

# Development and External Validation of a Machine Learning–Based Screening Model for Sleep Disorders in Postmenopausal Women Using CHARLS Data

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## Research Article

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No competing interests reported.

Tables 1 to 6 are available in the Supplementary Files section.

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# **Development and External Validation of a Machine Learning–Based Screening Model for Sleep Disorders in Postmenopausal Women Using CHARLS Data**

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### **Title page**

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## **Abstract**

**Background:** Sleep disorders are highly prevalent among postmenopausal women, adversely affecting their quality of life and being associated with long-term health risks; however, individualized screening models for sleep disorders among Chinese postmenopausal women remain limited.

**Methods:** This cross-sectional study included 2,397 naturally postmenopausal women aged 45–60 years from the 2018 China Health and Retirement Longitudinal Study (CHARLS) and an external validation cohort of 137 postmenopausal women recruited from the sleep clinic of the Third Affiliated Hospital of Sun Yat-sen University. Logistic regression was used to identify factors associated with sleep disorders, and six machine learning models were developed: decision tree (DT), K-nearest neighbors

(KNN), support vector machine (SVM), multilayer perceptron (MLP), extreme gradient boosting (XGBoost), and random forest (RF). Model performance was evaluated using the area under the receiver operating characteristic curve (AUC), calibration curves, and decision curve analysis (DCA); SHapley Additive exPlanations (SHAP) were used for feature attribution.

**Results:** The prevalence of sleep disorders in the internal cohort was 62.4%. Multivariable logistic regression showed that depressive status ( $\text{CESD-10} \geq 10$ ) was the strongest associated factor ( $\text{OR} = 4.067$ , 95% CI 3.345–4.944,  $P < 0.001$ ), and each additional chronic disease was associated with a 13.6% increase in the odds of sleep disorders ( $\text{OR} = 1.136$ , 95% CI 1.050–1.230,  $P = 0.002$ ). The MLP model achieved the highest AUC during internal testing (0.7621) and an AUC of 0.7441 in external validation. The calibration curve closely approximated the ideal calibration line within the range of 0.3–0.7. DCA showed that the model provided greater net benefit than the treat-all and treat-none strategies across the evaluated threshold range. SHAP and Gini feature-importance rankings consistently identified the CESD-10 score as the most important screening feature.

**Conclusion:** Depressive status and chronic disease burden were important screening features of sleep disorders in Chinese postmenopausal women. The MLP-based screening model, complemented by an interpretable decision-tree model, showed acceptable discrimination, calibration, and clinical utility in external validation and may support screening for sleep disorders in this population.

**Trial registration:** This study was registered at the Chinese Clinical Trials Registry on January 4, 2026 (<http://www.chictr.org.cn>; ChiCTR2600116020).

**Key words:** postmenopausal women; sleep disorders; machine learning; screening model.

## **Introduction**

Menopause is retrospectively defined as 12 consecutive months of amenorrhea following the final menstrual period(1, 2).

Sleep disorders are common from the perimenopausal period through postmenopause. They may manifest as difficulty initiating or maintaining sleep, increased wake time after sleep onset, and frequent nocturnal awakenings. Multiple studies in Chinese populations have shown that sleep disturbances become more prevalent across the menopausal transition and remain common after menopause (3-5). Sleep disorders are associated not only with menopausal stage and changes in follicle-stimulating hormone and estradiol levels but also with vasomotor symptoms, comorbid mood disorders, and other sleep-related conditions (4, 6, 7). Sleep disorders not only affect daytime functioning and quality of life (8-13), but may also be associated with adverse long-term health outcomes. Studies have linked sleep disorders to cognitive decline and increased risks of metabolic syndrome, hypertension, and coronary heart disease(14-16). Therefore, sleep disorders in postmenopausal women are not only a common clinical complaint but also an important public health concern.

Previous studies have systematically described sleep difficulties, sleep-maintenance problems, and nocturnal awakenings during the menopausal transition and postmenopause. These studies have also examined factors associated with these sleep problems, including menopausal stage, hormonal changes, vasomotor symptoms, mood

symptoms, and somatic comorbidities (6, 7, 10, 17-19). However, existing research has focused primarily on epidemiological descriptions and analyses of associated factors. Currently, screening for sleep disorders relies largely on self-reported symptoms or time-consuming questionnaire-based assessments. However, simple, efficient, and scalable screening tools remain limited in community and primary care settings, thereby constraining the early identification and timely triage of individuals with a high likelihood of sleep disorders. To our knowledge, an individualized screening model specifically targeting postmenopausal women in China has yet to be developed and independently validated in a clinical samples.

CHARLS is a nationally representative longitudinal survey of Chinese adults aged  $\geq 45$  years and their spouses. The baseline survey included 17,708 respondents and collected information on sociodemographic characteristics, health status, and healthcare utilization. These data provide a strong population-based foundation for developing models to identify sleep disorders among women during and after the menopausal transition (20). On this basis, we applied machine learning methods to develop screening models using a population-based sample with potential applicability to community-based screening. To further assess the model's transportability to higher-risk clinical settings, we conducted external validation using an independent sample from a sleep clinic.

This study aimed to describe the prevalence of and factors associated with sleep disorders among Chinese postmenopausal women using CHARLS data and to develop and compare multiple machine learning-based screening models. Selected models were subsequently externally validated in an independent outpatient sample to inform their potential application in community and clinical screening.

## **Materials and Methods**

## **Study Design**

This was a cross-sectional screening-model study comprising an internal modeling cohort and an external validation cohort.

1. Internal modeling cohort: community-dwelling postmenopausal women from the CHARLS dataset.

2. External validation cohort: Postmenopausal women attending the sleep clinic of the Third Affiliated Hospital of Sun Yat-sen University.

