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# Application of machine learning algorithms in osteoporosis analysis based on cardiovascular health assessed by life's essential 8: a cross-sectional study

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## Abstract

**Background** Life's Essential 8 (LE8) for assessing cardiovascular health (CVH) has been demonstrated to be inversely associated with osteoporosis (OP). This study aims to create a machine learning (ML) model to assess the clinical association value of lifestyle and behavioral factors, assessed by LE8, on OP risk in the United States.

**Methods** This cross-sectional analysis utilized data from the National Health and Nutrition Examination Survey (NHANES), encompassing participants aged ≧ 50 with comprehensive LE8 and OP information. Initially, the study compared the characteristics of participants with OP against those with normal bone health. Linear and nonlinear associations of LE8 and OP were analyzed by multifactor logistic regression and restricted cubic spline (RCS). Subsequently, LE8 features were integrated into six distinct ML models for OP analysis. Evaluate model performance using relevant metrics and curves. The best-performing model was further analyzed using SHapley Additive exPlanations (SHAP) to rank and clarify the positives and negatives of the contribution of individual LE8 components.

**Results** Among 3,902 participants, 364 (9.33%) were identified as having OP. Conventional regression showed that health behaviors (HB) and health factors (HF) in LE8 were negatively and positively correlated with OP, respectively, and that total LE8 was nonlinearly associated with OP. Through comparison of the Area Under the Curve (AUC), Accuracy, F1-Score, Precision, Recall, Specificity, Receiver Operating Characteristic (ROC), Decision Curve Analysis (DCA), and Calibration Curve Analysis (CCA), the optimal performance achieved by the Light Gradient Boosting Machine (LightGBM) model incorporating the 20 features. SHAP analysis revealed that the contributions of LE8 components were ranked as follows: Body Mass Index (BMI) > sleep health > blood glucose > nicotine exposure > blood lipids > blood pressure > Healthy Eating Index-2015 (HEI-2015) > physical activity. Where sleep health, blood lipids, and HEI-2015 were the main negative contributors to OP, BMI was the main positive contributor.

**Conclusions** The integration of LE8 with a LightGBM model offers a promising strategy for analysing OP in the American population, underscoring the potential of ML approaches in enhancing clinical assessments.

**Keywords** Life's essential 8, Cardiovascular health, Osteoporosis, Machine learning

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## Background

Osteoporosis (OP) is a systemic skeletal disorder, diagnosed in men over 50 years old and postmenopausal women with a bone mineral density (BMD) T-score ≤ 2.5 or a history of fragility fractures in specific sites, rendering bones more prone to fragility fractures [1]. Epidemiological data indicate a global OP prevalence of 19.7%, with marked variations by country and sex. In developing countries, the prevalence is 22.1%, markedly higher than the 14.5% observed in developed nations [2]. Among individuals over ≧50, osteoporosis in women is roughly fourfold greater than in males [3]. The spine and hip are the most common sites for osteoporotic fractures. Post-65 years of age, hip fractures manifest in approximately one-third of women and one-sixth of men [4]. Statistically, one-fifth of individuals with hip fractures succumb within one year [5]. Due to the aging global population, OP poses a substantial challenge to global healthcare.

The pathogenesis of OP is complex, involving the interplay of multiple factors. Certain risk factors cannot be altered, like age and sex, while others can be modified, including blood glucose levels, BMI, smoking, physical activity, and psychological status [6, 7]. Preventive strategies can target these modifiable factors, which in turn may mitigate the impact of non-modifiable risks. Establishing association models that incorporate these risk factors can enable the prompt identification of patients at elevated risk for OP, allowing timely lifestyle interventions for its prevention [6].

Based on a range of lifestyle and behavioral factors, the scoring system LE8 was introduced by the American Heart Association as an advanced metric for assessing CVH [8]. The LE8 score encompasses assessments of four health behaviors and factors. To date, LE8 has been successfully employed in association models for various cardiovascular diseases, chronic illnesses, and overall as well as cardiovascular mortality [9–11]. Notably, an NHANES-based study indicated that LE8 exhibits an inverse correlation with OP risk in multivariable regression analyses [7].

Machine learning (ML) is increasingly employed in modeling clinical associations to learn patterns and relationships within data, thereby forecasting disease onset and progression and aiding clinicians in making precise therapeutic decisions. ML has achieved significant advancements in analysing various diseases; for example, a study employing ML on the Ansan/Anseong cohort successfully predicted OP in an Asian population [6]. This research employed data from NHANES to construct machine learning models, with the objective of exploring the clinical relevance of lifestyle and behavioral factors evaluated through LE8 in relation to OP risk within the U.S. population. Our objectives are to identify the optimal ML model and to rank the positivity and negativity of the individual components of LE8. The insights gained may inform targeted strategies for OP management by focusing on modifiable risk factors.

## Methods

### Survey design

The NHANES database was established by the National Centre for Health Statistics, and the data from it were collected for this cross-sectional study. Started in the 1960s and ongoing since 1999, NHANES excludes institutionalized persons, active duty military personnel, and nonresidents, drawing a stratified and multistage sample of noninstitutionalized civilians of all ages from across the U.S. NHANES travels to communities across the U.S. via Mobile Examination Centers (MECs) with no fixed location to collect data, including questionnaires (face-to-face and home interviews) and medical examinations (physical measurements, laboratory tests, and imaging). Participants answer questions about health, diet, and lifestyle during face-to-face interviews. Sometimes, the investigator also conducts interviews in the participant's home to collect home-related information. Medical screening includes participants taking physical measurements such as height, weight, and blood pressure at MECs; providing biological samples such as blood and urine for laboratory testing; and undergoing imaging tests such as X-rays and ultrasounds to assess health status. After obtaining ethical clearance and informed consent from the participants, the NHANES prospectively collected data and opened the database to the public for further analyses and research on www.cdc.gov/nchs/nhanes/. After participant inclusion and exclusion, a total of 3902 participants proceeded to the final analysis (Fig. 1). This cross-sectional study followed the Strengthening the Reporting of Observational Studies in Epidemiology reporting guideline [see Additional file 1, Table S1] [12].

The sample combined NHANES data from 2005 to 2010, 2013–2014, and 2017–2018, including participants aged 40 years or older with complete LE8 score and OP data. Initially, 50,463 participants were included. After excluding participants with missing OP data ($n = 24{,}242$), missing LE8 score data ($n = 9{,}744$), under the age of 50 ($n = 6{,}782$), and missing data for partial covariates (chronic diseases and diet), a total of 3,902 participants proceeded to the final analysis. The data were divided into an 80% training set ($n = 3{,}122$) and a 20% testing set ($n = 780$). The training set was further partitioned using 5-fold cross-validation (i.e., 64% for training and 16% for validation). Six ML models were built: K-Nearest Neighbors (KNN), Random Forest, Decision Tree, Support Vector Machine (SVM), Logistic Regression, and LightGBM. LightGBM was used to assess feature importance, selecting the top 7, 12, and 17 covariates based

