag{11}$$

(p=1) corresponds to Lasso, (p=2) corresponds to Ridge, and (λ) is the regularization coefficient, controlling the parameter amplitude and reducing the risk of overfitting.

For decision tree or ensemble tree models, model complexity can be controlled through pruning or limiting the tree depth $(d_{\max})$.

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Learning Rate and Iteration Constraints

For gradient boosting models, a learning rate (η) is introduced:

$$F^{(m)}(x)=F^{(m-1)}(x)+\eta h_m(x) \tag{12}$$

A small learning rate can improve model stability.

Combined with a limitation on the number of iterations (M), overfitting is prevented.

Through regularization, pruning, and learning rate control, the machine learning model constructed in this study can capture the complex relationship between bone density indicators and risk levels while ensuring generalization ability and the stability of hierarchical prediction.

3.3 Interpretation and Stratified Output Method of Bone Mineral Mineral Risk Prediction Results

3.3.1 Individualized Risk Stratification Output Mechanism

Once the machine learning model has made a risk prediction about bone density, one needs to convert the continuous probability or score prediction of the model to discrete risk levels to get individualized risk stratification. Suppose that the model gives a multi-class probability vector of the (i)th sample:

$$\hat{p}_i=[\hat{p}_{i0},\hat{p}_{i1},\hat{p}_{i2}] \tag{13}$$

Where ($\hat{p}_{ik}$) is the probability predicted that the sample falls within the permitted risk level (k).. The rule of the discretization mapping may be defined as:

$$y_i=\begin{cases}0, & \hat{p}_{i0}=\max\{\hat{p}_{i0},\hat{p}_{i1},\hat{p}_{i2}\}\\ 1, & \hat{p}_{i1}=\max\{\hat{p}_{i0},\hat{p}_{i1},\hat{p}_{i2}\}\\ 2, & \hat{p}_{i2}=\max\{\hat{p}_{i0},\hat{p}_{i1},\hat{p}_{i2}\}\end{cases} \tag{14}$$

Such a technique guarantees that every single sample is captured to the risk level that is most likely, and provides a distinct stratified output.

In case the risk level is represented as a continuous score (S_i), one can predetermine a threshold (θ_0,θ_1) by which the continuous score is mapped to a discrete risk level:

$$y_i=\begin{cases}0, & S_i\le\theta_0\\ 1, & \theta_0<S_i\le\theta_1\\ 2, & S_i>\theta_1\end{cases} \tag{15}$$

This scoring mapping method is continuous and offers a better risk control opportunity and assists in the further individual risk management.

3.3.2 Feature Contribution and Model Interpretability Methods

In order to make the model results of the risk stratifications readable and interpretable, this study brings about feature contribution analysis and interpretability techniques. Assuming the model input features are ($\mathbf{x}_i=[x_{i1},x_{i2},\ldots,x_{iM}]$), their contribution to risk prediction ($\hat{y}_i$) can be measured as follows:

Global Feature Importance

For tree models (random forests or gradient boosting trees), feature importance (F_{Ij}) can be defined as the average reduction in impurity of the feature at all split nodes of the tree:

$$FI_j=\frac{1}{T}\sum_{t=1}^{T}\sum_{n\in Nt(j)}\Delta Int \tag{16}$$

(T) shows how many trees there are overall.. ($N_t(j)$) represents the set of nodes in the (t)th tree that use feature (x_j). (ΔI_{nt}) shows how impurity decreases both prior to and after the node (n) splitting..

This method can generate a global feature ranking, reflecting which bone mineral density or clinical indicators have the greatest impact on overall risk stratification.

Local Interpretability

For a single sample, the SHAP (SHapley Additive exPlanations) value (ϕ_{ij}) can be used to represent the contribution of feature (x_j) to the prediction of the (i)th sample:

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$$\hat{y}i=\phi_0+\sum j=1^{M}\phi_{ij} \tag{17}$$

(ϕ_0) is the baseline predicted value.

(ϕ_{ij}) is the contribution of feature (x_j) to sample (i).

SHAP values are additive, and allow a combination of local and global interpretations.

A unique risk profile can be derived using both global and local interpretation strategies, i.e., which of the factors are the major contributors to their bone mineral density level of risk. This does not only contribute to model transparency but also makes it easy to make individual intervention decisions, which can be made by clinicians.