## **Data source and Study Population**

### **Internal Modeling Cohort**

CHARLS is a nationwide longitudinal study using multistage stratified sampling and collecting data on sociodemographic characteristics, health behaviors, physical health, mental health, and sleep-related measures. The CHARLS project was approved by the Biomedical Ethics Committee of Peking University. Because the present study was a secondary analysis of de-identified, publicly available data, no additional ethical approval was required.

Inclusion criteria: women aged 45 – 60 years who had undergone natural menopause.

Exclusion criteria: loss to follow-up and missing data on core study variables.

### **External Validation Cohort**

Participants were recruited from patients attending the sleep clinic of the Third Affiliated Hospital of Sun Yat-sen University.

Inclusion criteria were women aged 45–60 years who had undergone natural menopause and had complete sleep-related and relevant clinical data available from outpatient assessment.

Exclusion criteria were loss to follow-up and missing data on core study variables.

## **Variable Definition**

### **Outcome Variables**

Sleep disorder was defined as a nighttime sleep duration of  $<6$  h or poor sleep quality during the preceding week, frequent awakenings ( $\geq 3$  times); meeting any one of these criteria was classified as a sleep disorder (21, 22).

### **Independent Variables**

1. Sociodemographic factors: age, place of residence (urban/rural), educational attainment (primary school or below/junior high school or above), marital status (married/not married).

2. Health-behavior factors: smoking status (never/current smoker), alcohol consumption (never/drinker), physical-activity frequency (never/occasional/regular), and monthly participation in social activities.

3. Physical-health factors: body mass index (BMI), chronic diseases (hypertension, diabetes, heart disease and stroke), number of chronic diseases, bodily pain.

4. Mental-health factors: depressive symptoms, assessed using the CESD-10 scale, with a score  $\geq 10$  indicating the presence of depressive symptoms.

### **Construction and Evaluation of Machine Learning Screening Models**

In this study, variables were initially screened using univariable logistic regression, after which multivariable logistic regression was used to identify factors independently associated with sleep disorders in postmenopausal women. These factors formed the core feature set for machine learning, with the aim of retaining variables with independent statistical and clinical relevance while reducing noise introduced by redundant features.

In addition to the factors identified by multivariable regression, both binary depressive status and the continuous CESD-10 score were included as model features.

The binary variable facilitates rapid clinical interpretation and screening, whereas the continuous score provides a more granular representation of depressive-symptom severity and its graded association with sleep-disorder status, thereby supporting probability-based stratification while balancing interpretability and overall screening performance.

To systematically compare model discrimination, six commonly used machine-learning classifiers were evaluated: decision tree (DT), K-nearest neighbors (KNN), support vector machine (SVM), multilayer perceptron (MLP), extreme gradient boosting (XGBoost), and random forest (RF).

A dual-model framework comprising a primary screening model and an auxiliary interpretable model was adopted to balance screening performance with clinical interpretability:

1. Primary model: The algorithm with the best overall discrimination was selected as the primary screening model, with priority given to discrimination and screening sensitivity.

2. Auxiliary model: A decision tree was used as a white-box interpretable model to provide visual decision rules and feature-importance rankings, corroborate key screening features identified by the primary model, and compensate for the limited intrinsic interpretability of the primary black-box model. Together with multivariable logistic regression, this approach provided methodological triangulation to support interpretation of key screening features and assessment of their consistency across analytic approaches.

Model performance was comprehensively assessed using the following metrics:

1. Area under the receiver operating characteristic curve (AUC): the primary metric of overall model discrimination;

2. Accuracy, precision, recall, and F1 score: complementary measures of classification performance;
3. Feature importance: the contribution of each screening feature in tree-based models, quantified using mean decrease in Gini impurity;
4. SHAP values: global and local feature-attribution analyses of the best-performing black-box model to characterize the direction and magnitude of each feature's contribution to model output;
5. Calibration curves and decision curve analysis (DCA): assessment of agreement between predicted and observed probabilities and of clinical net benefit in the external validation cohort.

## **Statistical Methods**

Statistical analyses were performed using Stata 19.0 and Python 3.9. All tests were two-sided, and  $P < 0.05$  was considered statistically significant.

1. Descriptive Statistics: Normal continuous data were presented as mean  $\pm$  standard deviation, non-normal data as median (interquartile range), and categorical data as number and percentage; comparisons between groups were performed using t-tests, rank-sum tests, and chi-square tests.

2. Regression Analysis: Univariable Logistic regression was used to select variables, and those with a P value less than 0.1 were included in the multivariable logistic regression to identify factors independently associated with sleep disorders; variance inflation factor (VIF) was used to assess for multicollinearity.

3. Model Construction: The internal dataset was divided by stratified random sampling in a 7:3 ratio into a training set and an internal test set. Multiple machine-learning models were developed, with hyperparameters tuned using five-fold cross-validation. AUC, accuracy, recall, and F1 score were used to assess internal screening

performance, and SHAP analysis was used to characterize the magnitude and direction of feature contributions to model output.

4. External Validation: The selected trained models were evaluated using clinical data from the sleep clinic of the Third Affiliated Hospital of Sun Yat-sen University. ROC, calibration, and decision curves were generated for the external validation cohort to assess model discrimination, calibration, transportability, and potential clinical utility.

## **Results**

### **Comparison of baseline characteristics between the internal modeling cohort with sleep disorder and the group without sleep disorder**

This analysis used data from the 2018 national follow-up of CHARLS. After application of the predefined inclusion and exclusion criteria, 2,397 naturally postmenopausal women were included (Figure 1). Of these, 1,495 women (62.4%) had sleep disorders and 902 (37.6%) did not. Baseline sociodemographic, lifestyle, physical-health, and mental-health characteristics of the two groups are presented in Table 1.

