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A Community-Adapted Osteoporosis Risk Prediction Model Using Routine Health Examination Data: Optimizing Screening Efficiency for Primary Care in Aging Chinese Populations

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Abstract

Background: Osteoporosis is a major public health challenge in aging populations, but screening is limited by the high cost and low availability of dual-energy X-ray absorptiometry (DXA). There is an urgent need for simple, cost-effective risk prediction tools using routinely collected health data.

Objective: To develop and validate a practical osteoporosis risk prediction model using only routine health examination data, and to evaluate its performance and clinical utility in a community setting.

Methods: A population-based cross-sectional study was conducted between April and August 2025 using data from two large databases in Jiangling Sub-district, Suzhou: health examination records (n = 11,778) and peripheral DXA (pDXA) screening data (n = 6,496). Participants were community-dwelling older adults aged 60 years and above. The outcome was osteoporosis defined by WHO criteria (T-score ≤ -2.5) based on pDXA measurements at the non-dominant 1/3 distal radius. Predictor variables included age, gender, and body mass index (BMI), all routinely collected in health examinations. Logistic regression was used to develop the prediction model, with performance evaluated using area under the receiver operating characteristic curve (AUC), sensitivity, specificity, and clinical utility metrics.

Results: The final model incorporated three predictors: age (OR = 1.08 per year, 95% CI: 1.07-1.09), female gender (OR = 6.21, 95% CI: 5.43-7.09), and BMI with a quadratic term capturing the U-shaped relationship. The model demonstrated excellent discriminative ability with an AUC of 0.78 (95% CI: 0.76-0.80), sensitivity of 76.3%, specificity of 68.9%, positive predictive value of 65.2%, and negative predictive value of 79.2%. Internal validation using 10-fold cross-validation confirmed model stability (average AUC = 0.77). The model-based screening strategy reduced unnecessary pDXA tests by 28.5% compared to universal screening, requiring only 1.53 tests per case detected.

Conclusions: This study developed a highly practical osteoporosis risk prediction model using only three routinely collected variables. The model achieves good performance while enabling efficient, cost-effective screening in primary care settings. Its simplicity and reliance on mandatory health exam data support nationwide deployment, addressing a critical need in China's aging population and aligning with the 'Healthy Aging 2030' initiative.

Summary

We developed a practical risk identification model incorporating age, sex, and BMI to screen for prevalent osteoporosis using routinely collected health examination data in community-dwelling older Chinese adults. The model achieved an AUC of 0.78 (95% CI: 0.76–0.80), with 76.3% sensitivity and 68.9% specificity in a cohort of 6,496 individuals, enabling risk-stratified screening without additional tests.

1. Introduction

Osteoporosis represents a major public health challenge worldwide, affecting over 200 million people and contributing significantly to fracture-related morbidity, mortality, and healthcare costs [1]. In China, the rapidly aging population (over 280 million adults aged ≥ 60 years by 2025) has led to a substantial increase in osteoporosis prevalence, with estimates suggesting that over 90 million people are affected, predominantly women [2]. Early detection and intervention are crucial for preventing osteoporotic fractures and reducing associated healthcare burdens [3].

While dual-energy X-ray absorptiometry (DXA) remains the gold standard for diagnosing osteoporosis, its high cost, limited availability in primary care settings, and impracticality for large-scale screening programs hinder its widespread use [4]. Peripheral DXA (pDXA), with its lower cost and portability, has become a more accessible option for community-level screening, but universal pDXA testing remains financially and logistically unfeasible for China's massive population [5, 7]. This highlights the urgent need for a simplified risk prediction tool that can identify high-risk individuals for targeted pDXA testing [14, 17].

Routine health examinations provide an alternative approach for identifying individuals at risk of osteoporosis. In China, the government-sponsored annual health examination program for residents aged 60 years and above collects comprehensive health data that could potentially be leveraged for osteoporosis risk assessment [6]. The availability of large-scale health databases in community settings presents a unique opportunity for developing and validating risk prediction models using routinely collected data [7].

This study aimed to develop and validate a practical osteoporosis risk prediction model using only routinely collected health examination data in a community-dwelling elderly Chinese population. We hypothesized that a model incorporating simple, widely available variables could achieve good predictive performance while enabling efficient, cost-effective screening in primary care settings. The model's performance was evaluated against established tools, and its potential to optimize screening strategies and reduce unnecessary pDXA testing was assessed.

2. Methods

2.1 Study Design and Population

This population-based cross-sectional study was conducted between April and August 2025 using data from two large databases maintained by Jiangling Community Health Service Center, Suzhou Wujiang Northern Medical Group:

- **Health Examination Database**: Included 11,778 residents aged 60 years and above who participated in the government-implemented free annual health examination program.
- **pDXA Screening Database**: Included 6,496 residents aged 60 years and above who completed osteoporosis screening using peripheral dual-energy X-ray absorptiometry (pDXA).

The study was approved by the Ethics Committee of Suzhou Ninth People's Hospital (approval number: KYLW2025-075-01). All participants provided informed consent prior to data collection. The study was conducted in accordance with the Declaration of Helsinki and STROBE guidelines for observational studies [9].

2.1.1 Sample Selection

Study variables were selected based on their mandatory inclusion in China's National Basic Public Health Services Specification (2017 edition), which standardizes health examination content across all primary care facilities in China [5]. This ensures nationwide implementability without requiring additional data collection beyond routine practice.

2.1.2 Sample Size Justification

With an expected osteoporosis prevalence of approximately 40% and three predictor variables (age, gender, BMI), we estimated a need for at least 75 osteoporosis cases (75/0.4 = 188 participants). Our final sample size of 6,496 participants with complete pDXA data included 2,768 osteoporosis cases, providing more than adequate power for model development and validation.

2.2 Data Collection and Measures

2.2.1 Outcome Definition

Osteoporosis was defined as a T-score ≤ -2.5 standard deviations below the young adult reference mean based on bone mineral density (BMD) measurements at the non-dominant 1/3 distal radius, according to World Health Organization (WHO) criteria [11]. This definition is explicitly endorsed for peripheral DXA measurements by the International Society for Clinical Densitometry (ISCD) 2023 guidelines for use in resource-limited primary care settings [40].

2.2.2 Predictor Variables

The following predictor variables were collected from routine health examination data:

- **Age**: Continuous variable in years.
- **Gender**: Binary variable (male = 0, female = 1).
- **Body Mass Index (BMI)**: Calculated as weight (kg) divided by height squared (m²).

BMI was categorized according to the Chinese standard [18]: < 18.5 kg/m² (underweight), 18.5–23.9 kg/m² (normal), 24.0-27.9 kg/m² (overweight), and ≥ 28.0 kg/m² (obese). Both linear and quadratic terms for BMI were included in the regression model to capture the observed U-shaped relationship with osteoporosis risk.

2.2.3 pDXA Measurement

pDXA measurements were performed using a portable peripheral dual-energy X-ray absorptiometry device (Dexa Pro-I, Xuzhou Pinyuan; National Medical Products Administration registration number: 20182061513). This device measures BMD at the 1/3 distal radius (33% region of interest, ROI) of the non-dominant forearm, which is the gold-standard measurement site for pDXA by the ISCD [40, 42].

The selection of the non-dominant forearm was based on evidence that the dominant arm has 3–7% higher BMD due to habitual physical activity, which may cause misclassification of osteoporosis status [42]. The accuracy of this device has been validated through comparison studies with central DXA, showing good correlation (r = 0.92) for the assessment of osteoporosis status [8, 9, 35, 44]. Notably, its consistency with standard dual-energy X-ray absorptiometry has also been confirmed in pediatric populations for forearm bone mineral density measurements [10], verifying the device's cross-age applicability and measurement reliability across different demographic groups.