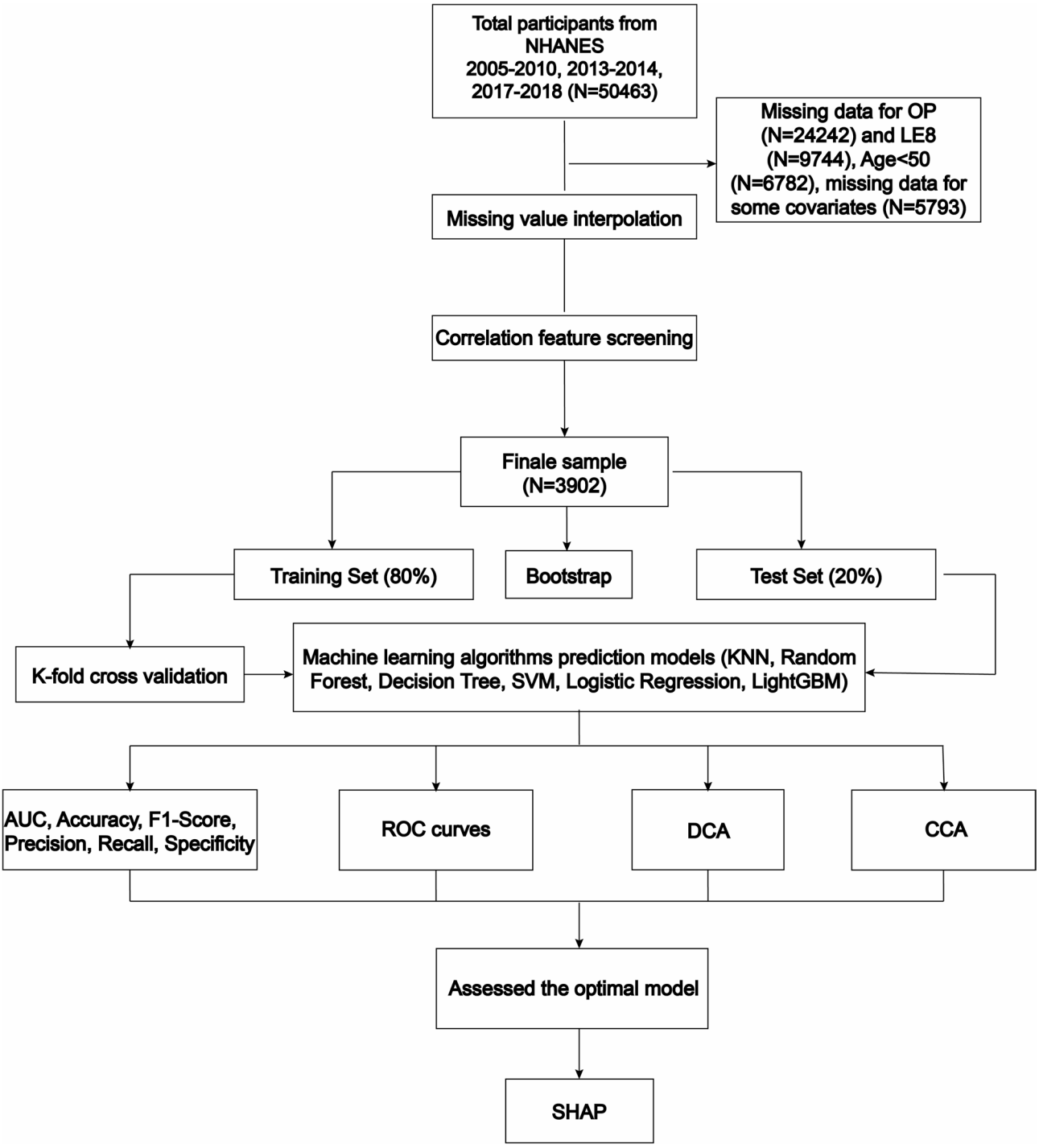


**Fig. 1** Flow chart of data collection, data preprocessing, and model development

on gain values, which were jointly modeled to contain 15, 20, and 25 features with the 8 components of LE8. Lambda_l1 and lambda_l2 regularization parameters were incorporated in this study to mitigate overfitting. Model performance was evaluated using AUC, Accuracy, F1-Score, Precision, Recall, Specificity, ROC curves, CCA, and DCA to assess discrimination, calibration, and clinical utility, thereby guiding model selection and clinical decision-making. The best-performing model was further analyzed using bootstrap to evaluate generalization ability, and SHAP to rank the importance of LE8 components.

### Assessments of LE8 scores and OP

The LE8 scores include assessments of four HB (diet, physical activity, nicotine exposure, and sleep health) and four HF (BMI, blood lipids, blood glucose, and blood pressure). The HEI-2015 assessed diet scores. This research adopted the scoring methodology outlined in prior NHANES-associated publications to compute the LE8 score, as detailed in the supplementary materials [see Additional file 2, Table S2] [13]. Each CVH component was assigned a score ranging from 0 to 100. The eight component fractions added together and divided by 8 is the total LE8 score.

Dual-energy x-ray absorptiometry (DXA) scans were employed to measure femur (total femur, femoral neck, trochanter, intertrochanter, Ward's triangle) and spine (total spine, L1, L2, L3, L4) BMD. According to the World Health Organization classification criteria, OP was defined as men over 50 and postmenopausal women having a BMD T-score ≤ −2.5 compared to reference population (healthy adults aged 20–29 of the same sex) [T-score = (Individual BMD - Mean BMD of the reference population) / BMD standard deviation of the reference population], or a history of low-trauma fractures of certain sites (hip, cone, proximal humerus, pelvis, distal forearm) in this age group [1, 14]. In this study, any participant with a T-score ≤ −2.5 at any of the ten sites [see Additional file 2, Table S3], or who reported a hip, vertebral, or wrist low-trauma fracture from a fall at or below standing height when age ≥ 50 on the Osteoporosis Questionnaire (OSQ), or who had been diagnosed with OP by a physician, was classified as having OP.

### Collection of baseline features

Based on previous studies and clinical experience, an initial set of 45 features was selected for the dataset, comprising 27 continuous and 18 categorical variables. These features were collected from five domains: demographics, lifestyle, medical status, dietary conditions, and laboratory test indicators.

### Pre-processing of machine learning features

After collecting all 45 features, calculating the proportions of missing values and extreme values, and testing for normality, the random forest algorithm was employed to impute missing values [see Additional file 2, Table S4, Table S5, and Table S6]. In participants' baseline traits and multifactor logistic regression, sampling weights were incorporated in line with NHANES sampling methodology (sampling weights: WTMEC2YR; cluster identifier: SDMVPSU; stratification variable: SDMVSTRA). To prevent multicollinearity, Spearman correlation analysis was performed, and features with correlation coefficients exceeding 0.8 were removed (phosphorus intake and waist circumference) [see Additional file 2, Fig. S1]. To eliminate the impact of different dimensions on model performance, all continuous variables were subjected to Min-Max normalization before model training, scaling them to the [0,1] range. To address class imbalance, the Synthetic Minority Over-sampling Technique (SMOTE) was applied to optimize model training [15]. Automated hyperparameter tuning was performed via Bayesian grid search to determine the parameter tuning range and optimal parameters [see Additional file 2, Table S7 and Table S8]. To enhance the robustness of the results, LightGBM was used to screen covariates with a feature importance gain value > 300, which were then incorporated into multivariate logistic regression and RCS to evaluate the linear and non-linear associations between LE8 and OP. Due to the odds ratio (OR) of LE8 being too negligible to discern in regression analysis, the study utilized LE8 divided by ten (LE8/10) as a scaled metric instead of the original LE8 value.

### Statistical analysis

In the section on participants' baseline traits, continuous variables were presented as median, Q1, Q3, Mann-Whitney U test to compare differences; categorical variables were presented as percentages, chi-square test to compare differences. Statistical analyses were conducted in Python 3.8.10 using Scikit-learn, with NumPy for numerical computations, Pandas for data handling, and Matplotlib for visualization (Fig. 1). Complete code was presented in the supplementary material [see Additional file 3, core]. Statistical significance was set at $P < 0.05$.

## Results

### Population baseline description

Among 3,902 participants, 364 (9.33%) were diagnosed with OP (Table 1). Compared to those without OP, the OP group was older, had lower household income and educational level, and included a higher proportion of females. They also had a greater prevalence of history of arthritis, thyroid diseases, cancer, asthma, pulmonary emphysema, chronic bronchitis, cardiovascular disease, depression, history of hormone use, and family history of OP, along with lower calcium, phosphorus, and alcohol intake. In laboratory measures, the OP group exhibited higher levels of blood phosphorus, blood 25-OHD, blood platelet, alkaline phosphatase (ALP), lactate dehydrogenase (LDH), high-density lipoprotein cholesterol (HDL-C), and lower levels of hemoglobin, alanine aminotransferase (ALT), aspartate aminotransferase (AST), creatinine, γ-glutamyl transferase, total bilirubin, uric acid.