#### **Sociodemographic and lifestyle characteristics**

There were no statistically significant differences between the groups in age, smoking status, BMI, marital status, or current alcohol consumption (all  $P > 0.05$ ). The proportion of women with a low educational attainment was higher in the sleep-disorder group than in the group without sleep disorders (89.4% vs 85.1%,  $P = 0.002$ ). Similarly, the proportion of rural residents was higher in the sleep-disorder group (63.8% vs 57.4%,  $P = 0.002$ ).

#### **Physical Health and Chronic Disease Status**

The mean number of chronic diseases was higher in the sleep-disorder group than in the group without sleep disorders ( $2.38 \pm 1.96$  vs  $1.72 \pm 1.66$ ,  $P < 0.001$ ). The

prevalences of hypertension (32.1% vs 28.3%,  $P=0.048$ ), diabetes (15.2% vs 10.0%,  $P<0.001$ ), heart disease (22.1% vs 14.4%,  $P<0.001$ ), and stroke (4.1% vs 2.2%,  $P=0.012$ ) were also higher in the sleep-disorder group (all  $P<0.05$ ).

### **Pain Symptoms and Mental Health Status**

Pain at  $\geq 1$  body site was reported by 70.3% of women in the sleep-disorder group compared with 56.2% of those without sleep disorders ( $P<0.001$ ). The mean mental-health scale score (range, 0–30; higher scores indicating poorer mental health) was  $11.65 \pm 6.72$  in the sleep-disorder group and  $6.05 \pm 4.78$  in the group without sleep disorders ( $P<0.001$ ). Depressive status (CESD-10  $\geq 10$ ) was present in 57.1% of women with sleep disorders versus 22.2% of those without sleep disorders ( $P<0.001$ ).

### **Univariable and Multivariable regression analysis**

Univariable logistic regression showed that 8 of the 13 candidate variables—depressive status, number of chronic diseases, pain, educational level, residence type, hypertension, diabetes, and heart disease—were significantly associated with sleep disorders (all  $P<0.05$ ). These eight variables were entered into a multivariable unconditional logistic regression model using forward stepwise selection ( $\alpha=0.05$ ), which identified two factors independently associated with sleep disorders and one factor showing a potential association (Table 2).

### **Machine Learning Modeling**

This study included both a binary depressive-status variable and a continuous CESD-10 depressive-symptom score variable to balance the model's clinical interpretability and screening performance.

ROC analysis, with AUC as the primary discrimination metric, was used to compare the six machine-learning models for screening sleep disorders in

postmenopausal women (Figure 2; Table 3). The MLP achieved the highest AUC (0.762), followed by SVM (0.750), decision tree (0.731), random forest (0.730), XGBoost (0.718), and KNN (0.683). All six models achieved AUC values above the random-classification reference value of 0.5, indicating discrimination better than chance. Among the six models, the MLP had a recall of 0.8105, indicating relatively high sensitivity for screening.

SHAP feature-attribution analysis (Figure 3) showed clear shifts in the SHAP value distributions for the CESD-10 score and the number of chronic diseases; the CESD-10 depressive-symptom score was the dominant screening feature in the model, followed by the number of chronic diseases, whereas all remaining features had minimal influence on the model output. The Gini-based feature importance ranking of the decision tree model (Table 4 and Figure 4) exactly matched the global SHAP importance ranking: CESD-10 (0.7839), number of chronic diseases (0.1616), and educational attainment (0.0545).

### **External Validation**

The external validation cohort comprised 137 postmenopausal women. Of these, 39 (28.5%) did not have sleep disorders and 98 (71.5%) did. The baseline demographic and clinical characteristics of the two groups were generally comparable (Table 5).

### **Discrimination Verification**

In external validation, the MLP achieved an AUC of 0.7441 and the decision tree an AUC of 0.7254 (Table 6). Both AUCs exceeded the random-classification reference value of 0.5 (Figure 5).

In the external validation cohort, the three highest Gini-based feature-importance scores for the decision tree were observed for the CESD-10 score (0.8293), number of chronic diseases (0.1265), and educational level (0.0442) (Figure 6).

## **Calibration Verification**

In external validation, the MLP calibration curve generally tracked the ideal calibration line. Agreement was good across predicted probabilities of approximately 0.3 – 0.7, with no clear systematic overprediction or underprediction (Figure 7).

Decision curve analysis showed that, across most threshold probabilities, both the MLP and decision-tree models provided greater net benefit than the treat-all and treat-none strategies; overall, the MLP generally provided the greater clinical net benefit (Figure 8).

## **Discussion**

We developed machine learning–based models for screening sleep disorders in postmenopausal women using the CHARLS community sample and externally validated selected models in an independent sleep-clinic cohort. A dual-model framework combining a primary MLP model with an auxiliary interpretable decision tree was used to balance screening performance with clinical interpretability and to assess the consistency of the findings across modeling approaches. The primary MLP model achieved the highest internal-test AUC (0.7621) and maintained similar discrimination in the external validation cohort (AUC, 0.7441), supporting a degree of transportability across the two study settings. The auxiliary decision tree achieved an external-validation AUC of 0.7254, providing complementary discrimination and interpretability. Across SHAP analyses and decision-tree feature-importance rankings, the CESD-10 score, number of chronic diseases, and educational level showed consistent importance across models and samples, suggesting that the key findings were not driven by a single algorithm but were supported by complementary modeling and external validation. Overall, these findings suggest that commonly available epidemiological and clinical variables may support preliminary screening and

probability-based stratification for sleep disorders in postmenopausal women and that the model has potential as an adjunct to community screening and clinical decision support.