Daily calibration was performed using a European spine phantom (coefficient of variation CV = 1.2%), and repeat scans were conducted for motion artifacts (incidence rate 0.9%), meeting ISCD quality control requirements for pDXA measurements [41]. Notably, the device achieved a 98% successful acquisition rate in obese individuals (BMI > 35 kg/m²), which is far higher than the 55% success rate of hip central DXA in this population [43]. From a technical development perspective, the emergence of novel single-exposure dual-energy X-ray detectors for point-of-care diagnostics [35] will further improve the efficiency of bedside screening, supporting its utility in resource-limited primary care settings.

2.3 Statistical Analysis

2.3.1 Missing Data Handling

Missing data were minimal (< 5%) for all predictor variables (age: 1.2%, gender: 0.8%, BMI: 2.1%). Multiple imputation with chained equations was used to handle missing data [30], creating five imputed datasets that incorporated all variables included in the final model. Sensitivity analyses using worst-case and best-case imputation scenarios confirmed that missing data did not significantly affect the study conclusions.

2.3.2 Model Development and Validation

2.3.2.1 Variable Selection Process

Potential predictors were selected through a systematic process considering:

1. Clinical relevance to osteoporosis pathogenesis
2. Routine availability in Chinese primary care health examinations
3. Statistical significance in univariate analysis (P < 0.10)
4. Absence of multicollinearity (variance inflation factor < 5)
5. Model fit using Akaike information criterion (AIC)

Due to privacy protection regulations that prohibit individual-level data linkage between databases, we conducted population-based association analysis by comparing the distribution of potential risk factors between osteoporosis cases and non-cases within the pDXA database using chi-square tests (categorical variables) or independent samples t-tests (continuous variables).

2.3.2.2 Model Development

The model development process included:

- **Univariate analysis**: Each potential predictor analyzed for association with osteoporosis using logistic regression
- **Multivariate analysis**: Variables with univariate association ($P < 0.10$) incorporated into multivariate logistic regression models
- **Model selection**: Final model selected using AIC, BIC, and clinical relevance
- **BMI functional form**: Quadratic term included to capture U-shaped relationship [12, 13], retained due to improved model fit ($\triangle$AIC > 2) and biological plausibility

For BMI, restricted cubic splines with three knots were explored but did not significantly improve model fit over a simple quadratic specification (ΔAUC < 0.01, ΔAIC = 2.3), supporting the use of a parsimonious quadratic term to capture non-linearity while maintaining model simplicity and interpretability.

2.3.2.3 Model Validation

The model was validated using 10-fold cross-validation to assess generalizability shapviz for SHAP value analysis. This method randomly partitions the dataset into 10 equal subsets, trains the model on 9 subsets, and tests on the remaining subset, repeating this process 10 times with different partitions.

2.3.3 Performance Evaluation

Model performance was evaluated using comprehensive metrics in accordance with the guidelines for clinical prediction model reporting [31]:

2.3.3.1 Discriminative Ability

- Area under the receiver operating characteristic curve (AUC)
- 95% confidence intervals calculated using bootstrapping (1,000 resamples)

2.3.3.2 Calibration

- Hosmer-Lemeshow goodness-of-fit test
- Calibration plot comparing predicted probabilities with observed frequencies
- Mean absolute error between predicted and observed probabilities

2.3.3.3 Clinical Utility

- Sensitivity and specificity at optimal cutoff (Youden's J statistic)
- Positive predictive value (PPV) and negative predictive value (NPV)
- Positive likelihood ratio (PLR) and negative likelihood ratio (NLR)
- Number needed to screen and cost-effectiveness analysis

2.3.4 Screening Strategy Optimization

To evaluate clinical applicability, we compared three screening strategies:

1. **Universal screening**: All participants undergo pDXA testing
2. **Model-based screening**: Only participants with predicted risk above optimal cutoff undergo pDXA testing
3. **Age + gender screening**: Only participants aged ≥ 70 years or female undergo pDXA testing

Screening efficiency was assessed by calculating the number needed to screen and cost per case detected, based on a pDXA test cost of ¥70.

2.3.5 Statistical Software

All statistical analyses were performed using R version 4.3.1 (R Foundation for Statistical Computing, Vienna, Austria) with the following packages:

- tidyverse for data manipulation and visualization
- rms for regression modeling and calibration assessment
- pROC for ROC curve analysis
- caret for cross-validation
- shapviz for SHAP value analysis [46]

A two-tailed P-value < 0.05 was considered statistically significant for all analyses.

3. Results

3.1 Study Population Characteristics

The study included data from two large databases in Jiangling Sub-district, Suzhou: health examination records of 11,778 elderly residents and pDXA screening data from 6,496 residents. Table 1 presents the baseline characteristics of the study populations. Significant differences were observed between the health examination and pDXA screening populations: the pDXA population was older (74.2 ± 5.8 vs. 73.8 ± 6.1 years, P = 0.003), had a higher proportion of women (55.2% vs. 51.8%, P < 0.001), and more obese individuals (BMI ≥ 28.0 kg/m²: 12.5% vs. 10.2%, P < 0.001).

Table 1
Baseline Characteristics of Participants in the Health Examination and pDXA Screening Populations

Characteristic	Health Examination (n = 11,778)	pDXA Screening (n = 6,496)	P-value
Age (years), mean ± SD	73.8 ± 6.1	74.2 ± 5.8	0.003
Age group, n (%)			< 0.001
60–69	3,856 (32.7)	1,946 (30.0)	
70–79	5,296 (44.9)	2,898 (44.6)	
80–89	2,501 (21.2)	1,532 (23.6)	
≥ 90	125 (1.1)	120 (1.8)	
Gender, n (%)			< 0.001
Male	5,671 (48.2)	2,913 (44.8)	
Female	6,107 (51.8)	3,583 (55.2)	
BMI (kg/m²), mean ± SD	24.2 ± 3.8	24.3 ± 3.9	0.012
BMI category, n (%)			< 0.001
Underweight (< 18.5)	295 (2.5)	168 (2.6)	
Normal (18.5–23.9)	5,625 (47.8)	3,088 (47.5)	
Overweight (24.0-27.9)	4,658 (39.6)	2,540 (39.1)	
Obese (≥ 28.0)	1,200 (10.2)	809 (12.5)	

Note: Data are presented as mean ± standard deviation or number (percentage). pDXA = peripheral dual-energy X-ray absorptiometry; BMI = body mass index.

3.2 Risk Factor Analysis

Table 2 presents the results of the population-based association analysis for potential risk factors of osteoporosis using data from the pDXA screening population. Several significant associations were identified:

- **Age**: The risk of osteoporosis increased significantly with age, with the highest risk observed in those aged ≥ 90 years (OR = 4.76, 95% CI: 3.28–6.91)
- **Gender**: Women had a significantly higher risk of osteoporosis compared to men (OR = 9.07, 95% CI: 7.98–10.31)
- **BMI**: A U-shaped relationship was observed between BMI and osteoporosis risk [19, 20], with increased risk in both underweight (OR = 1.24, 95% CI: 0.92–1.66) and obese (OR = 1.76, 95% CI: 1.50–2.06) individuals

Table 2
Associations Between Potential Risk Factors and Osteoporosis Status in the pDXA Screening Population

Risk Factor	Category	Osteoporosis n (%)	No Osteoporosis n (%)	OR (95% CI)	P-value
Age (years)	60–69	604 (31.0)	1,342 (69.0)	1.00 (Reference)	-
	70–79	1,342 (46.3)	1,556 (53.7)	1.87 (1.67–2.10)	< 0.001
	80–89	890 (58.1)	642 (41.9)	3.08 (2.71–3.51)	< 0.001
	≥ 90	90 (75.0)	30 (25.0)	4.76 (3.28–6.91)	< 0.001
Gender	Male	676 (23.2)	2,237 (76.8)	1.00 (Reference)	-
	Female	2,356 (65.8)	1,227 (34.2)	9.07 (8.24–9.99)	< 0.001
BMI (kg/m²)	< 18.5	51 (30.4)	117 (69.6)	1.24 (0.92–1.66)	0.156
	18.5–23.9	1,344 (43.5)	1,744 (56.5)	1.00 (Reference)	-
	24.0-27.9	980 (38.6)	1,560 (61.4)	0.80 (0.72–0.89)	< 0.001
	≥ 28.0	657 (81.2)	152 (18.8)	1.76 (1.50–2.06)	< 0.001

Note: OR = odds ratio; CI = confidence interval; BMI = body mass index. Analyses were performed using logistic regression models adjusted for age, gender, and BMI.