**Table 1** Participants' baseline traits categorized by OP (weighted)

| Characteristic | Normal | Osteoporosis | *P* value |
|---|---|---|---|
| N | 3538 (90.67%) | 364 (9.33%) | |
| Age (year) | 56.00 (52.00, 60.00) | 61.00 (57.00, 65.00) | < 0.001 |
| Gender | | | < 0.001 |
| Male | 2248 (59.32%) | 41 (7.91%) | |
| Female | 1290 (40.68%) | 323 (92.09%) | |
| Race | | | 0.677 |
| Non-Hispanic White | 1983 (24.40%) | 185 (23.02%) | |
| Other Race | 1555 (75.60%) | 179 (76.98%) | |
| Education level | | | 0.032 |
| ≤High school | 1701 (39.72%) | 189 (45.92%) | |
| > High school | 1837 (60.28%) | 175 (54.08%) | |
| Marital status | | | 0.072 |
| Married/living with partner | 2370 (71.88%) | 202 (66.18%) | |
| Without partner | 1168 (28.12%) | 162 (33.82%) | |
| Family PIR | 4.10 (2.16, 5.00) | 3.16 (1.62, 5.00) | < 0.001 |
| History of disease | | | |
| Arthritis | 1015 (29.53%) | 263 (69.19%) | < 0.001 |
| Gout | 216 (5.09%) | 23 (3.97%) | 0.408 |
| Thyroid diseases | 361 (11.78%) | 89 (30.61%) | < 0.001 |
| Cancer | 325 (11.20%) | 68 (21.54%) | < 0.001 |
| Asthma | 422 (11.79%) | 89 (22.72%) | < 0.001 |
| Pulmonary emphysema | 61 (1.48%) | 33 (10.96%) | < 0.001 |
| Chronic bronchitis | 204 (5.61%) | 55 (15.07%) | < 0.001 |
| Liver disease | 178 (4.79%) | 26 (4.42%) | 0.694 |
| Kidney disease | 107 (2.17%) | 18 (3.76%) | 0.108 |
| Cardiovascular disease | 421 (9.81%) | 74 (18.38%) | 0.001 |
| Depression | 294 (6.43%) | 54 (10.95%) | 0.004 |
| History of hormone use | 170 (5.77%) | 60 (16.11%) | < 0.001 |
| Family history of osteoporosis | 401 (14.89%) | 125 (40.55%) | < 0.001 |
| Daily milk intake | 2250 (65.01%) | 229 (63.48%) | 0.657 |
| Waist circumference (cm) | 101.80 (91.80, 111.70) | 96.20 (83.90, 107.70) | < 0.001 |
| Calcium intake (mg) | 850.50 (616.00, 1202.00) | 757.00 (597.50, 1045.50) | 0.003 |
| Phosphorus intake (mg) | 1311.50 (1006.50, 1702.00) | 1080.00 (864.00, 1341.00) | < 0.001 |
| Alcohol intake (gm) | 0.00 (0.00, 11.15) | 0.00 (0.00, 0.00) | < 0.001 |
| Caffeine intake (mg) | 173.00 (72.00, 302.50) | 148.00 (51.00, 254.50) | 0.164 |
| Vitamin D intake (mcg) | 3.40 (2.20, 5.55) | 3.40 (1.95, 5.50) | 0.663 |
| Blood calcium (mmol/L) | 2.35 (2.30, 2.40) | 2.35 (2.30, 2.42) | 0.452 |
| Blood phosphorus (mmol/L) | 1.20 (1.07, 1.32) | 1.26 (1.13, 1.32) | < 0.001 |
| Blood 25-OHD (nmol/L) | 69.20 (53.50, 85.90) | 77.40 (60.80, 94.50) | < 0.001 |
| Leucocyte (×103/uL) | 6.80 (5.50, 8.20) | 6.60 (5.60, 8.20) | 0.666 |
| Hemoglobin (g/dL) | 14.70 (13.80, 15.60) | 13.80 (13.10, 14.50) | < 0.001 |
| Blood platelet (103/uL) | 241.00 (204.00, 286.00) | 261.00 (218.00, 308.00) | < 0.001 |
| Alanine aminotransferase ALT ((U/L) | 23.00 (18.00, 31.00) | 20.00 (15.00, 26.00) | < 0.001 |
| Aspartate aminotransferase AST (U/L) | 24.00 (20.00, 28.00) | 23.00 (19.00, 27.00) | 0.007 |
| Albumin (g/L) | 42.00 (40.00, 44.00) | 42.00 (40.00, 44.00) | < 0.001 |
| Alkaline phosphatase (u/L) | 70.00 (58.00, 85.00) | 74.00 (59.00, 91.00) | 0.037 |
| Creatinine (umol/L) | 79.56 (68.07, 90.17) | 70.72 (61.88, 81.33) | < 0.001 |
| Blood urea nitrogen (mmol/L) | 5.00 (3.93, 6.07) | 5.00 (3.93, 6.07) | 0.453 |
| γ-glutamyl transferase (U/L) | 23.00 (16.00, 36.00) | 19.00 (14.00, 30.00) | < 0.001 |
| Lactate dehydrogenase (U/L) | 138.00 (122.00, 157.00) | 148.00 (127.00, 167.00) | < 0.001 |
| Total bilirubin (umol/L) | 11.97 (8.55, 15.39) | 10.26 (6.84, 11.97) | < 0.001 |
| Triglycerides (mmol/L) | 1.50 (1.02, 2.23) | 1.47 (1.03, 1.98) | 0.088 |
| High density lipoprotein (mmol/L) | 1.29 (1.06, 1.58) | 1.50 (1.16, 1.76) | < 0.001 |

**Table 1** (continued)

| Characteristic | Normal | Osteoporosis | *P* value |
|---|---|---|---|
| Uric acid (umol/L) | 333.10 (273.60, 386.60) | 291.50 (237.90, 350.90) | < 0.001 |
| Globulin (g/L) | 28.00 (26.00, 31.00) | 28.00 (25.00, 30.00) | 0.662 |

PIR: income-to-poverty ratio. Continuous variables were presented as median, Q1,Q3, Mann-Whitney U test to compare differences; categorical variables were presented as percentages, chi-square test to compare differences

**Table 2** Association between LE8 scores and osteoporosis (weighted)

| | OR (95%CI), *P* value | |
|---|---|---|
| **Independent variable** | **Crude model** | **Adjusted model** |
| LE8 score/10 | 1.00 (0.99, 1.01), 0.8215 | 0.99 (0.87, 1.14), 0.9189 |
| Health behaviors score/10 | 0.95 (0.88, 1.03), 0.2607 | 0.83 (0.76, 0.91), **0.0003** |
| Health factors score/10 | 1.05 (0.96, 1.14), 0.2750 | 1.26 (1.11, 1.43), **0.0015** |
| HEI-2015 score/10 | 0.99 (0.93, 1.06), 0.8263 | 0.95 (0.89, 1.03), 0.2409 |
| Physical activity score/10 | 0.99 (0.94, 1.03), 0.5339 | 0.97 (0.92, 1.03), 0.3402 |
| Nicotine exposure score/10 | 1.00 (0.97, 1.03), 0.8890 | 0.99 (0.94, 1.05), 0.8292 |
| Sleep health score/10 | 0.92 (0.88, 0.97), **0.0045** | 0.84 (0.79, 0.91), **0.0001** |
| BMI score/10 | 1.06 (1.01, 1.12), **0.0342** | 1.19 (1.12, 1.27), **< 0.0001** |
| Blood lipids score/10 | 1.02 (0.97, 1.06), 0.5015 | 1.09 (1.01, 1.18), **0.0274** |
| Blood glucose score/10 | 0.99 (0.93, 1.05), 0.6464 | 0.95 (0.88, 1.03), 0.2178 |
| Blood pressure score/10 | 1.00 (0.95, 1.04), 0.8503 | 0.98 (0.92, 1.04), 0.5579 |

The adjusted model was adjusted by gender, arthritis, age, family history of osteoporosis, blood urea nitrogen, history of hormone use, vitamin D intake, hemoglobin, thyroid disease, caffeine intake, and blood calcium. Health behaviors score/10, health factors score/10, and each LE8 component/10 in the adjusted model added adjustments to each other. Significant *P* values were in bold

### Association between LE8 and OP

Table 2 illustrates the association between LE8 as a whole and as components with OP (Table 2). In the adjusted model, HB and sleep health scores therein were significantly negatively associated with OP, while HF and BMI, blood lipids therein scores were positively associated with OP. RCS analysis revealed a non-linear association between total LE8 and OP (*P*-nonlinear = 0.0499) (Fig. 2).

RCS was adjusted by gender, arthritis, age, family history of osteoporosis, blood urea nitrogen, history of hormone use, vitamin D intake, hemoglobin, blood calcium, thyroid disease, and caffeine intake. Akaike Information Criterion (AIC) is used to select the optimal number of knots.

### Developing machine learning models for osteoporosis analysis

Using feature importance derived from LightGBM's gain values, the research selected the 8 LE8 components and top 7, 12, and 17 features [see Additional file 2, Table S9], and applied them to train six ML algorithms on the NHANES sample to generate the optimal OP association model (Table 3). In 20 features, LightGBM attained the optimal Accuracy and Specificity, while Random Forest attained the optimal F1-Score, Precision, and Recall. Logistic Regression of 25 features achieved the highest AUC. Using the LightGBM model with 20 features as the reference, DeLong's test showed no significant differences in AUC when compared with other models; there were also no significant differences in AUC when SMOTE was not introduced. The relevant code for DeLong's test can be found in the supplementary material [see Additional file 4, DeLong's test_auc]. After applying SMOTE, the averages of various metrics had only small differences, with slight improvements in AUC and Accuracy.

The ROC curves indicated that LightGBM of 20 features achieved high AUC in the train set (AUC = 0.9632), validation set (AUC = 0.9626), and test set (AUC = 0.9167) (Fig. 3). Subsequently, 100 iterations of bootstrap resampling were used for internal validation (mean AUC = 0.92) (Fig. 4).