4. Results and Discussion

4.1 Research Subjects and Grouping Methods

This study addressed individuals with type 2 diabetes who were frequently transferred to the hospital. Every participant satisfied the type 2 diabetes diagnostic criteria set out by the World Health Organization (WHO). The individuals were separated into various obesity groups based on their physical characteristics and weight-related prevalence features.

Based on body mass index (BMI) and fat distribution indicators, the subjects were divided into the following categories:

(1) Non-obese group;

(2) Simple generalized obesity group;

(3) Abdominal obesity group;

(4) Mixed obesity group.

The groups were kept comparable in terms of gender and age composition for subsequent bone mineral density difference analysis.

4.2 Clinical and Body Composition Indicator Measurement

All participants completed the relevant tests in the morning on an empty stomach. Measurements included: height, weight, and BMI calculation.

$$\text{BMI}=\frac{\text{weight（kg）}}{\text{height}^2\text{（m}^2\text{）}} \tag{18}$$

Measure the measurements of the waist nad the hips to find the waist-to-hip ratio (WHR):

$$\text{WHR}=\frac{\text{waistline}}{\text{Hip circumference}} \tag{19}$$

Dual-energy X-ray absorptiometry (DXA) was applied to calculate body fat percentage (PBF) and specialized weight distribution variables.

4.3 Bone Mineral Density Measurement and Classification

Dual-energy X-ray absorptiometry (DXA) was used to measure the individuals' bone mineral content (BMD). The femoral neck, the whole hip, and the lumbar spine (L1–L4) were all measured. BMD data were categorized using WHO guidelines and reported as T-scores.

$$T=\frac{BMD_{\text{Measured values}}-BMD_{\text{Youth Reference Values}}}{\text{Standard deviation}} \tag{20}$$

The following categories apply to bone the amount of minerals status:

Appropriate bone thickness: ($T \geq -1.0$)

Osteopenia : ($-2.5 < T < -1.0$)

Bone density: ($T \leq -2.5$)

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4.4 Analysis of Differences in Bone Mineral Density among Different Obesity Types

This study compared the differences in bone mineral density (BMD) at various measurement sites among different obesity groups. The continuous variables are given as $(\bar{x}\pm s)$. Inter-group comparisons were done using one-way ANOVA, and a post-hoc pairwise comparison carried out when homogeneity of variance was met.

The difference in over BMDs has the following statistical model:

$$BMD_{ij}=\mu+\alpha_i+\varepsilon_{ij} \tag{21}$$

Where (α_i) is the impact of various obesity types.

4.5 Correlation Analysis between Obesity Indicators and Bone Mineral Demand

The correlation between the overweight-related measures body mass index, body fat percentage and bone density was studied with the help of Richardson or Bonferonni correlation coefficients.

The following equation is used to determine the correlations coefficient :

$$r=\frac{\sum(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum(x_i-\bar{x})^2\sum(y_i-\bar{y})^2}} \tag{22}$$

The test to be conducted is the evaluation of correlation direction and strength of various obesity indicators at various locations of bone mineral density measurements.

4.6 Multivariate Regression Analysis

A model of multiple linear regression with the bone mineral density as the dependent variable and the type and associated body composition indicators of obesity as the independent variable was created with confounding variables of age, gender, and disease duration being corrected.

The model format is:

$$BMD=\beta_0+\beta_1 BMI+\beta_2 WHR+\beta_3 PBF+\beta_4 Age+\beta_5 Sex+\varepsilon \tag{23}$$

The independent impact of different types of obesity on bone mineral density was assessed using regression coefficients and significance levels.

4.7 Risk Analysis of Abnormal Bone Mineral Demand

Osteopenia and osteoporosis were combined into a single outcome variable, "abnormal bone mineral density," and logistic regression analysis was used to analyze the relationship between different types of obesity and the risk of abnormal bone mineral density.

The risk model is expressed as:

$$\ln\left(\frac{P}{1-P}\right)=\beta_0+\sum_{i=1}^{n}\beta_i X_i \tag{24}$$

determining each category of obesity's odds ratio (OR) and confidence level of 95% range.