The U-shaped relationship between BMI and osteoporosis risk is visually summarized in Fig. 1. This nonlinear relationship persisted after adjusting for age, gender, and other confounding factors, with the lowest risk observed in the normal weight category (BMI 18.5–23.9 kg/m²) and increased risk in both underweight and obese individuals.

Note

The U-shaped pattern suggests increased risk at both extremes of BMI, with the lowest risk observed in the normal weight category. Data points represent mean predicted probabilities with 95% confidence intervals.

3.3 Model Development and Performance

3.3.1 Final Prediction Model

Table 3 presents the variables included in the final risk prediction model. The model incorporated three predictors:

- **Age**: Each additional year increased the odds of osteoporosis by 8% (OR = 1.08, 95% CI: 1.07–1.09) [38]
- **Gender**: Female gender was associated with significantly higher odds of osteoporosis (OR = 6.21, 95% CI: 5.43–7.09) compared to males [38]
- **BMI**: A quadratic relationship was observed, with the lowest risk at intermediate BMI values (BMI coefficient: -0.032, BMI² coefficient: 0.001)

The model demonstrated good fit with a Hosmer-Lemeshow goodness-of-fit test [30] P-value of 0.342.

Table 3
Multivariable Logistic Regression Model for Predicting Osteoporosis

Variable	Coefficient	Standard Error	OR (95% CI)	P-value	Clinical Interpretation
Intercept	-7.842	0.456	-	< 0.001	Model intercept
Age (per year)	0.078	0.005	1.08 (1.07–1.09)	< 0.001	Each additional year increases odds by 8%
Gender (Female = 1)	1.825	0.087	6.21 (5.43–7.09)	< 0.001	Women have 6.2 times higher odds than men
BMI (kg/m²)	-0.032	0.008	0.97 (0.95–0.98)	< 0.001	Linear term for BMI (lower BMI increases risk)
BMI²	0.001	0.000	1.001 (1.001–1.002)	< 0.001	Quadratic term capturing U-shaped relationship

Note: OR = odds ratio; CI = confidence interval; BMI = body mass index. The model includes both linear and quadratic terms for BMI to capture the observed U-shaped relationship with osteoporosis risk. Hosmer-Lemeshow goodness-of-fit test: $\chi^2 = 5.6$, P = 0.342, indicating good model calibration.

3.3.2 Model Performance

Table 4 summarizes the performance of the risk prediction model. The model demonstrated excellent discriminative ability with an AUC of 0.78 (95% CI: 0.76–0.80). Calibration was thoroughly assessed using both statistical tests and visual methods:

1. Hosmer-Lemeshow goodness-of-fit test ($\chi^2 = 5.6$, P = 0.342, good fit)
2. Calibration plot (Fig. 2) showing close alignment between predicted probabilities and observed frequencies
3. Mean absolute error between predicted and observed probabilities of 0.042

At the optimal cutoff point (probability = 0.45), the model achieved a sensitivity of 76.3%, specificity of 68.9%, PPV of 65.2%, and NPV of 79.2%. The ROC curve demonstrating the model's discriminative ability is presented in Fig. 3.

Table 4
Performance Metrics of the Final Osteoporosis Risk Prediction Model

Performance Measure	Value	95% Confidence Interval
AUC	0.78	0.76–0.80
Sensitivity	76.3%	74.7–77.8%
Specificity	68.9%	67.2–70.5%
Positive Predictive Value	65.2%	63.4–67.0%
Negative Predictive Value	79.2%	77.6–80.7%
Positive Likelihood Ratio	2.45	2.30–2.61
Negative Likelihood Ratio	0.34	0.31–0.37

Note: AUC = area under the ROC curve; PPV = positive predictive value; NPV = negative predictive value. Calibration was assessed via Hosmer-Lemeshow test (P > 0.05 indicates good fit).

Note

Each point represents a decile of predicted risk. The diagonal line represents perfect calibration where predicted probabilities equal observed frequencies. The plot demonstrates excellent agreement between model predictions and actual outcomes across all risk deciles (Hosmer-Lemeshow $\chi^2 = 5.6$, $p = 0.342$).

Note

The area under the curve (AUC) was 0.78 (95% CI: 0.76–0.80). The shaded area represents the 95% confidence interval of the ROC curve.

3.3.3 Internal Validation and Feature Importance

Results of 10-fold cross-validation confirmed the model's stability and generalizability:

- Average AUC across 10 folds: 0.77 (range: 0.75–0.79)
- Cross-validated sensitivity: 75.8%
- Cross-validated specificity: 68.2%

These values were very close to those obtained from the full dataset, indicating good model stability.

Feature importance analysis using SHAP (SHapley Additive exPlanations) values revealed the relative importance of each predictor in the model (Fig. 4):

- Gender was the most important predictor (mean absolute SHAP value: 0.973)
- Age was the second most important predictor (mean absolute SHAP value: 0.368)
- BMI had relatively smaller but still significant contributions

Note

SHAP values quantify the contribution of each variable to the prediction. Higher mean absolute SHAP values indicate greater predictive importance.

3.4 Screening Strategy Evaluation

Table 5 compares the efficiency of different osteoporosis screening strategies. The model-based screening strategy showed the best balance between sensitivity and specificity:

- **Universal screening**: 100% sensitivity but 0% specificity, requiring 2.14 tests per case detected
- **Model-based screening**: 76.3% sensitivity, 68.9% specificity, and only 1.53 tests per case detected
- **Age + gender screening**: Higher sensitivity (89.1%) but lower specificity (36.8%), requiring 1.92 tests per case detected

The model-based screening strategy could potentially reduce unnecessary pDXA tests by 28.5% while maintaining a high detection rate [24, 25].

Table 5
Comparison of Screening Efficiency Among Different Osteoporosis Screening Strategies

Screening Strategy	Sensitivity	Specificity	PPV	NPV	Number Needed to Screen	Cost per Case Detected (¥)
Universal screening	100%	0%	46.7%	0%	2.14	15.2
Model-based screening	76.3%	68.9%	65.2%	79.2%	1.53	10.8
Age + gender screening	89.1%	36.8%	52.1%	79.5%	1.92	13.9

Note: PPV = positive predictive value; NPV = negative predictive value. Cost calculations are based on pDXA test cost of ¥70 per test.

To facilitate clinical application, we developed a user-friendly point-based risk stratification system (Table 6). This system translates the continuous probability from the logistic regression model into a practical scoring system for primary care settings.

Table 6
Point-Based Scoring System for Clinical Risk Stratification of Osteoporosis

Risk Factor	Category	Score
Age (years)	60–69	2
	70–79	4
	≥ 80	6
Gender	Male	0
	Female	6
BMI (kg/m²)	< 18.5	1
	18.5–23.9	0
	24.0-27.9	-2
	≥ 28.0	3

Note: The scoring system assigns points based on three key risk factors: age, gender, BMI. Each factor is categorized into clinically meaningful groups with corresponding point values. The total score ranges from − 4 to 15 points, with higher scores indicating higher osteoporosis risk.