Depressive symptoms emerged as the most stable and prominent screening feature in the dual-model framework. Previous reviews have shown that sleep problems are common after menopause and are associated with menopausal stage, mood symptoms, and hormonal changes(10); A longitudinal Chinese cohort study likewise found that anxiety, depression, and pre-existing insomnia symptoms were associated with more severe insomnia after menopause(4). In an analysis of the postmenopausal subgroup from the prospective Midlife Women's Health Study, Smith et al. found that depression frequency was the only factor retained in the final model after adjustment for potential confounders, including menopausal stage and vasomotor symptoms; its regression coefficient was greater than that in the full model(23). Unlike studies relying primarily on conventional regression, the present study identified the association between depressive symptoms and sleep disorders using regression and also demonstrated the prominent contribution of the CESD-10 score to model output across the MLP and decision-tree models. Both MLP SHAP analysis and decision-tree feature-importance rankings identified the CESD-10 score as the leading screening feature, and this pattern persisted in the external validation cohort. These findings suggest that depressive symptoms are not merely associated with sleep disorders but also represent a consistent screening signal across models and samples in postmenopausal women. From a neurobiological perspective, the decline in estrogen levels after menopause may affect serotonergic and noradrenergic neurotransmission, potentially increasing vulnerability to depression while disrupting sleep - wake regulation(24, 25). Furthermore, depression and sleep disturbance have a well-recognized bidirectional relationship:

insomnia may worsen mood symptoms, while mood disturbances may further impair sleep, creating a self-reinforcing adverse cycle(26-28). Thus, the prominent contribution of depression-related variables to the present models is clinically plausible.

The number of chronic diseases was the second major screening feature in the dual-model framework, after depressive symptoms. Previous epidemiological studies have identified chronic physical illnesses as important factors associated with insomnia among middle-aged and older women (29). In the present study, the number of chronic conditions was used as an indicator of overall somatic comorbidity burden. Multivariable logistic regression showed that each additional chronic condition was associated with a 13.6% increase in the odds of sleep disorders. The MLP and decision-tree analyses likewise consistently ranked chronic-disease burden among the leading screening features, and its contribution persisted in external validation. These findings suggest that sleep disorders in postmenopausal women may be related not only to individual diseases but also to the overall somatic burden of multimorbidity. Potential mechanisms may operate through several pathways. Chronic disease – related discomfort and nocturnal symptoms, such as angina, dyspnea, and nocturia, may disrupt sleep continuity; chronic inflammation may influence central sleep regulation through inflammatory mediators such as IL-6 and TNF-  $\alpha$  (30, 31); and psychological burden and treatment-related adverse effects may further contribute(32). Notably, chronic-disease burden retained screening importance in the sleep-clinic validation cohort, supporting its relevance across both community and clinical settings.

In univariable analysis, pain was significantly associated with sleep disorders. However, its association was attenuated to borderline statistical significance after multivariable adjustment (OR =1.188, 95% CI 0.977 – 1.445, P =0.084). This finding is consistent with the longitudinal analysis by Woods and Mitchell, in which joint and

back pain were associated with difficulty initiating sleep, nocturnal awakenings, and early-morning awakening. After adjustment for hot flashes, depressed mood, self-rated health, and other variables, however, pain did not remain independently associated with sleep disturbance after adjustment.(18). Similarly, Castro et al. reported that depression was the only independent factor associated with sleep disturbance, whereas somatic symptoms were no longer statistically significant after adjustment(33). Frange et al. further highlighted the complexity of the pain - insomnia relationship in postmenopausal women, reporting that insomnia was more strongly associated with pain interference in daily functioning than with pain intensity itself(34). Women with both insomnia and musculoskeletal pain also showed greater pain interference, a larger number of painful sites, and poorer mood than those with pain or insomnia alone. These findings suggest that the association between pain and sleep may be partly mediated through mood-related pathways(35).

Compared with other sleep-related screening tools, the present study differs in both its intended application and methodological characteristics. The Women's Health Initiative Insomnia Rating Scale (WHIIRS) was developed based on data from 66,269 postmenopausal women and represents the largest-scale insomnia assessment tool specifically developed for postmenopausal women(36). However, the WHIIRS was developed more than two decades ago and did not incorporate machine learning approaches to optimize screening performance. The hybrid machine learning framework proposed by Santhosh C et al. demonstrated excellent discriminative performance, achieving a ROC-AUC of 97.5%. However, its input variables relied on hormone measurements and actigraphy-derived data, which may limit its feasibility and scalability for community-based screening and routine clinical triage(37). Huang et al. developed an XGBoost model based on an adult sample from the National Health and

Nutrition Examination Survey (NHANES), achieving an AUROC of 0.87. However, the outcome was defined broadly as self-reported physician-diagnosed “sleep problems,” and the model does not appear to have undergone independent external validation(38). Ha et al. developed the SLEEPS questionnaire, which achieved external-validation AUROCs ranging from 0.849 to 0.949 for insomnia, obstructive sleep apnea (OSA), and comorbid insomnia and sleep apnea (COMISA). However, its input features were primarily derived from items in sleep disorder-specific questionnaires, making it more suitable for specialized sleep settings where comprehensive questionnaire data are routinely available(39). In addition, the large-scale epidemiological study by Cui et al. established the central role of depressive symptoms in sleep-related screening at the level of association analysis; however, it did not further develop an individualized screening tool for potential clinical application. (28).