Table 1. Comparing the general physiological characteristics of people with diabetes who are Type 2 with other forms of obesity($x\pm s$)

Indicator	Non-obese group (n=68)	General obesity group (n=72)	Abdominal obesity group (n=75)	Combined obesity group (n=70)	P value
Age (years)	56.3 ±8.4	55.7 ±7.9	57.1 ±8.1	56.9 ±8.6	0.62
Male proportion (%)	51.5	54.2	56	55.7	0.81
BMI (kg/m²)	23.1 ±1.9	29.4 ±2.3	26.2 ±1.8	30.1 ±2.6	<0.001
Waist circumference (cm)	84.3 ±6.2	93.7 ±7.1	97.8 ±6.8	102.4 ±7.6	<0.001
Duration of diabetes (years)	6.1 ±3.8	6.5 ±4.1	6.3 ±3.9	6.7 ±4.0	0.74

The typical clinical features of type 2 diabetes among patients with various forms of obesity are contrasted in Table 1. Age, sex, and length of diabetes did not differ statistically significantly amongst the groups (P value were 0.62, 0.81, and 0.74, separately). Specifically, the age and sex composition were similar between the non-obese group and each obesity type group, showing no significant bias and ensuring baseline consistency across groups. BMI values differed significantly among the groups ($P<0.001$). The generalised overweight group's BMI was substantially higher than the normal-weight

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group's (29.4 ± 2.3 kg/m² vs. 23.1 ± 1.9 kg/m²). Similarly, the mixed and obesity-related abdominal groups' BMIs were substantially greater than the normal-weight group's. Furthermore, waist circumference showed significant differences among different obesity groups (P<0.001). The waist circumference in the generalized obesity group (93.7 ± 7.1 cm) and the abdominal obesity group (97.8 ± 6.8 cm) was higher than that in the non-obese group (84.3 ± 6.2 cm), while the waist circumference in the mixed obesity group (102.4 ± 7.6 cm) was the highest. These results indicate that changes in body composition vary significantly among different obesity groups depending on the type of obesity. However, the duration of diabetes did not show significant differences among the obesity groups (P=0.74), suggesting that there is no significant time difference in the duration of diabetes among patients with different types of obesity, which may reflect the disease control...

The non-obese subgroup's cervical spine (L1–L4) bones mineral density (BMD) was 0.98 ± 0.12 g/cm², which was substantially less than the generalized overweight or obese group's BMD of 1.05 ± 0.14 g/cm². The BMD level was higher in the generalized obesity group, while it was lower in the abdominal obesity group (0.95 ± 0.11 g/cm²) and the mixed obesity group (0.92 ± 0.13 g/cm²). This suggests that obesity type, especially generalized obesity, may be positively correlated with BMD in the lumbar spine. The BMD of non-obese group was found to be 0.87 +-0.10 g/cm2 in the femoral neck region, and significantly less than that of the generalized obesity group (0.93 +-0.11 g/cm2), and the BMD of the abdominal obesity and mixed obesity groups (0.84 +-0.09 g/cm2) and generalized obesity group (0.81 +-0.10 g/cm2) were significantly lower than that of the The results also indicate that, although the bone mineral density (BMD) was more valuable in the generalized obesity group, the bone metabolism in the abdominal obesity group and the mixed obesity group was lower which indicated that the abdominal and the mixed obesity conditions might adversely affect the bone metabolism. The BMD in the non-obese group was also less than that one in the generalized obesity group (0.90 +- 0.11 g/cm2) in total hip BMD measurement. Consistent with other sites, the relatively lower BMD levels in the abdominal obesity group (0.88 ± 0.10 g/cm²) and the mixed obesity group (0.85 ± 0.11 g/cm²) further support the negative impact of abdominal obesity on bone mineral density.

According to the correlation analysis results, there were correlations of different directions and degrees between obesity-related indicators and bone mineral density in patients with type 2 diabetes, and all correlations were statistically significant (P<0.05). The quantity of bone minerals in the cervical spine, proximal neck, and whole hip was substantially positively linked with body mass index (BMI), with correlations values of 0.31, 0.28, and 0.30, respectfully. This result suggests that in patients with type 2 diabetes, weight gain may have a "surface protective effect" on bone mineral density to some extent, especially in weight-bearing bones. However, this positive correlation does not fully reflect the true impact of fat distribution on bone metabolism. Furthermore, body fat percentage was also negatively correlated with bone mineral density, with correlation coefficients ranging from −0.17 to −0.23, suggesting that increased overall fat content may have an adverse effect on bone metabolism. Compared with BMI, body fat percentage and abdominal obesity-related indicators showed a more direct negative correlation in reflecting changes in bone mineral density.