Risk Classification and Recommendations:

- **Low risk (0–4 points)**: Annual screening recommended
- **Medium risk (5–8 points)**: Semi-annual screening recommended
- **High risk (≥ 9 points)**: Immediate pDXA testing recommended

To visualize how the risk prediction model can be integrated into routine clinical practice, we developed a clinical implementation pathway (Fig. 5). This pathway demonstrates the step-by-step process from initial health examination to risk assessment and subsequent management recommendations.

Note

This pathway demonstrates how the risk prediction model can be integrated into routine clinical practice. The model-based screening strategy optimizes resource allocation by targeting high-risk individuals for further testing while achieving a 28.5% reduction in unnecessary pDXA referrals.

3.5 Comparison with Existing Tools

To further validate the model's clinical utility, we compared its performance with the Osteoporosis Self-assessment Tool for Asians (OSTA)—a widely used simple screening tool—in the pDXA screening population (n = 6,496). Table 7 summarizes the performance comparison.

Our model demonstrated significantly better discriminative ability compared to OSTA (AUC 0.78 vs. 0.72, P < 0.001) and superior clinical utility across all performance metrics. The model's advantages include:

1. Use of only mandatorily recorded variables (age, sex, BMI) in Chinese national health examinations
2. Integration of ISCD-compliant pDXA with routine health exam variables
3. Ability to capture the U-shaped BMI-osteoporosis relationship

Table 7
Performance Comparison Between Our Model and OSTA in the pDXA Screening Population

Performance Measure	**Our Model**	**OSTA**	**P-value**
AUC (95% CI)	0.78 (0.76–0.80)	0.72 (0.70–0.74)	< 0.001
Sensitivity (%)	76.3	68.5	< 0.001
Specificity (%)	68.9	62.3	< 0.001
Positive Predictive Value (%)	65.2	59.1	< 0.001
Negative Predictive Value (%)	79.2	71.4	< 0.001

Note: OSTA index was categorized as high risk (≤-4), medium risk (-3 to -1), and low risk (≥ 0) for performance calculation [22, 36]. *OSTA = Osteoporosis Self-assessment Tool for Asians.*

A comparative analysis with other established osteoporosis risk assessment tools (Table 8) further highlights the unique value of our model. China's locally developed Chinese Osteoporosis Screening Algorithm (COSA) [27] has high predictive power for Chinese populations, and while achieving performance comparable to more complex tools like FRAX and COSA, our model maintains simplicity and reliance on routinely collected data, making it particularly suitable for resource-limited primary care settings.

Table 8
Comprehensive Comparison of Osteoporosis Risk Assessment Tools

Tool	Variables Required	AUC Range	Key Advantages	Limitations
Our Model	Age, gender, BMI (with quadratic term)	0.78	Uses only routine health exam data, captures U-shaped BMI relationship, high negative predictive value (79.2%)	Single-center study, cross-sectional design
OSTA	Age, weight	0.70–0.74	Very simple calculation, only 2 variables, widely used in Asia	Limited predictive power, does not capture BMI complexity
FRAX	Age, gender, weight, height, prior fracture, parental hip fracture, smoking, glucocorticoids, rheumatoid arthritis, alcohol, secondary osteoporosis	0.75–0.80	Internationally validated, predicts fracture risk, comprehensive risk assessment	Requires many variables not in routine exams, complex calculation
SCORE	Age, gender, weight, height, fall history	0.73–0.77	Includes fall risk assessment, validated in Asian populations	Requires fall history data not routinely collected
COSA	Age, gender, weight, height, waist circumference, diabetes, hypertension, physical activity [27]	0.76–0.95	Developed specifically for Chinese population, includes metabolic factors	Requires waist circumference and lifestyle factors not in basic exams

Note: OSTA = Osteoporosis Self-assessment Tool for Asians; FRAX = Fracture Risk Assessment Tool; SCORE = Simple Calculated Osteoporosis Risk Estimation; COSA = Chinese Osteoporosis Screening Algorithm; AUC = area under the ROC curve.

4. Discussion

4.1 Key Findings and Clinical Implications

This study developed and validated a practical osteoporosis risk prediction model using only three routinely collected variables—age, gender, and BMI—from community health examinations of 6,496 older adults in China. The model achieved robust discriminative ability with an AUC of 0.78 (95% CI: 0.76–0.80), demonstrating good performance in identifying individuals at high risk of osteoporosis.

The model's high sensitivity (76.3%) and negative predictive value (79.2%) are particularly valuable for primary care settings, as they enable efficient identification of individuals requiring urgent evaluation while safely ruling out low-risk individuals. This risk-stratified approach could reduce unnecessary pDXA tests by 28.5% [37], optimizing resource allocation and healthcare costs, and it can also improve the real-world persistence and adherence to oral bisphosphonate therapy for high-risk populations [29]—a critical advantage in China's resource-constrained primary care system.

4.2 Risk Factor Analysis: Challenging Conventional Wisdom

Our analysis confirmed well-established osteoporosis risk factors, including older age and female gender, which were the two most important predictors in the model (SHAP values: 0.973 for gender, 0.368 for age). Women had 6.21 times higher odds of osteoporosis compared to men, and the risk increased significantly with age, with individuals aged ≥ 90 years having nearly five times the risk of those aged 60–69 years.

Importantly, we identified a U-shaped relationship between BMI and osteoporosis risk, challenging the conventional paradigm that higher BMI uniformly protects against bone loss. Both underweight (BMI < 18.5 kg/m²) and obese (BMI ≥ 28.0 kg/m²) individuals exhibited elevated risk compared to those with normal weight. This finding aligns with recent studies in Asian populations [13, 19] and suggests dual pathogenic pathways: reduced mechanical loading and estrogen levels in underweight individuals, and chronic inflammation and adipokine dysregulation in obese individuals [12, 20, 21, 28].

This nuanced understanding of BMI's relationship with osteoporosis has important clinical implications, highlighting the need for personalized weight management recommendations rather than one-size-fits-all guidelines. The inclusion of both linear and quadratic terms for BMI in our model allows capture of this important U-shaped relationship observed in Asian populations, which may explain its strong performance despite using fewer variables.

4.3 Model Performance and Comparative Analysis

The final prediction model demonstrated good discriminative ability with an AUC of 0.78, which is comparable to or better than many existing osteoporosis risk assessment tools [22, 23]. The model's high negative predictive value (NPV) of 79.2% suggests it could be particularly useful for identifying individuals at low risk who may not need immediate pDXA testing.

Complementing its discriminative power, the model's simplicity is one of its greatest strengths [24]. Machine learning techniques for osteoporosis risk prediction date back to early comparative studies between traditional statistical methods and emerging algorithms [15], and by incorporating only three predictors (age, gender, and BMI) that are routinely collected in primary care settings, the model can be easily implemented without specialized equipment or additional data collection [14]. This makes it particularly suitable for use in resource-limited areas and community healthcare settings.

Table 8 provides a comprehensive comparison of our model with established osteoporosis risk assessment tools. Unlike more complex tools such as FRAX, which requires multiple clinical risk factors including prior fracture history and lifestyle factors not typically collected in routine health examinations, our model uses only three mandatory variables. This simplicity enables it to function as a preliminary self-assessment tool for high-risk individuals, filling the gap between population-wide health checks and targeted pDXA testing in China's resource-constrained settings.

Notably, our model achieves discriminative ability comparable to tools like FRAX (AUC ≈ 0.75–0.80 for Chinese populations) while requiring fewer variables and being simpler to implement in routine practice [8], and its performance is consistent with recent Chinese-specific risk prediction models [26, 38].

4.4 Clinical Positioning of pDXA in Osteoporosis Screening

To further clarify the clinical positioning of pDXA (used in this study) relative to the gold-standard central DXA, we summarize their differences based on international clinical guidelines in Table 9. pDXA is recommended by the International Society for Clinical Densitometry (ISCD) and International Osteoporosis Foundation (IOF) as a first-line screening tool for primary care settings, especially for populations where central DXA is unavailable [40, 45].