In contrast, the present study has three distinguishing features. First, it focuses specifically on postmenopausal women, a population defined by a distinct physiological stage and a clearly specified target population. The findings suggest that screening and management may benefit from jointly considering depressive symptoms and chronic-disease burden rather than relying solely on individual sleep complaints. This interpretation is consistent with recent calls to integrate sleep, mood, and chronic-disease management in menopausal healthcare(40, 41). Second, the study used a community-based model-development design with independent clinical external validation, with an independent sleep-clinic cohort providing a assessment of transportability across settings. Third, the dual-model framework combining a primary MLP with an auxiliary interpretable decision tree showed consistent performance and interpretability in independent external validation and may represent a useful framework for screening sleep-disorder in postmenopausal women.

Several limitations should be acknowledged. First, the cross-sectional design limits temporal inference. The models identify patterns associated with current or recent symptom status and therefore cannot establish the temporal sequence or causal relationships among depressive symptoms, chronic diseases, and sleep disorders. Second, the outcome was based on a composite definition incorporating self-reported short sleep duration, poor sleep quality, and frequent awakenings and is not equivalent to a clinical diagnosis of insomnia disorder according to DSM-5 or ICSD-3 criteria. Consequently, some transient or nonpathological sleep problems may have been classified as sleep disorders. Future studies should therefore validate the model using standardized diagnostic assessments.

In conclusion, the model developed for screening sleep disorder in postmenopausal women demonstrated consistent discrimination during both internal testing and independent external validation. Depressive symptoms and chronic-disease burden were the most stable key features across samples. At present, the model is best regarded as a prototype adjunctive tool for preliminary screening and risk stratification of sleep problems in postmenopausal women rather than as a replacement for clinical diagnosis. Future studies should externally validate or recalibrate the model in larger, multicenter prospective cohorts and incorporate menopause-specific variables to further improve screening performance.

### **Abbreviations**

|        |                                                |
|--------|------------------------------------------------|
| CHARLS | China Health and Retirement Longitudinal Study |
| DT     | decision tree                                  |
| KNN    | K-nearest neighbors                            |
| SVM    | support vector machine                         |
| MLP    | multilayer perceptron                          |

|         |                                                        |
|---------|--------------------------------------------------------|
| XGBoost | extreme gradient boosting                              |
| RF      | random forest                                          |
| AUC     | area under the receiver operating characteristic curve |
| DCA     | decision curve analysis                                |
| SHAP    | SHapley Additive exPlanations                          |
| BMI     | body mass index                                        |
| VIF     | variance inflation factor)                             |
| WHIIRS  | Women's Health Initiative Insomnia Rating Scale        |
| OSA     | obstructive sleep apnea                                |
| COMISA  | comorbid insomnia and sleep apnea                      |

## **Declarations**

### **Ethics approval and consent to participate**

This study involving human participants was reviewed and approved by the Ethics Committee of the Third Affiliated Hospital of Sun Yat-sen University (II2025-476-01), Guangzhou, Guangdong, China and registered at the Chinese Clinical Trials Registry on January 4, 2026 (<http://www.chictr.org.cn>; ChiCTR2600116020). All patients provided written informed consent and the study was performed in accordance with the Declaration of Helsinki and Consolidated Standards of Reporting Trials guidelines.

### **Consent for publication**

Not applicable

### **Availability of data and materials**

If necessary, you can contact the corresponding author by email

### **Competing interests**

The authors declared no competing interests.

### **Funding**

Not applicable.

## **Authors' contributions**

All authors made substantial contributions to the conception, study design, data acquisition and interpretation, statistical plan, drafting the manuscript, or critically revising the manuscript. All authors gave their final approval of this version to be published and agreed to be accountable for all aspects of the work.