DCA was conducted to assess the clinical efficacy among the six models using the 20 features in the test set (Fig. 5). Across all threshold probability levels, all six models provided greater net benefit than the "treat-all" or "treat-none" strategies. LightGBM demonstrated the highest net benefit across all threshold probabilities.

CCA for the 20 features in the test set was plotted (Fig. 6). Among the six models, LightGBM demonstrated the closest alignment with the ideal calibration line and had the lowest Brier score (Brier = 0.054). LightGBM for the vast majority of predicted probabilities tended to underestimate the event occurrence probability, only overestimated when predicted probabilities were high.

### SHAP analysis

SHAP summary plot was performed to evaluate the significance ranking of LE8 components in OP association (Fig. 7a). The ranked contributions of LE8 components to the model were as follows: BMI > sleep health > blood

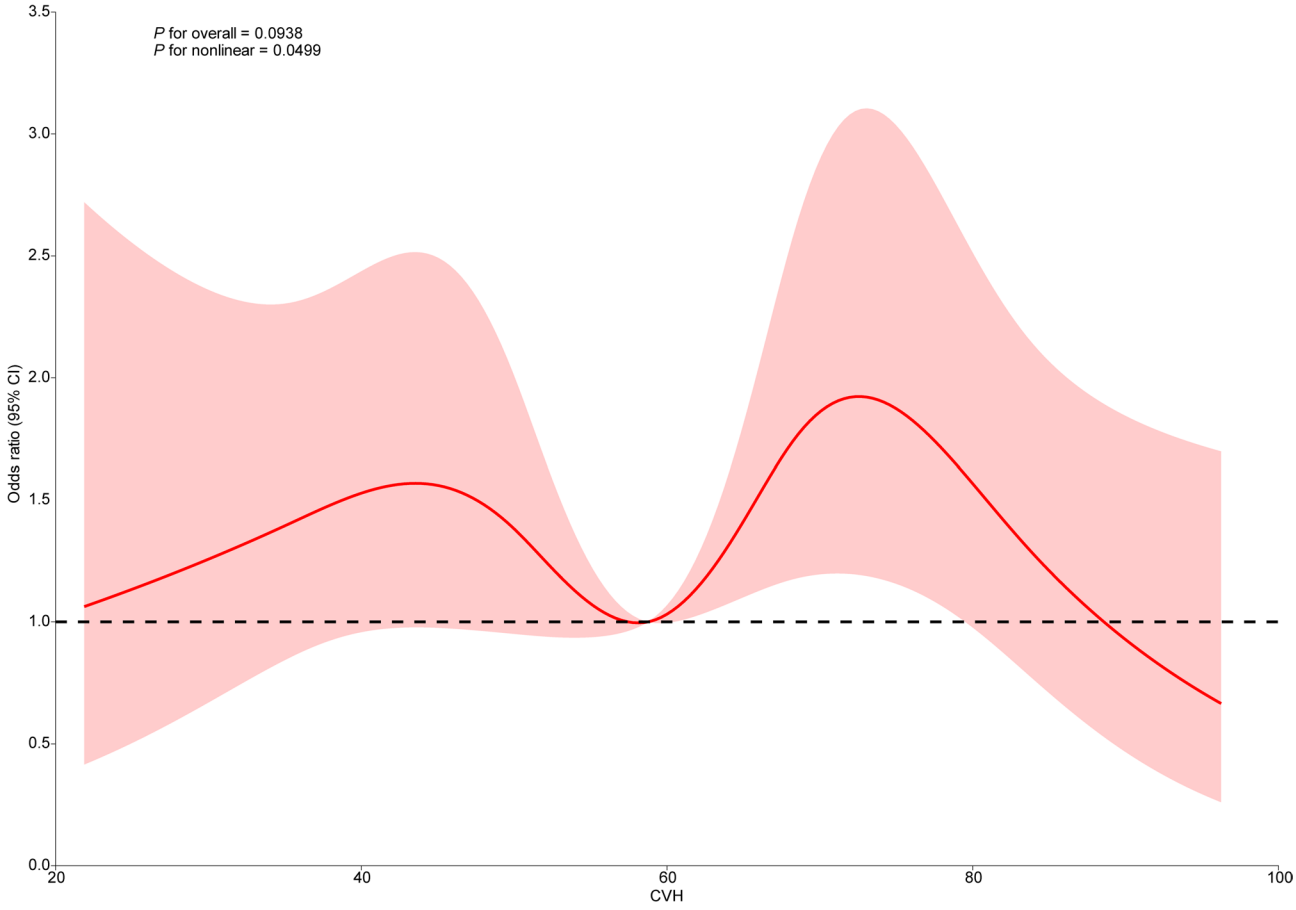


**Fig. 2** Restricted Cubic Spline analysis between LE8 and OP

glucose > nicotine exposure > blood lipids > blood pressure > HEI-2015 > physical activity. The SHAP waterfall plot showed that in the OP analysis, the components of LE8 including sleep health (-0.47), blood lipids (-0.25), and HEI-2015 (-0.23) scores were the main negative contributors, while the BMI score (+0.44) showed a positive contribution (Fig. 7b). Meanwhile, age (-1.56), gender (+1.24), and arthritis (-0.91) ranked among the top three features in their contributions to OP. The cumulative association level of the 20 features resulted in a final analysis range from 0.205 to -1.367. The SHAP force plot indicated that sleep health and blood lipids scores in LE8 reduced the likelihood of OP, while the BMI score increased the likelihood of OP (Fig. 7c).

## Discussion

This study employs traditional regression and ML algorithms to investigate the analytical role of LE8 in OP using NHANES data. Traditional regression showed that HB and HF were negatively and positively correlated with OP, respectively, while total LE8 exhibited a nonlinear association with OP. Among six ML models, LightGBM demonstrated superior performance, achieving the excellent AUC, Accuracy, F1-Score, Precision, Recall, and Specificity when utilizing the 20 features. Its ROC curves exhibit good generalizability, and the bootstrap results are stable. DCA and CCA exhibited optimal performance. SHAP analysis ranked the contributions of LE8 components to the model as follows: BMI > sleep health > blood glucose > nicotine exposure > blood lipids > blood pressure > HEI-2015 > physical activity. Sleep health, blood lipids, and HEI-2015 scores were the main negative contributors to OP, and BMI score was the main positive contributor.

This study is, to our knowledge, the first research to create and evaluate a ML model to analyse OP that includes LE8. Previous studies have increasingly employed ML models to explore lifestyle and health factors related to OP. A cohort study from Ansan/Anseong found that eXtreme Gradient Boosting (XGBoost) exhibited strong OP analytical capability (AUC = 0.890), with body height and weight ranking high in feature importance and SHAP analysis [6]. However, OP in this study was diagnosed based on ultrasonographic bone density of the tibia and radius, without considering a history of fragility fractures. Wen-Yu et al. developed an ML model