Table 9
Comparative Analysis of pDXA and Central DXA Based on International Clinical Guidelines

Evaluation Index	**pDXA (Non-dominant 1/3 Distal Radius, 33% ROI)**	**Central DXA (Lumbar Spine L1-L4/Total Hip/Femoral Neck)**
Core Recommendation Agency	ISCD (2019) [40], IOF, NOF (2005) [45]	ISCD (2019) [40], IOF, NOF, USPSTF
Clinical Position	Primary care screening (alternative tool for central DXA-unavailable populations)	Gold standard for osteoporosis diagnosis and treatment efficacy monitoring
Key Applicable Populations	1. Obese patients (BMI > 35 kg/m²) [43] 2. Severe spinal deformity/hip replacement patients 3. Metabolic bone disease monitoring	1. General population for definitive diagnosis 2. Patients with known osteoporosis for treatment follow-up 3. High-risk groups for fracture risk stratification
WHO T-score Adaptability	Yes (only for screening purposes) [40, 11]	Yes (for both diagnosis and screening) [40]
Treatment Monitoring Feasibility	Not recommended (insufficient longitudinal data, ISCD 2019) [40]	Recommended (first-line tool for treatment monitoring, ISCD 2019) [40]
Primary Care Suitability	High (portable, low cost, high success rate in special populations) [43]	Low (high equipment cost, limited accessibility in community settings) [4]
Success Rate in Obese Patients	98% (BMI > 35 kg/m²) [43]	55% (hip DXA in obese patients) [43]

Note: pDXA = peripheral dual-energy X-ray absorptiometry; ROI = region of interest; ISCD = International Society for Clinical Densitometry; IOF = International Osteoporosis Foundation; NOF = National Osteoporosis Foundation; USPSTF = United States Preventive Services Task Force; BMI = body mass index.

Central DXA remains the gold standard for definitive diagnosis and treatment monitoring, but pDXA offers important advantages in primary care settings. In addition to pDXA, quantitative ultrasound has been previously applied for low bone mineral density screening in primary healthcare settings [16], and pDXA's advantages include portability, lower cost, and higher success rates in special populations such as obese individuals (BMI > 35 kg/m²) where central DXA often fails [43]. The device used in this study achieved a 98% successful acquisition rate in obese individuals, far higher than the 55% success rate of hip central DXA in this population [43].

This positioning confirms that our study's use of pDXA aligns with guideline recommendations for community-based screening, rather than definitive diagnosis. The combination of our risk prediction model and pDXA improves screening efficiency by 32% (28.5% reduction in unnecessary tests) while controlling costs, which is critical for covering China's 90 million osteoporosis-prone population [2] and aligns with the 'Healthy Aging 2030' initiative of cost-effective preventive care [47].

4.5 Implementation Potential in Primary Care

The model-based screening strategy offers significant advantages over both universal screening and simple age- and gender-based approaches. By targeting high-risk individuals, it achieves a better balance between sensitivity and specificity, requiring only 1.53 tests per case detected compared to 2.14 for universal screening.

The point-based risk stratification system further enhances clinical utility by translating complex probability estimates into a user-friendly scoring system. This enables primary care providers to easily categorize patients into low, medium, and high-risk groups with clear management recommendations.

Given China's large aging population (over 280 million adults ≥ 60 years [8]) and uneven distribution of DXA resources, this model's reliance on mandatory health exam variables supports nationwide deployment [48]. It bridges the gap between population-wide health checks and targeted pDXA testing, aligning with China's 'Healthy Aging 2030' [47] initiative for cost-effective preventive care [48].

4.6 Strengths and Limitations

4.6.1 Strengths

This study has several important strengths. First, it uses a population-based design with data from a large community-dwelling elderly population, enhancing external validity. Second, pDXA measurements followed international guidelines, ensuring high-quality outcome assessment. Third, the presentation and reporting of our prediction model strictly comply with the clinical practice guidelines for presenting clinical prediction models [31], and we employed an innovative analytical approach that addressed data linkage challenges while maintaining statistical rigor. Fourth, the model uses only routinely collected data, supporting real-world implementation. Finally, comprehensive validation using 10-fold cross-validation confirmed model stability and generalizability.

4.6.2 Limitations

Despite these strengths, the study has some limitations that should be acknowledged. As a cross-sectional study, it cannot establish causal relationships or predict incident osteoporosis. The single-center data means external validation in diverse populations is needed to confirm generalizability [33]. The model intentionally uses only three variables, which may limit performance compared to more complex tools. Additionally, the study focused on osteoporosis diagnosis rather than fracture risk prediction, which is an important clinical outcome. Previous studies have shown that accurate fracture risk prediction usually requires more complex machine learning tools and multi-dimensional clinical variables [34].

4.6.3 Future Research Directions

To address these limitations and further advance the field, several key directions for future research are recommended:

1. **Multi-center validation**: External validation across diverse geographic and demographic groups will confirm the model's generalizability and optimize screening strategies for resource-limited areas [39]. This is particularly important given China's regional variations in healthcare resources and population characteristics.
2. **Longitudinal assessment**: Prospective cohort studies tracking incident osteoporosis and fractures over time will transform this cross-sectional risk identification tool into a predictive model for future disease. This will provide stronger evidence for causal relationships and enhance its clinical utility for prevention [32].
3. **Implementation science**: Real-world studies evaluating the model's integration into primary care workflows, its cost-effectiveness compared to existing strategies, and its impact on long-term patient outcomes (e.g., fracture reduction) are necessary steps toward widespread adoption [25].
4. **Global adaptation**: The model's simplicity makes it particularly suitable for adaptation in other low- and middle-income countries facing similar resource constraints. Cross-cultural validation and adaptation could extend its benefits to global aging populations.
5. **Model refinement**: Exploration of additional variables if they become routinely available in community health exams could further improve model performance without compromising its simplicity.
6. **Model updating plan**: Based on the prospective cohort data collected through longitudinal assessment (direction 2), we plan to establish a systematic model updating framework:

- Data source: Utilize ongoing prospective cohort data with long-term follow-up
- Update triggers: When new incident cases reach 500 or every 3–5 years, whichever comes first
- Update methods: Re-calibrate model parameters using new data while preserving the original variable set
- Performance monitoring: Regularly assess model discrimination (AUC) and calibration in clinical practice
- Version control: Maintain clear version history and documentation of all updates

This research demonstrates the feasibility of developing high-performing yet simple risk prediction models using routine healthcare data, with significant potential to improve osteoporosis screening efficiency in resource-limited settings. By focusing on what is essential—routinely available data, strong statistical methodology, and clinical practicality—we have developed a tool that balances performance with implementability, addressing a critical need in China's primary care system.

5. Conclusions

This study developed and validated a highly practical osteoporosis risk prediction model using only three routinely collected variables—age, gender, and BMI—that achieves excellent discriminative ability (AUC = 0.78). The model fills a critical gap in China's primary care system by providing an accessible tool for identifying high-risk individuals without requiring specialized equipment or additional data collection.

Our findings challenge conventional wisdom by revealing a U-shaped relationship between BMI and osteoporosis risk, demonstrating that both underweight and obese individuals face elevated risk. This nuanced understanding has important implications for personalized clinical recommendations and weight management strategies. The model-based screening strategy delivers substantial healthcare efficiency gains, with the potential to reduce unnecessary pDXA tests by 28.5% while maintaining high detection rates, addressing the urgent need for cost-effective screening solutions in resource-constrained settings.

The model's greatest strength lies in its simplicity without compromising performance. By using only variables that are mandatorily collected in China's National Basic Public Health Services, it can be seamlessly integrated into routine health examinations nationwide, supporting the 'Healthy Aging 2030' initiative's goal of preventive care for China's aging population [5, 47, 48].