The findings of the logistical regression study presented in Figure 1 indicate that the risk of abnormal bone mineral density (DMD) in individuals with type 2 diabetes was significantly influenced by different forms of obesity. There was no significant correlation detected between general obesity and the risk of DMD after controlling for confounding variables such age and sex (OR=0.78, 95%CI: 0.52–1.16, P=0.21), indicating that simple universal increase in weight is not a distinct risk indicator for DMD. The limits of general obesity measures, including BMI, in evaluating bone health risk are further supported by this finding. Age and the risk of DMD were significantly positively linked in the covariate analysis (OR=1.05, 95%CI: 1.02–1.08, P<0.001), indicating that the risk of DMD progressively rises with age. Sex and the risk of DMD did not significantly correlate (P=0.35), suggesting that sex's independent impact on DMD was small in this study community.

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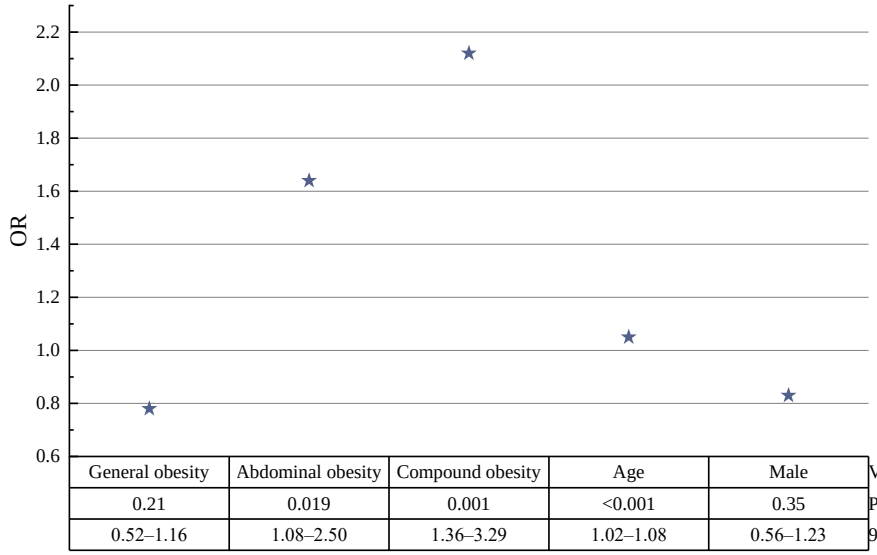

General obesity	Abdominal obesity	Compound obesity	Age	Male	Variable
0.21	0.019	0.001	<0.001	0.35	P value
0.52–1.16	1.08–2.50	1.36–3.29	1.02–1.08	0.56–1.23	95% CI

Figure 1. Logistic regression analysis of different obesity types and the risk of abnormal bone mineral density.

5. Conclusion

This paper examined how the various forms of obesity are related to bone mineral density (BMD) in type 2 diabetes patients. It was conducted in a systematic comparison in regards to BMD levels in non-obese, generalized obese, abdominally obese and mixed-type obese patients and it was also done in exploring the relationship between different indicators of obesity and BMD and the risk of abnormal BMD. The study, by a detailed evaluation of the overall clinical phenotypes, the outcomes of BMD measurements and the results of multivariate regression analysis, demonstrated comparatively comprehensive variations in the metabolic state of bone with regard to disparities in the various types of obesity. To a degree, the findings of this research contribute to the clinical evidence on the relationship between obesity and BMD in the sense that the use of BMI to determine the obesity status of patients with type 2 diabetes may not be sufficient to point at the risk of bone health in certain patients. The approach, which is founded on the type of obesity and multi-indicator combined analysis, assists in more precisely determining high-risk groups at risk of abnormal BMD, which can be used as a reference when it comes to the clinical evaluation of bone health and the development of patient-oriented management. It is necessary to note that this research is also limited to some extent. To begin with, the present study is cross-sectional analysis, so it is not easily established that there is a causal relationship between the type of obesity and alterations in the BMD. Second, the research participants belonged to a fairly homogenous sample, which meant that the findings were limited, and this could influence the generalization of findings. Moreover, the analysis did not fully cover some of the possible factors that influence bone metabolism. Further studies might increase the sample size and include longitudinal follow-up and additional indicators that are associated with metabolism to further investigate the long-term effects of the various types of obesity on bone mineral density and risk of fractures.

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