**Table 3** Metrics of the 6 machine learning models in analysing OP

| Model | AUC | *P* value | Accuracy | F1-Score | Precision | Recall | Specificity |
|---|---|---|---|---|---|---|---|
| 15 features | | | | | | | |
| KNN | 0.8976 ± 0.0216 | 0.7004 | 0.9206 ± 0.0125 | 0.9207 ± 0.0089 | 0.9230 ± 0.0068 | 0.9206 ± 0.0125 | 0.9562 ± 0.0201 |
| Random Forest | 0.9127 ± 0.0186 | 0.7789 | 0.9334 ± 0.0106 | 0.9355 ± 0.0097 | 0.9346 ± 0.0101 | 0.9388 ± 0.0102 | 0.9684 ± 0.0153 |
| Decision Tree | 0.8685 ± 0.0179 | 0.5194 | 0.8833 ± 0.0278 | 0.8925 ± 0.0168 | 0.9087 ± 0.0082 | 0.8833 ± 0.0278 | 0.9144 ± 0.0416 |
| SVM | 0.9189 ± 0.0109 | 0.9632 | 0.9230 ± 0.0142 | 0.9293 ± 0.0106 | 0.9320 ± 0.0096 | 0.9279 ± 0.0126 | 0.9493 ± 0.0211 |
| Logistic Regression | 0.9277 ± 0.0116 | 0.9172 | 0.9330 ± 0.0136 | 0.9332 ± 0.0118 | 0.9343 ± 0.0105 | 0.9330 ± 0.0136 | 0.9626 ± 0.0146 |
| LightGBM | 0.9165 ± 0.0147 | 0.8818 | 0.9347 ± 0.0107 | 0.9307 ± 0.0125 | 0.9332 ± 0.0081 | 0.9311 ± 0.0169 | 0.9684 ± 0.0152 |
| 20 features | | | | | | | |
| KNN | 0.8952 ± 0.0189 | 0.6569 | 0.9087 ± 0.0172 | 0.9037 ± 0.0157 | 0.9123 ± 0.0094 | 0.8986 ± 0.0228 | 0.9427 ± 0.0242 |
| Random Forest | 0.9152 ± 0.0173 | 0.8926 | 0.9379 ± 0.0090 | 0.9368 ± 0.0097 | 0.9373 ± 0.0119 | 0.9417 ± 0.0104 | 0.9735 ± 0.0069 |
| Decision Tree | 0.7995 ± 0.0421 | 0.2080 | 0.8606 ± 0.0361 | 0.8755 ± 0.0264 | 0.8972 ± 0.0132 | 0.8606 ± 0.0361 | 0.8926 ± 0.0388 |
| SVM | 0.9168 ± 0.0100 | 0.9696 | 0.9238 ± 0.0160 | 0.9308 ± 0.0112 | 0.9327 ± 0.0088 | 0.9296 ± 0.0131 | 0.9547 ± 0.0229 |
| Logistic Regression | 0.9324 ± 0.0088 | 0.8642 | 0.9358 ± 0.0077 | 0.9350 ± 0.0061 | 0.9353 ± 0.0063 | 0.9362 ± 0.0072 | 0.9684 ± 0.0115 |
| LightGBM | 0.9213 ± 0.0137 | Reference | 0.9394 ± 0.0045 | 0.9340 ± 0.0065 | 0.9347 ± 0.0060 | 0.9358 ± 0.0067 | 0.9770 ± 0.0091 |
| LightGBM (no SMOTE) | 0.9170 ± 0.0169 | 0.9811 | 0.9390 ± 0.0072 | 0.9389 ± 0.0109 | 0.9391 ± 0.0107 | 0.9405 ± 0.0125 | 0.9808 ± 0.0069 |
| 25 features | | | | | | | |
| KNN | 0.8975 ± 0.0216 | 0.8268 | 0.9168 ± 0.0098 | 0.9018 ± 0.0095 | 0.9112 ± 0.0109 | 0.8952 ± 0.0093 | 0.9545 ± 0.0093 |
| Random Forest | 0.9218 ± 0.0141 | 0.9249 | 0.9360 ± 0.0160 | 0.9359 ± 0.0113 | 0.9354 ± 0.0117 | 0.9388 ± 0.0115 | 0.9707 ± 0.0183 |
| Decision Tree | 0.8016 ± 0.0245 | 0.0932 | 0.8952 ± 0.0128 | 0.8972 ± 0.0117 | 0.8995 ± 0.0108 | 0.8952 ± 0.0128 | 0.9381 ± 0.0097 |
| SVM | 0.9265 ± 0.0079 | 0.8798 | 0.9274 ± 0.0124 | 0.9336 ± 0.0103 | 0.9352 ± 0.0085 | 0.9326 ± 0.0119 | 0.9558 ± 0.0162 |
| Logistic Regression | 0.9330 ± 0.0095 | 0.8434 | 0.9360 ± 0.0077 | 0.9350 ± 0.0057 | 0.9350 ± 0.0059 | 0.9358 ± 0.0062 | 0.9672 ± 0.0111 |
| LightGBM | 0.9221 ± 0.0149 | 0.9341 | 0.9385 ± 0.0057 | 0.9362 ± 0.0055 | 0.9354 ± 0.0060 | 0.9400 ± 0.0052 | 0.9751 ± 0.0126 |

*P* values are the results of DeLong's test of the AUC value of different machine learning models compared with the LightGBM model of 20 features. Bold refers to the optimal value under this indicator

for the Taiwanese population incorporating multiple health factors (smoking, blood pressure, glucose, lipids) for OP association, with Random Forest achieving the highest AUC among five ML models in both males (AUC = 0.843) and females (AUC = 0.811) [16]. However, the diagnosis of OP is based on the classification of DXA results, lacking the original T-score information. Compared to previous studies, our study adopts more comprehensive OP inclusion criteria (DXA of 10 lumbar and femoral sites, history of hip, vertebral, and wrist fragility fractures, and self-reported physician-diagnosed OP), yielding a more realistic OP prevalence and more clinically useful decisions. More importantly, the performance of this study (optimal mean AUC = 0.9330) outperformed the two aforementioned studies. This may be attributed to differences in the included features: (1) This study used the BMI score to integrate the proportional relationship between height and weight, excluding waist circumference due to its strong collinearity with the BMI score. This better reflects the bidirectional effects of obesity on bone health through mechanical loading, chronic inflammation, and hormonal metabolism [17]. (2) LE8 focuses on lifestyle factors. Unlike the scattered, simplistic, or even unconsidered assessment of dietary and sleep health indicators in previous studies, this study included HEI-2015 and sleep duration scores, which contain more comprehensive information. HEI-2015 quantifies overall diet quality by integrating dietary synergistic effects, avoiding collinearity issues among single nutrients while offering strong clinical interpretability due to its direct alignment with the US dietary guidelines. Its data dimensionality reduction properties also help improve model stability [18]. The sleep duration score captures the dose-response relationship between sleep and health, enabling more objective evaluation through quantified continuous benefits and precisely reflecting the circadian rhythm of growth hormone secretion, providing a basis for mechanistic explanations [19]. (3) History of arthritis, as an important feature for OP, drives bone loss through inflammatory responses, glucocorticoid medication side effects, and activity limitation leading to disuse [20, 21]. These features, which are potential clinical variables with significant contributions overlooked in previous studies, likely contributed to the superior model performance of this study compared to others. This warrants further exploration. ML models incorporating LE8 have also gained traction in recent years. Zhaoqi Yan et al. established that elevated CVH levels evaluated by LE8 forecasted reduced risks of all-cause and cardiovascular mortality in NHANES, with biological aging mediating the relationship [22]. Peter Graffy et al. used subgraph augmented non-negative matrix factorization (SANMF) to cluster longitudinal LE8 variables in participants from Coronary Artery Risk Development in Young Adults (CARDIA) to assess future adverse cardiovascular event phenotypes [23].