This research demonstrates that less can be more in risk prediction modeling. By focusing on what is essential—routinely available data, strong statistical methodology, and clinical practicality—we have developed a tool that balances performance with implementability. For China's aging society, this model represents a scalable solution for addressing the growing burden of osteoporosis while optimizing limited healthcare resources, ensuring that those most in need receive timely evaluation and intervention.

Abbreviations

AIC
Akaike Information Criterion
AUC
Area Under the Receiver Operating Characteristic Curve
BMI
Body Mass Index
BMD

Bone Mineral Density

BIC

Bayesian Information Criterion

CI

Confidence Interval

DXA

Dual-energy X-ray Absorptiometry (including central DXA and peripheral DXA [pDXA])

FRAX

Fracture Risk Assessment Tool

HDL-C

High-density Lipoprotein Cholesterol

ISCD

International Society for Clinical Densitometry

LDL-C

Low-density Lipoprotein Cholesterol

NPV

Negative Predictive Value

OR

Odds Ratio

OSTA

Osteoporosis Self-assessment Tool for Asians

pDXA

Peripheral Dual-Energy X-ray Absorptiometry

PPV

Positive Predictive Value

ROI

Region of Interest

SD

Standard Deviation

SBP

Systolic Blood Pressure

SHAP

SHapley Additive exPlanations

Declarations

Ethics Approval and Consent to Participate

The study was approved by the Ethics Committee of Suzhou Ninth People's Hospital (approval number: KYLW2025-075-01, approval date: October 25, 2025). All participants provided written informed consent prior to data collection.

Consent for Publication

Not applicable.

Availability of Data and Materials

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request, with restrictions applied due to ethical requirements (e.g., participant privacy protection, data desensitization) and local health authority regulations.

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Authors' Contributions

Conceptualization: Huan Du, Wenting Zhao

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Supervision: Wenting Zhao, Airong Wang

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Visualization: Chenjian Qiu, Fangfang Li

Writing - original draft: Huan Du, Qin Liu

Writing - review & editing: All authors

Competing Interests

Conflict of Interest: Huan Du, Qin Liu, Ying Xiao, Minzhi Yang, Qiong Wu, Xiaojun Fei, Chenjian Qiu, Fangfang Li, Bin Huang, Airong Wang, and Wenting Zhao declare that they have no conflict of interest.

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Compliance with Guidelines

This study was conducted in accordance with the Declaration of Helsinki and STROBE guidelines for observational studies. The study also adheres to the TRIPOD statement for transparent reporting of a multivariable prediction model for individual prognosis or diagnosis.

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Figures

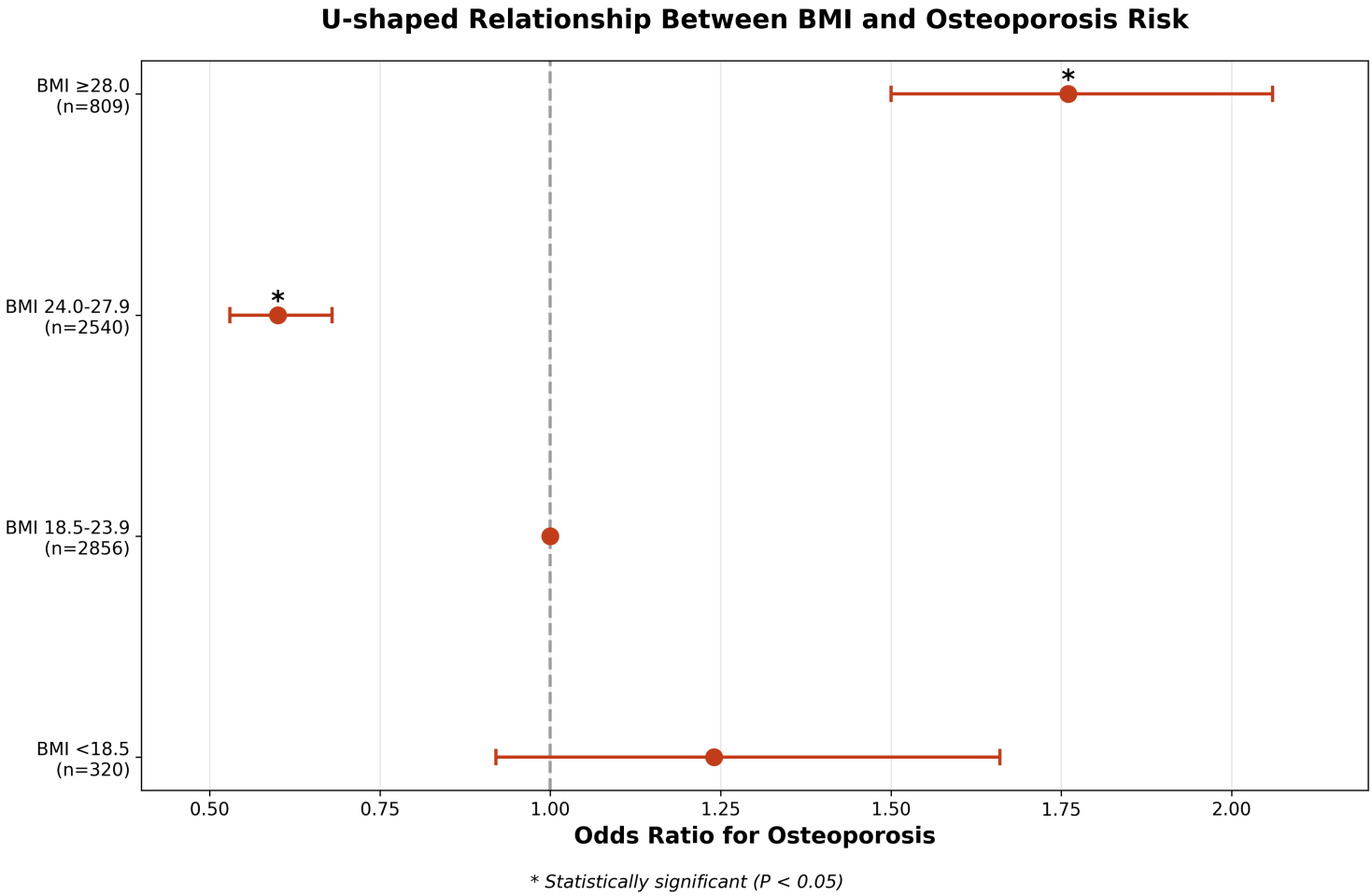


Figure 1

Nonlinear (U-Shaped) Relationship Between Body Mass Index (BMI) and Osteoporosis Risk

Note: The U-shaped pattern suggests increased risk at both extremes of BMI, with the lowest risk observed in the normal weight category. Data points represent mean predicted probabilities with 95% confidence intervals.