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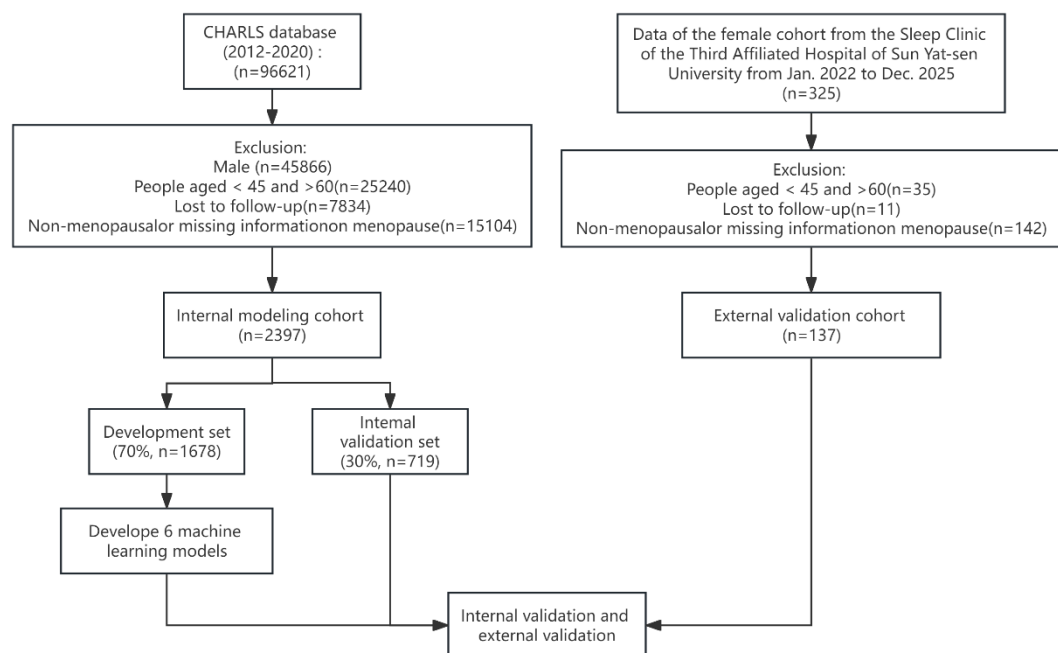
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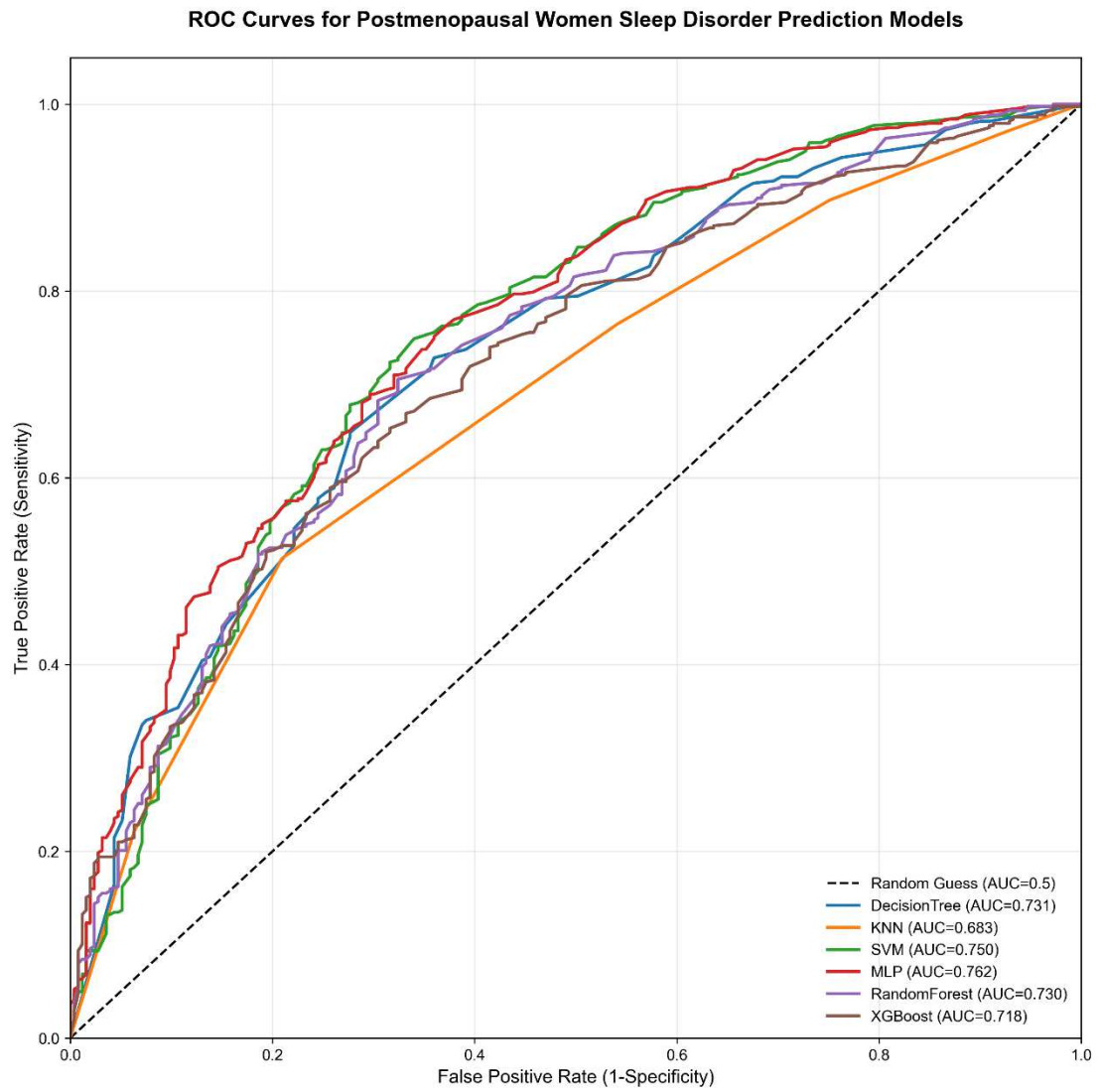


Figure 2. The receiver operating characteristic (ROC) curve for sleep disorders in postmenopausal women.

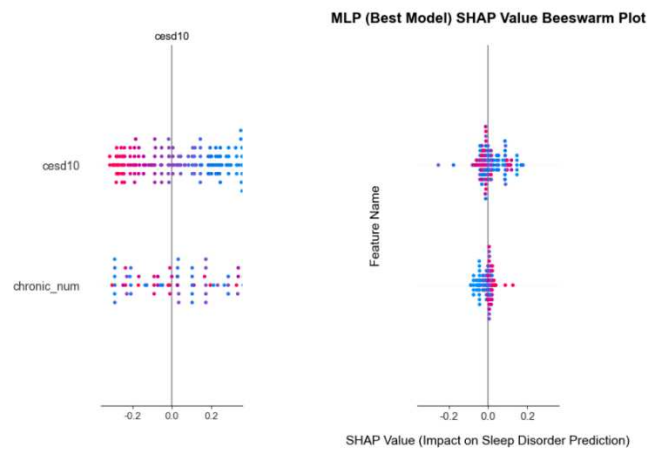


Figure 3. A global feature attribution SHAP swarm plot for the optimal screening model.