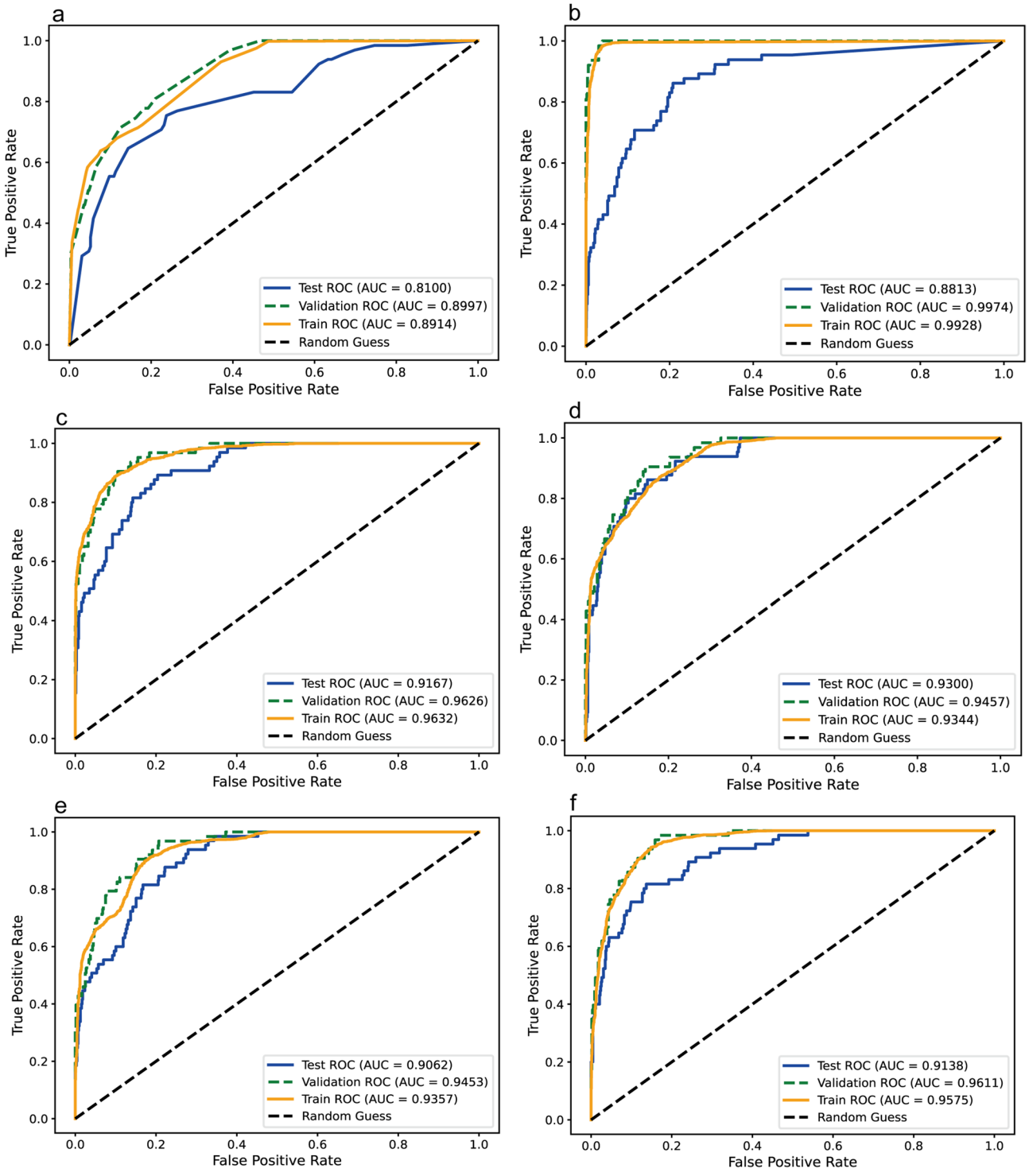


**Fig. 3** ROC curves of 20 features in the train set, validation set, and test set, validation set derived from 5-fold cross-validation. (**a**) Decision Tree (**b**) KNN (**c**) LightGBM (**d**) Logistic Regression (**e**) Random Forest (**f**) SVM

Compared to traditional statistical methods, ML models offer several advantages in clinical analysis. First, they achieve higher accuracy. For instance, in predicting all-cause mortality after transcatheter aortic valve implantation, ML models attained a C-statistic of 0.79, significantly outperforming traditional methods (C-statistic = 0.68) [24]. Second, ML can process high-dimensional data and complex nonlinear relationships, capturing intricate data patterns more effectively. In traumatic brain injury, ML models integrating multiple

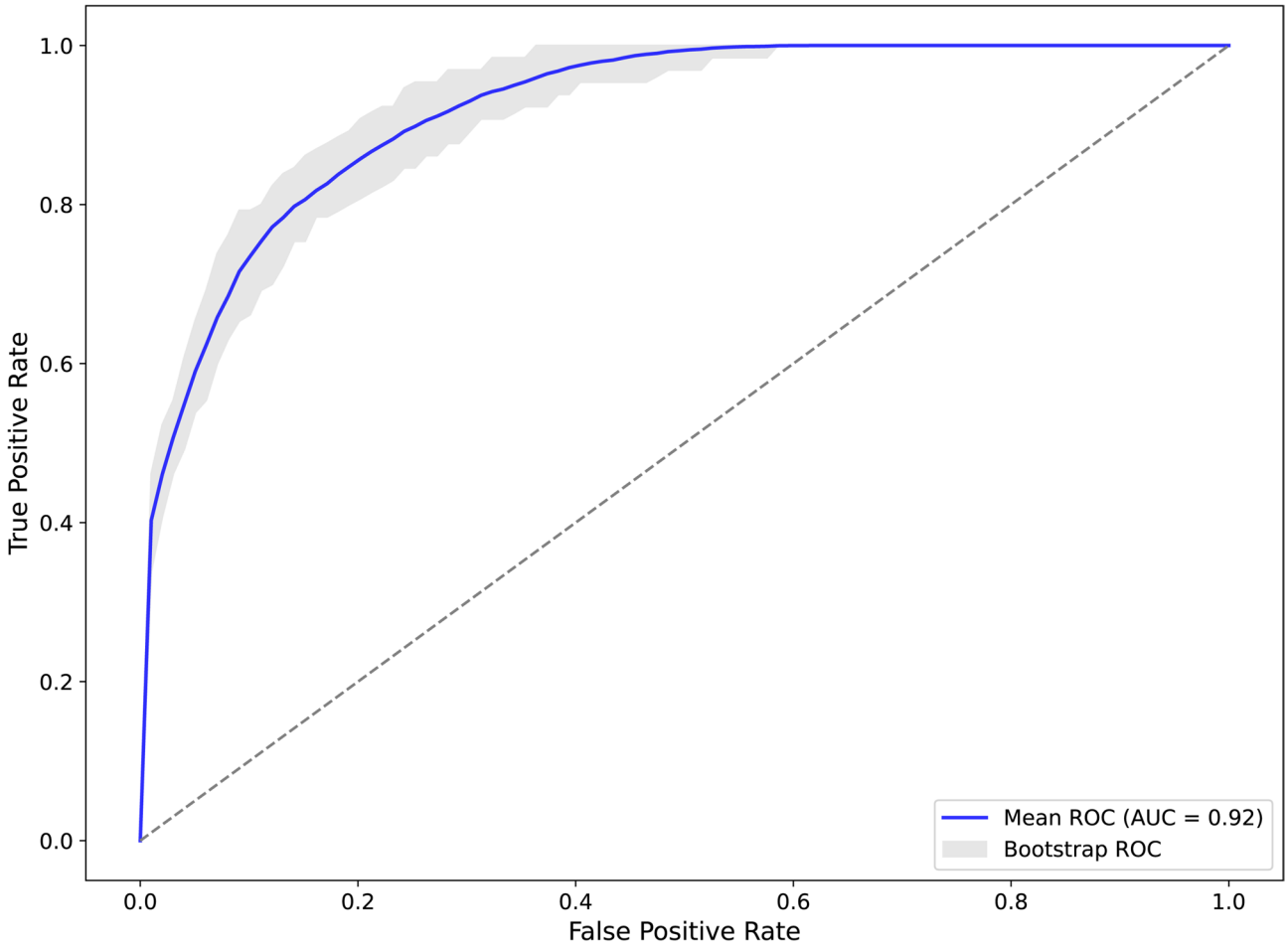


**Fig. 4** ROC curves of LightGBM with 20 features in bootstrap

biomarkers and clinical features yielded superior prediction accuracy (Random Survival Forest AUC = 0.80) [25]. Additionally, ML models exhibit greater flexibility, accommodating various data types and prediction tasks while enabling personalized analysis for precision medicine. XGBoost model based on seven simple features was applied to develop an online calculator for convenient prediction of depression risk in stroke patients [26]. LightGBM is a high-performance, distributed machine learning algorithm with strong predictive accuracy, built upon the gradient boosting framework. It utilizes a novel histogram-based approach for decision tree creation, which notably accelerates training processes and optimizes memory usage while preserving robust precision. In a prior NHANES investigation focusing on dietary antioxidants and cardiovascular-cancer comorbidities, LightGBM achieved an AUC of 0.951, surpassing other machine learning models [27]. Our research further indicates that the LightGBM model, when integrated with LE8, exhibits superior performance in OP analysis.

SHAP analysis revealed that within LE8, sleep health, blood lipids, and HEI-2015 scores were the major negative contributors to OP, while the BMI score served as the primary positive contributor. Yuchen Tang et al. conducted a multiple logistic regression analysis on NHANES data, showing a positive association between LE8 and OP risk in an unadjusted model, which turned negative after adjusting for covariates [7]. However, their study diagnosed OP solely based on femoral neck BMD and conducted only correlation analyses without association modeling. Previous research has primarily focused on specific CVH factors associated with OP. A meta-analysis found lower OP risk in overweight and obese individuals and higher risk in underweight individuals [28]. Junwei Tian et al. reported that prolonged sleep duration in women, postmenopausal women, and the elderly, as well as excessively long or short sleep duration in men, were associated with OP [29]. The Spanish Camargo cohort study found that triglycerides (TC), low-density lipoprotein cholesterol (LDL-C), and LDL-C/HDL-C were positively associated with lumbar spine and hip BMD [30]. Conversely, a study on the Korean population showed that TC, HDL-C, and total cholesterol were negatively associated with BMD [31]. The