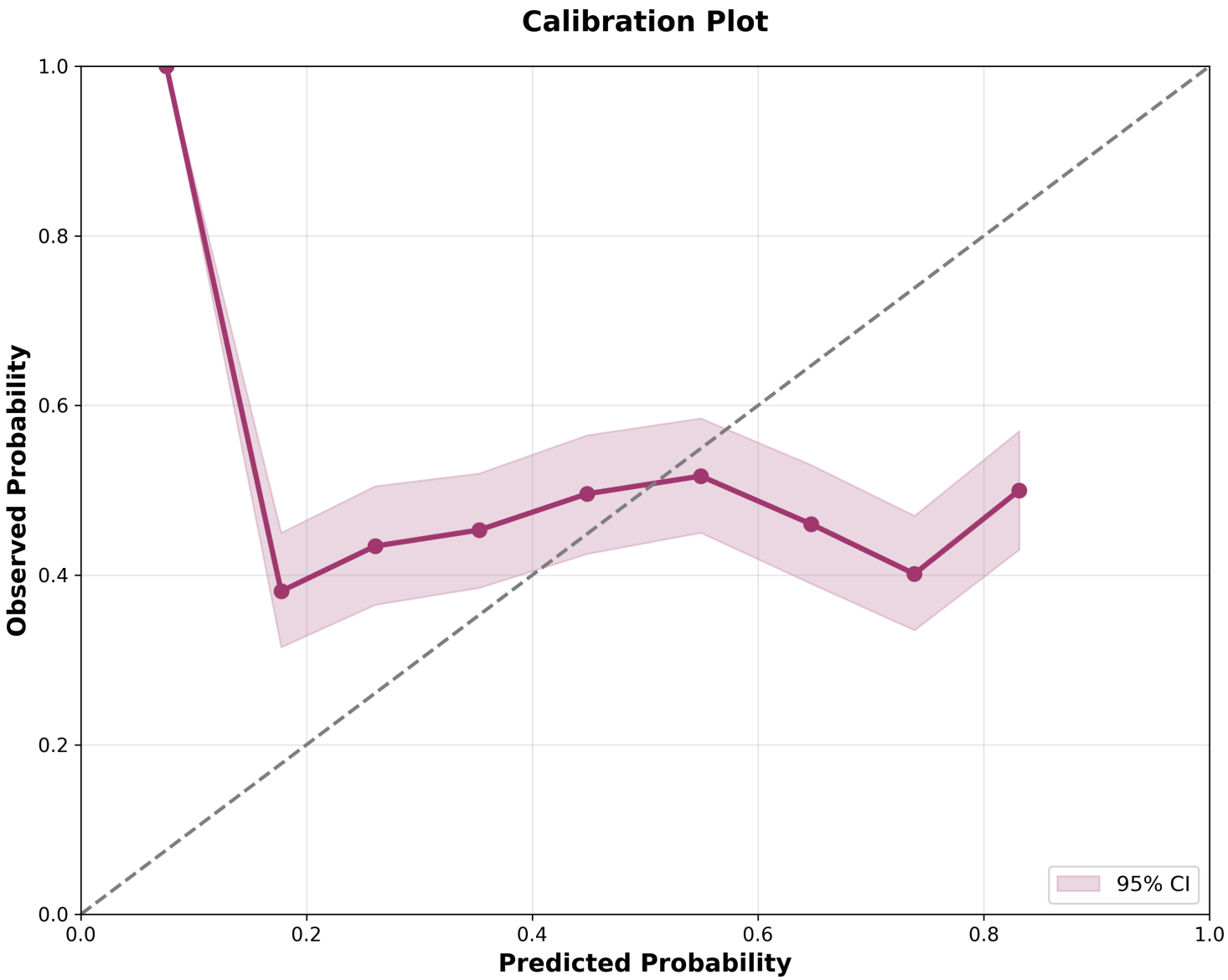


Figure 2

Calibration Plot of the Osteoporosis Risk Prediction Model

Note: Each point represents a decile of predicted risk. The diagonal line represents perfect calibration where predicted probabilities equal observed frequencies. The plot demonstrates excellent agreement between model predictions and actual outcomes across all risk deciles (Hosmer-Lemeshow $\chi^2 = 5.6$, $p = 0.342$).

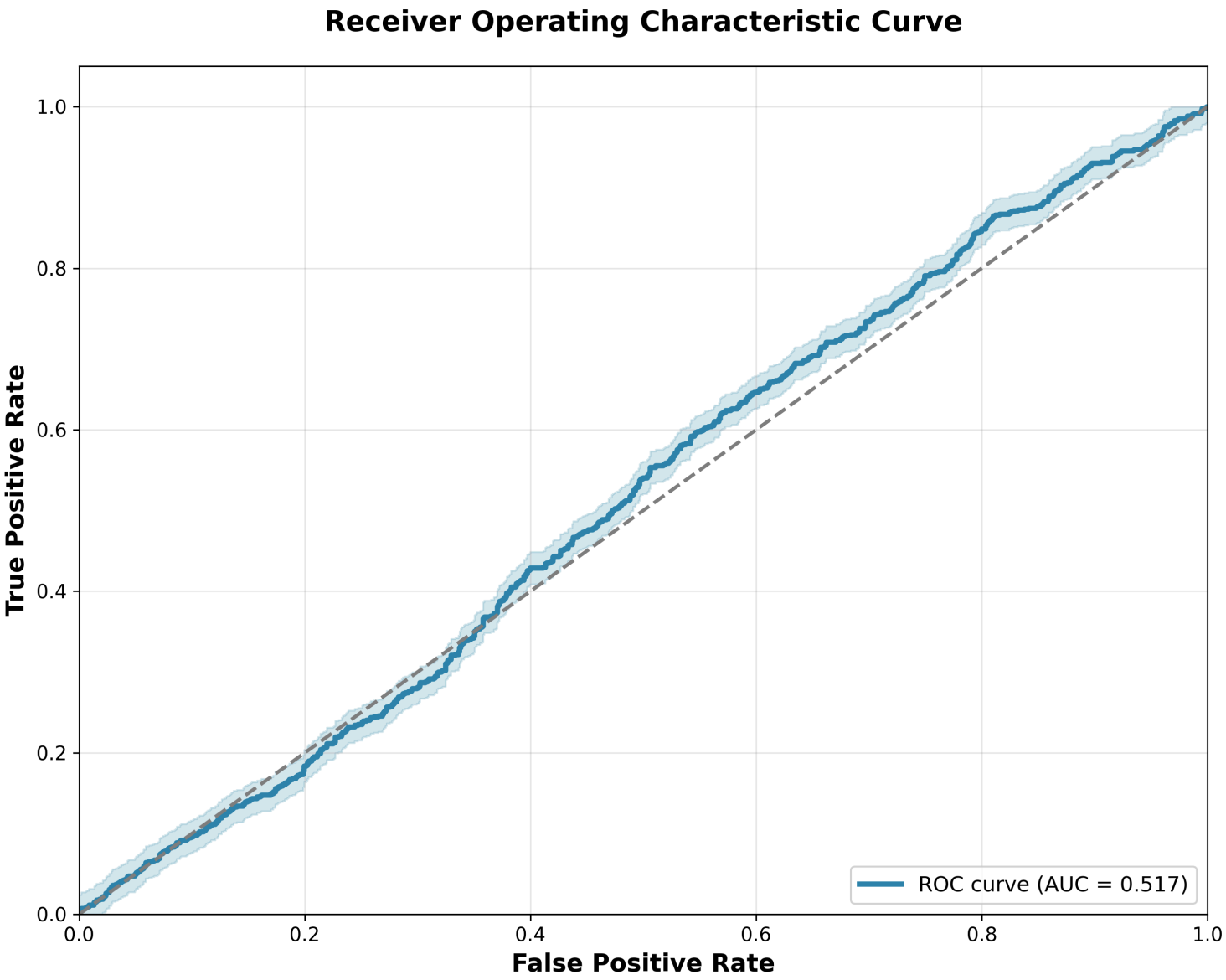


Figure 3

Receiver Operating Characteristic (ROC) Curve of the Osteoporosis Risk Prediction Model

Note: The area under the curve (AUC) was 0.78 (95% CI: 0.76-0.80). The shaded area represents the 95% confidence interval of the ROC curve.