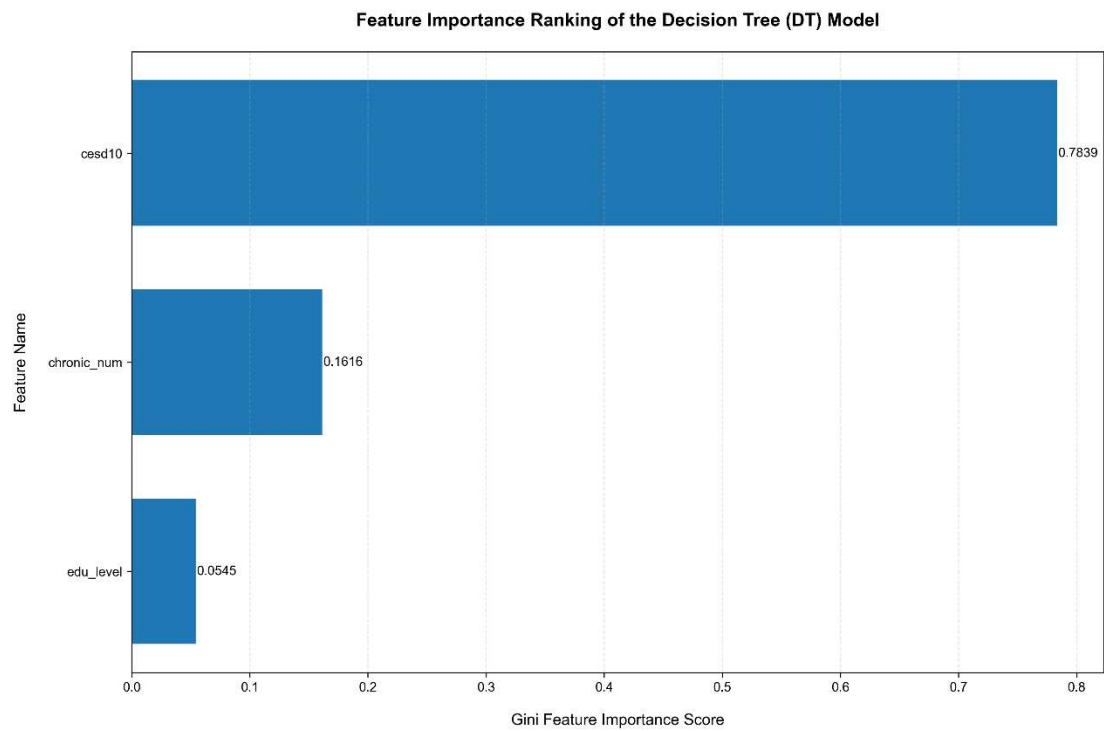


Figure 4. Decision tree model - Gini feature importance ranking chart.

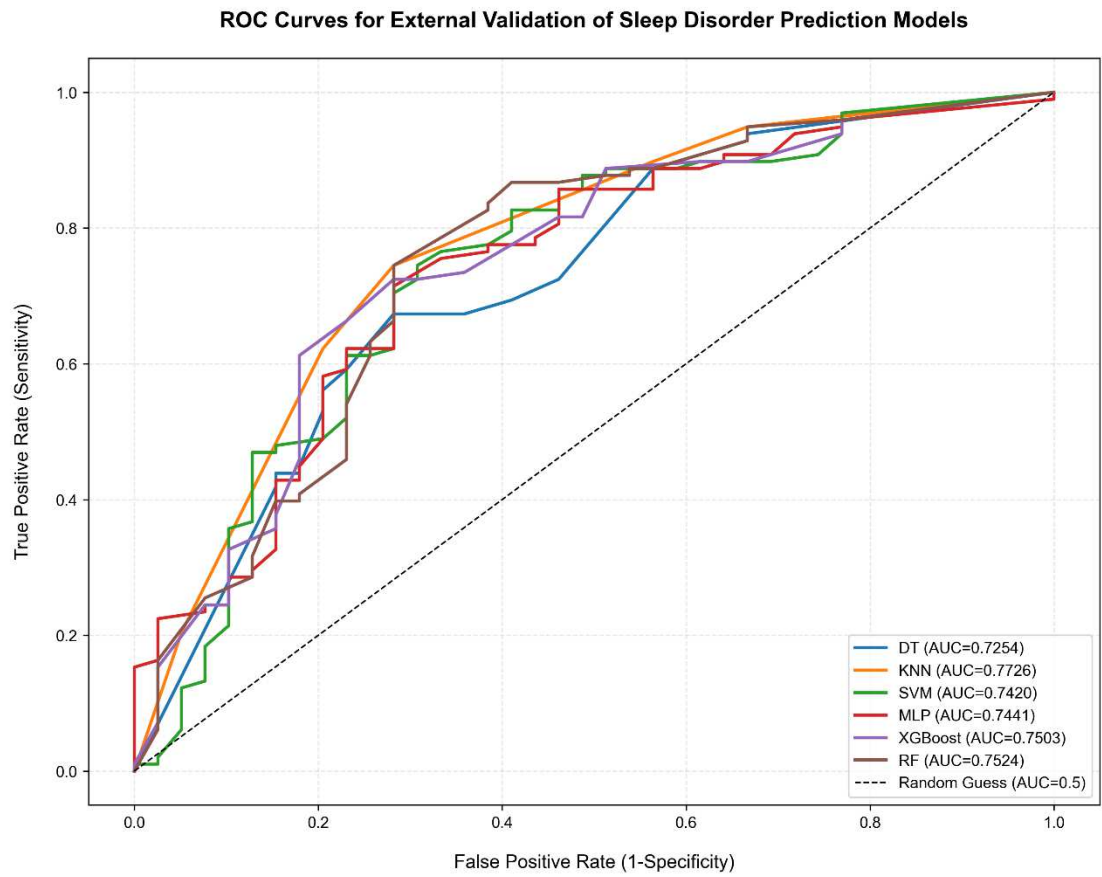


Figure 5. External validation ROC curve.