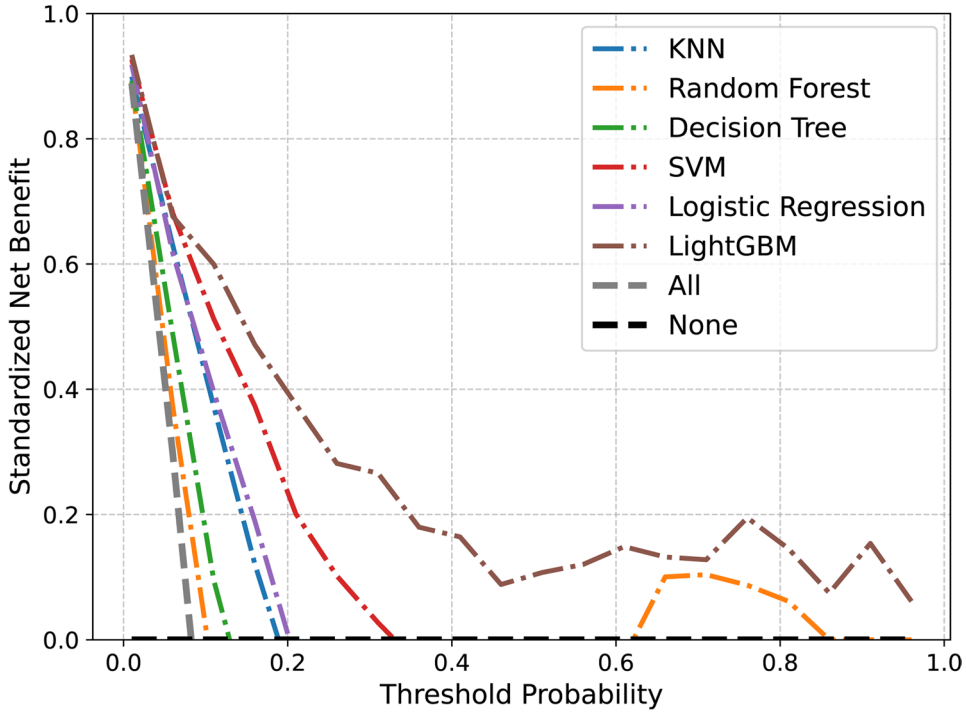


**Fig. 5** DCA of 20 features in the test set

discrepancies in findings of TC and OP among research may be ascribed to variations in nationality and ethnicity. A study based on NHANES revealed that higher dietary quality evaluated by the HEI-2015 is associated with a reduced risk of OP in middle-aged and older adults [18]. The above research supported the high contributions of HEI-2015, sleep, lipids, and BMI scores to OP association in this study. Other studies have identified well-controlled glucose and blood pressure, smoking cessation, and appropriate physical activity as protective factors against OP [7, 32, 33]. However, these factors contributed less to OP association in our model, indicating that specific risk factors might not exhibit substantial links to disease analysis.

The association role of LE8 on OP may stem from interconnected cardiometabolic-bone crosstalk involving six key pathways: (1) Endocrine regulation: Adipose-derived hormones (adiponectin, leptin) and sex steroids (estrogen, testosterone) modulated by obesity, dyslipidemia, Type 2 Diabetes Mellitus (T2DM), nicotine, and physical activity critically regulate bone metabolism [19, 31, 34–37]. Insulin resistance mediates bone remodeling through Insulin-like Growth Factor 1 (IGF-1) receptor signaling [34]. (2) Inflammation and oxidative stress: Hypertension and dyslipidemia elevate pro-inflammatory cytokines [Tumor Necrosis Factor alpha (TNF-α), Interleukin-6 (IL-6)] and oxidative stress, exacerbating bone resorption and vascular calcification via endothelial dysfunction [31, 38]. Exercise counteracts these effects through anti-inflammatory modulation [36]. (3) Vascular injury: Nicotine-induced vasoconstriction, atherosclerotic narrowing, and vascular calcification (sharing mineralization pathways with bone via bone morphogenetic protein, ALP, osteopontin) impair nutrient delivery to bone tissue [31, 37, 38]. (4) Mechanical loading: Moderate BMI and physical activity generate osteogenic mechanical stimuli through adipose/muscle-derived loading, enhancing bone microstructure and musculoskeletal synergy [17, 36]. (5) Dietary nutrition: Caloric/nutrient adequacy in higher BMI supports mineralization, while hypertension/sleep deprivation disrupts vitamin D/calcium homeostasis [19, 38, 39]. HEI-2015 components (whole grains, fruits, vegetables, soy) provide bone-beneficial nutrients (K, Mn, vitamins B/C/E/K, ω-3), contrasting with saturated fat's detrimental effects [18]. (6) Pharmacological mechanisms: T2DM/dyslipidemia medications (thiazides, statins) exhibit BMD-enhancing properties, whereas antihypertensives (Calcium Channel Blocker, Angiotensin-Converting Enzyme Inhibitor) may adversely affect bone metabolism [34, 38]. In addition, lipids, nicotine, and physical exercise can directly affect osteoblast and osteoclast activity [31, 36, 37]. It is worth noting that while dyslipidemia generally impairs bone health, oxysterols from cholesterol metabolism promote osteogenesis. Hypercholesterolemia correlates with reduced bone turnover markers (β-CrossLaps, Procollagen I N-Terminal Propeptide) and elevated BMD [30]. This bidirectional effect explains why

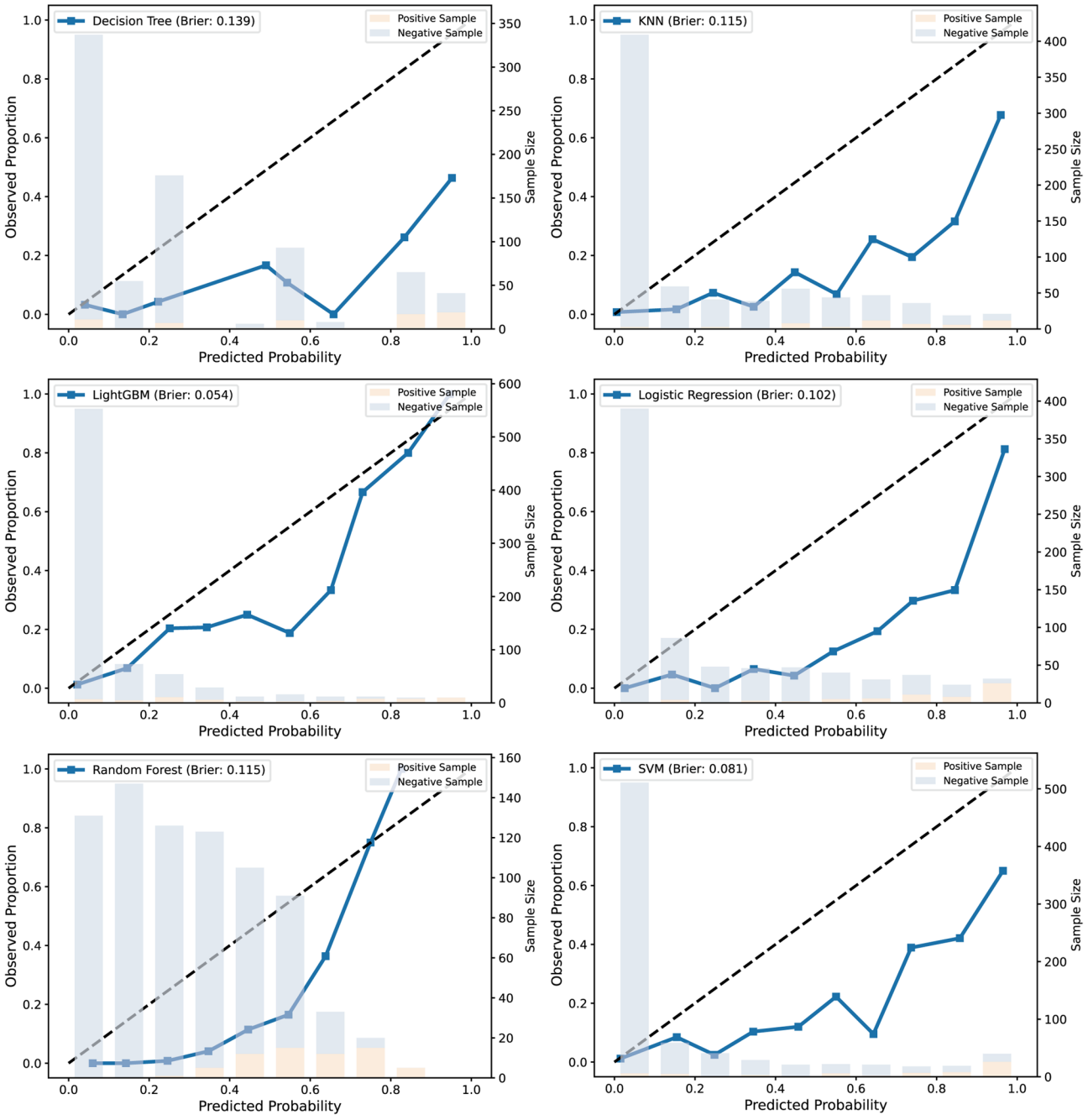


**Fig. 6** CCA of the 20 features in the test set

the blood lipids score showed a positive correlation with OP in regression analysis but a negative contribution in SHAP analysis. A similar dual impact is observed for the BMI score: moderate BMI stimulates osteoblast activity through mechanical loading, thereby increasing bone mineral density; excessively low BMI is associated with insufficient bone mass reserve; conversely, excessively high BMI accelerates bone loss via chronic inflammation and gonadal axis dysfunction [17]. This likely accounts for the positive contribution of the BMI score to OP in the SHAP analysis. Also, elevated fracture risk in T2DM patients despite higher BMD suggests compromised bone quality through microarchitectural deterioration and strength reduction [34].