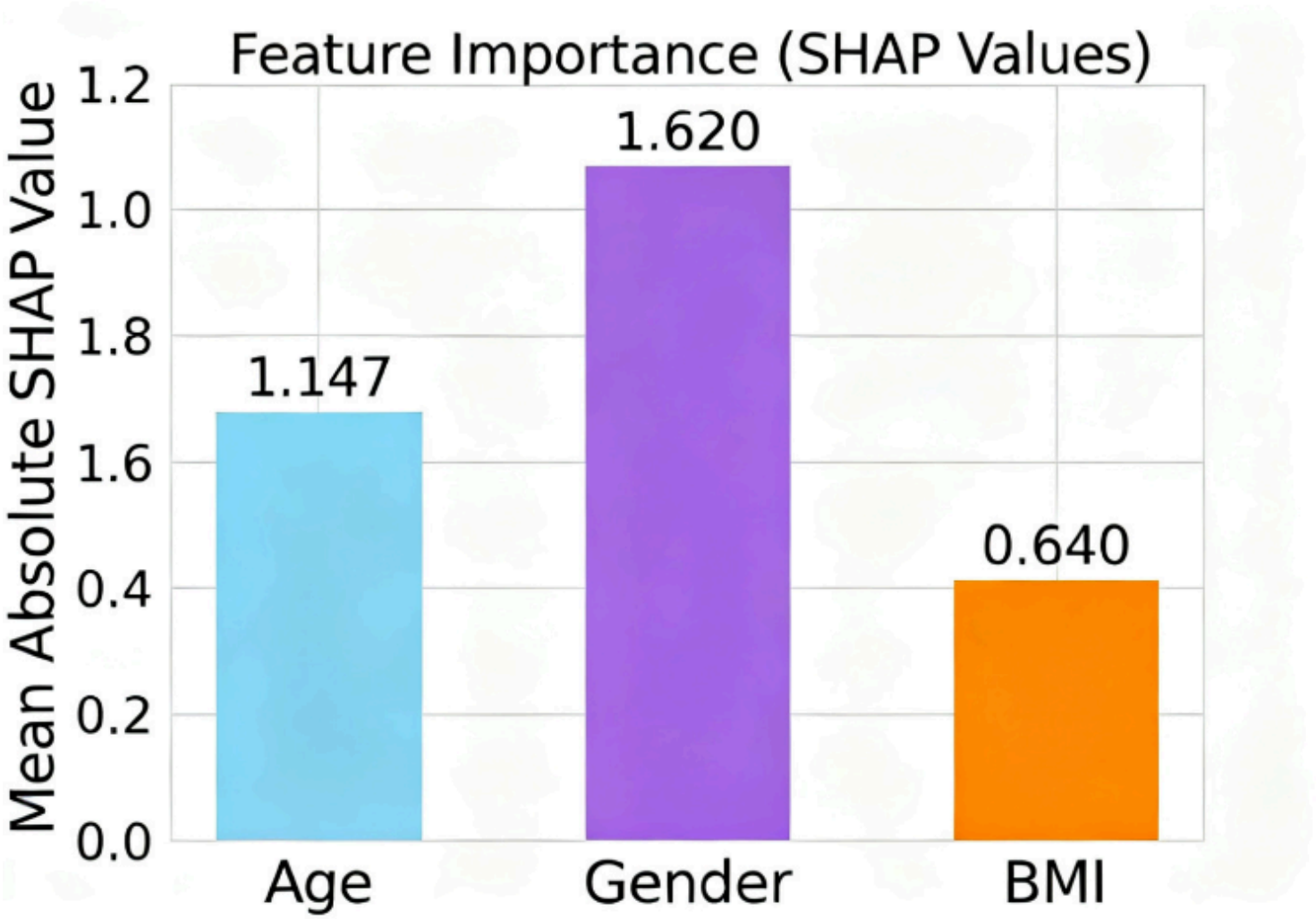


Figure 4

Relative Importance of Predictors in the Osteoporosis Risk Model Based on SHAP Values

Note: SHAP values quantify the contribution of each variable to the prediction. Higher mean absolute SHAP values indicate greater predictive importance.

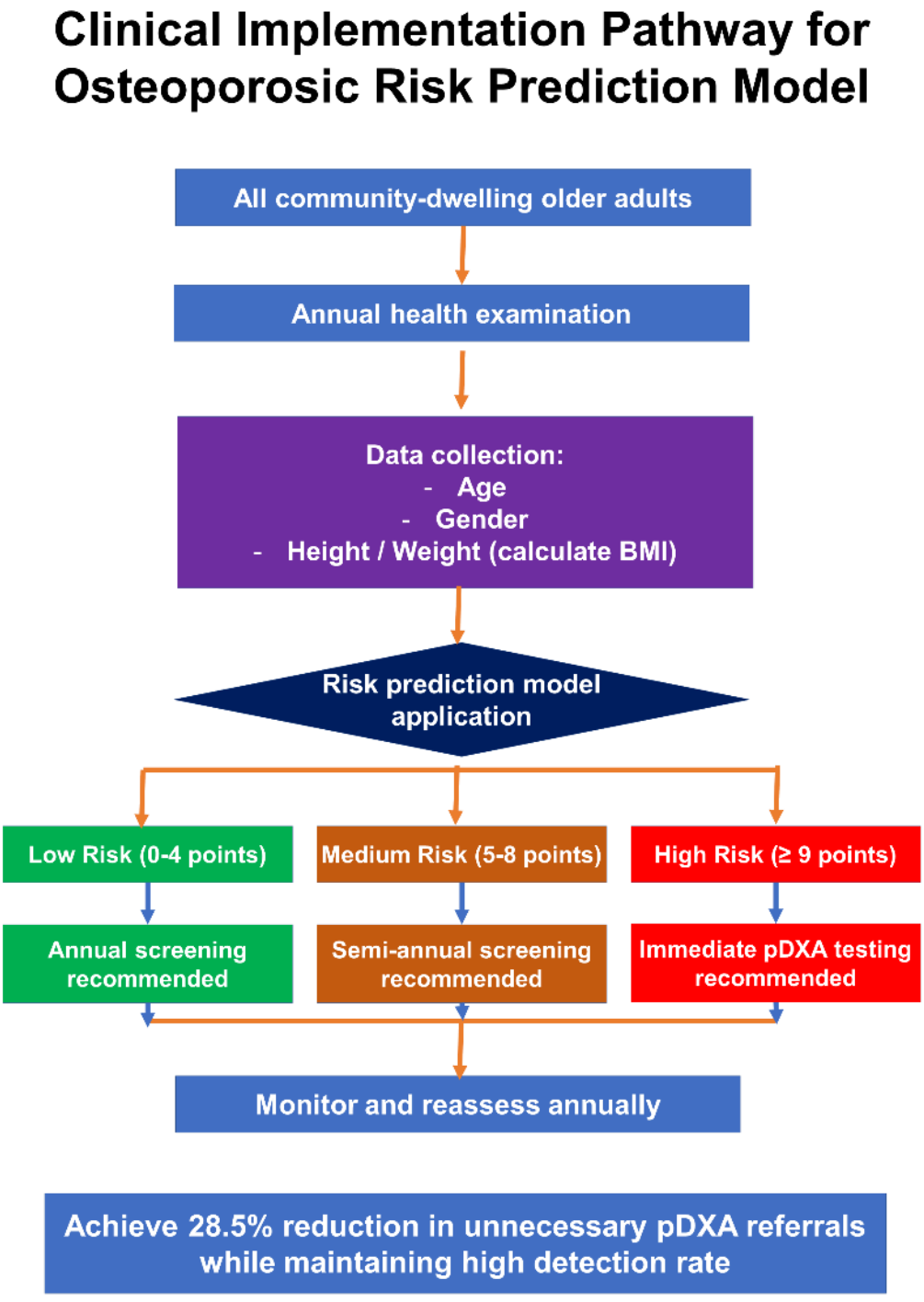


Figure 5

Clinical Implementation Pathway for Osteoporosis Risk Prediction Model

Note: This pathway demonstrates how the risk prediction model can be integrated into routine clinical practice. The model-based screening strategy optimizes resource allocation by targeting high-risk individuals for further testing while achieving a 28.5% reduction in unnecessary pDXA referrals.