This study presents multiple strengths, with its sample originating from a nationally representative survey that employs a stratified, multistage sampling strategy, ensuring broad applicability to the U.S. population. ML, compared to traditional analytical models, offers greater accuracy and flexibility, effectively handling complex data

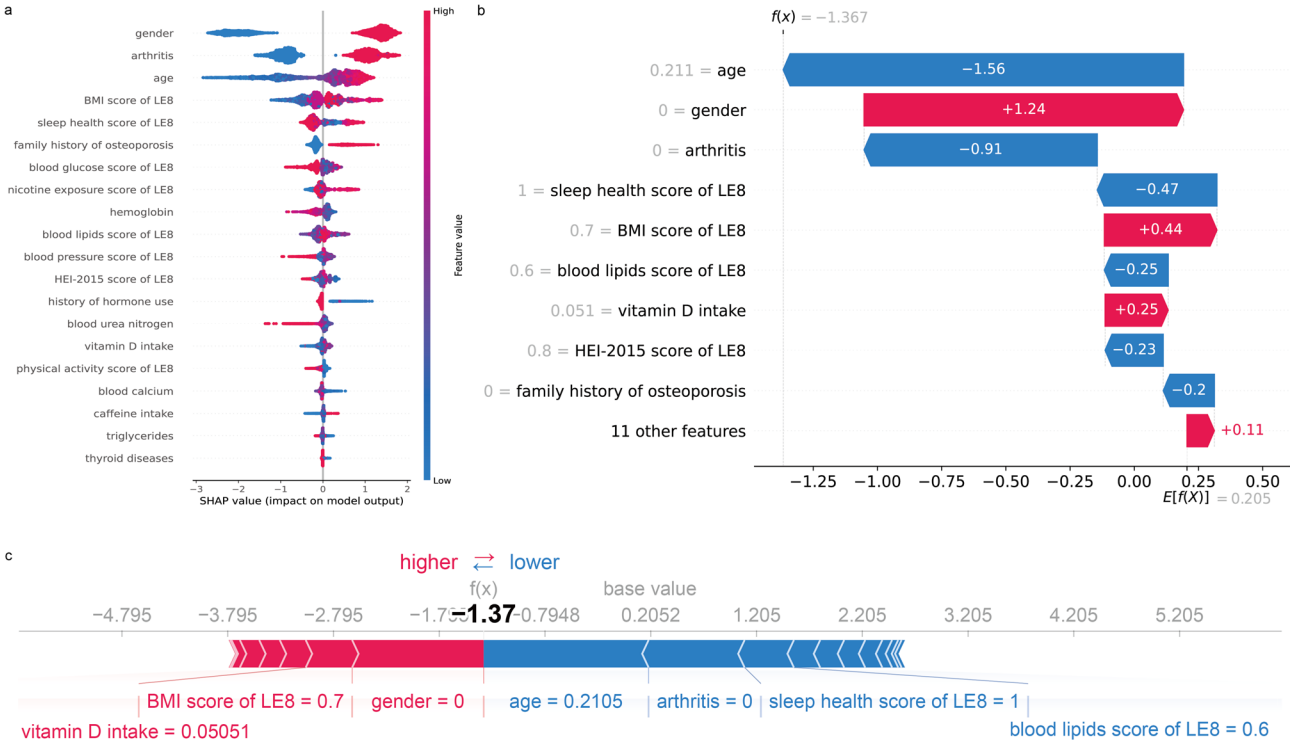


**Fig. 7** SHAP values of LE8 components for OP association as determined by LightGBM of 20 features. (**a**) SHAP summary plot (**b**) SHAP waterfall plot (**c**) SHAP force plot

relationships and large datasets. The inclusion of diverse demographic, lifestyle, health, dietary, and laboratory variables, along with the validation set and bootstrap, enhances the model's performance and generalizability. The OP diagnosis criteria comprehensively encompass BMD at 10 skeletal sites, fragility fracture history, and clinical diagnosis, yielding conclusions that more closely reflect real-world conditions. However, there are certain constraints. The study's cross-sectional design prevents causal inference. Second, due to NHANES data constraints, the study was unable to evaluate the dynamic alterations in LE8 over time with OP risk. Lastly, this study is limited to specific national and ethnic groups, and due to the current lack of suitable independent external datasets, it was unable to conduct rigorous external validation. This necessitates further prospective research to validate the model's generalizability across different populations and datasets.

## Conclusions

The integration of LE8 with LightGBM proves effective in OP analysis. This study demonstrates that comprehensive improvement of multiple lifestyle and physiological indicators within the LE8 framework is more effective than single-factor interventions. Identifying the core LE8 components strongly associated with OP provides a basis for prioritizing interventions. The complex non-linear associations discovered in the study highlight the importance of personalized interventions tailored to individual thresholds. Additionally, simple indicators such as LE8 have potential application value in primary care settings for screening OP and protecting bone health by promoting overall CVH.

### Abbreviations

| | |
|---|---|
| LE8 | Life's Essential 8 |
| CVH | Cardiovascular health |
| OP | Osteoporosis |
| ML | Machine learning |
| NHANES | National Health and Nutrition Examination Survey |
| RCS | Restricted cubic spline |
| SHAP | SHapley Additive exPlanations |
| HB | Health behaviors |
| HF | Health factors |
| AUC | Area Under the Curve |
| ROC | Receiver Operating Characteristic |
| DCA | Decision Curve Analysis |
| CCA | Calibration Curve Analysis |
| LightGBM | Light Gradient Boosting Machine |
| BMI | Body Mass Index |
| HEI-2015 | Healthy Eating Index-2015 |
| MECs | Mobile Examination Centers |
| KNN | K-Nearest Neighbors |
| SVM | Support Vector Machine |
| DXA | Dual-energy x-ray absorptiometry |
| BMD | Bone mineral density |
| OSQ | Osteoporosis Questionnaire |
| SMOTE | Synthetic Minority Over-sampling Technique |
| OR | Odds ratio |
| PIR | Income-to-poverty ratio |
| ALP | Alkaline phosphatase |
| LDH | Lactate dehydrogenase |
| HDL-C | High-density lipoprotein cholesterol |

| | |
|---|---|
| ALT | Alanine aminotransferase |
| AST | Aspartate aminotransferase |
| AIC | Akaike Information Criterion |
| XGBoost | eXtreme Gradient Boosting |
| SANMF | Subgraph augmented non-negative matrix factorization |
| CARDIA | Coronary Artery Risk Development in Young Adults |
| TC | Triglycerides |
| LDL-C | Low-density lipoprotein cholesterol |
| T2DM | Type 2 Diabetes Mellitus |
| IGF-1 | Insulin-like Growth Factor 1 |
| TNF-α | Tumor Necrosis Factor alpha |
| IL-6 | Interleukin-6 |

## Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s41043-025-00941-z.

Supplementary Material 1: Additional file 1: STROBE Statement. Checklist of items that should be included in reports of observational studies.

Supplementary Material 2: Additional file 2: Tables and figure supplement to the manuscript. More detailed data for this study.

Supplementary Material 3: Additional file 3: Core. The core code for model building.

Supplementary Material 4: Additional file 4: DeLong's test_auc. The relevant code for DeLong's test.

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**Author contributions**
HL S designed the study, organized the data, and wrote the manuscript. YY F analyzed the data and plotted the figures. XH M designed the study and revised the manuscript. All authors read and approved the final manuscript.

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**Data availability**
The datasets generated and analysed during the current study are available in the NHANES repository, [www.cdc.gov/nchs/nhanes/].

## Declarations

**Ethics approval and consent to participate**
The National Center for Health Statistics reviewed and approved the study for human participants (Protocol #2005-06, Protocol #2011-17, Protocol #2018-01). All participants signed informed written consent. Research data were open to the public and allowed for further analysis without additional ethical approval.

**Consent for publication**
Not applicable.

**Competing interests**
The authors declare no competing interests.

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