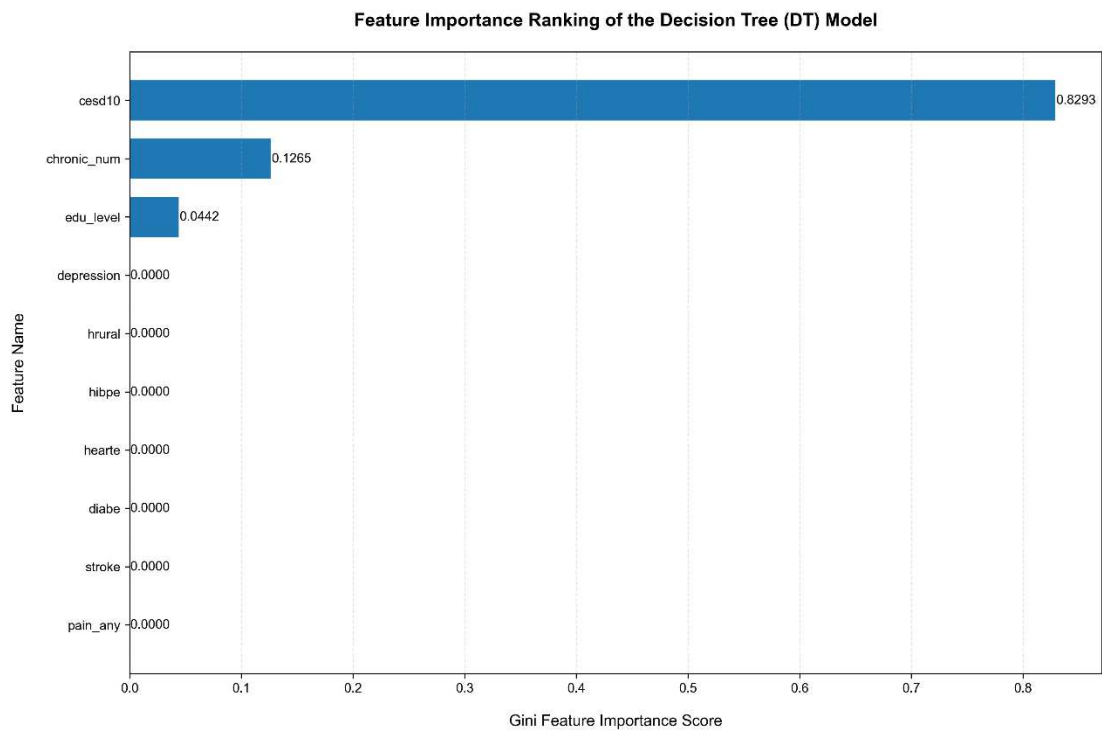


Figure 6. External validation feature importance ranking diagram of the decision

tree model.

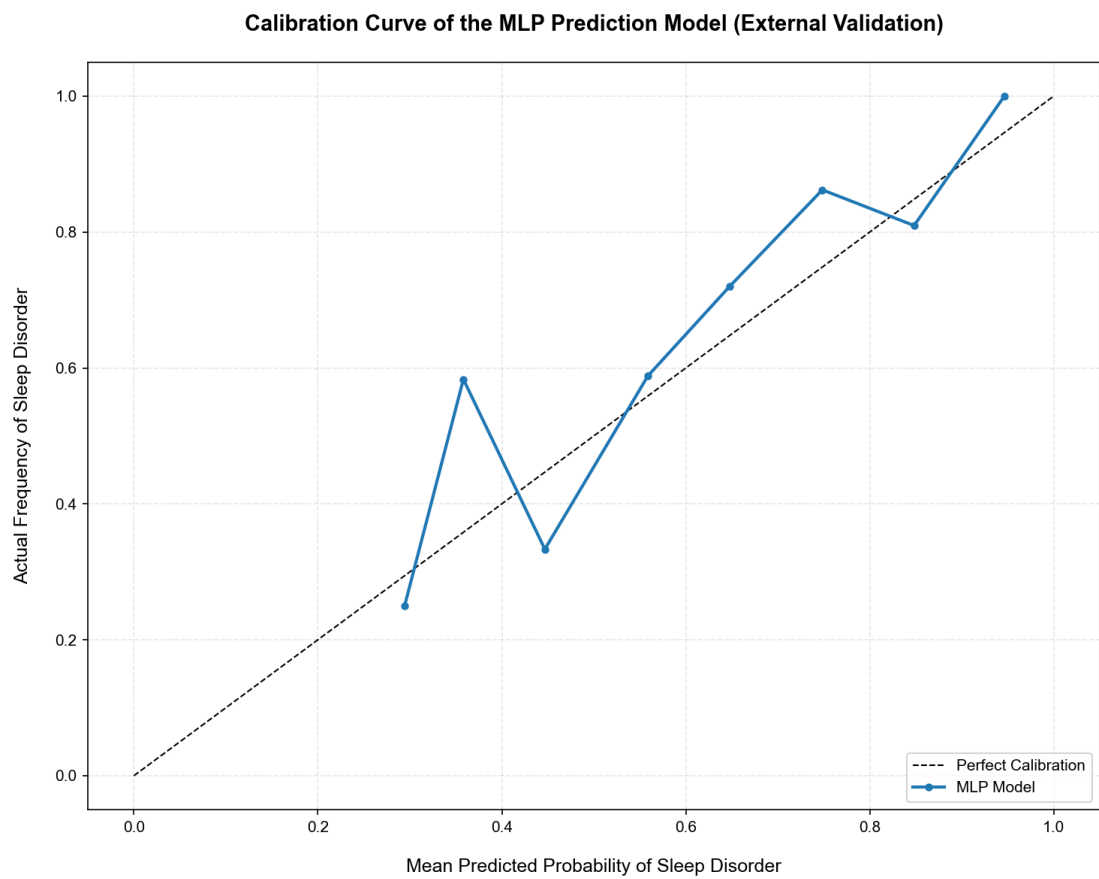


Figure 7. External validation calibration curve of MLP prediction model.

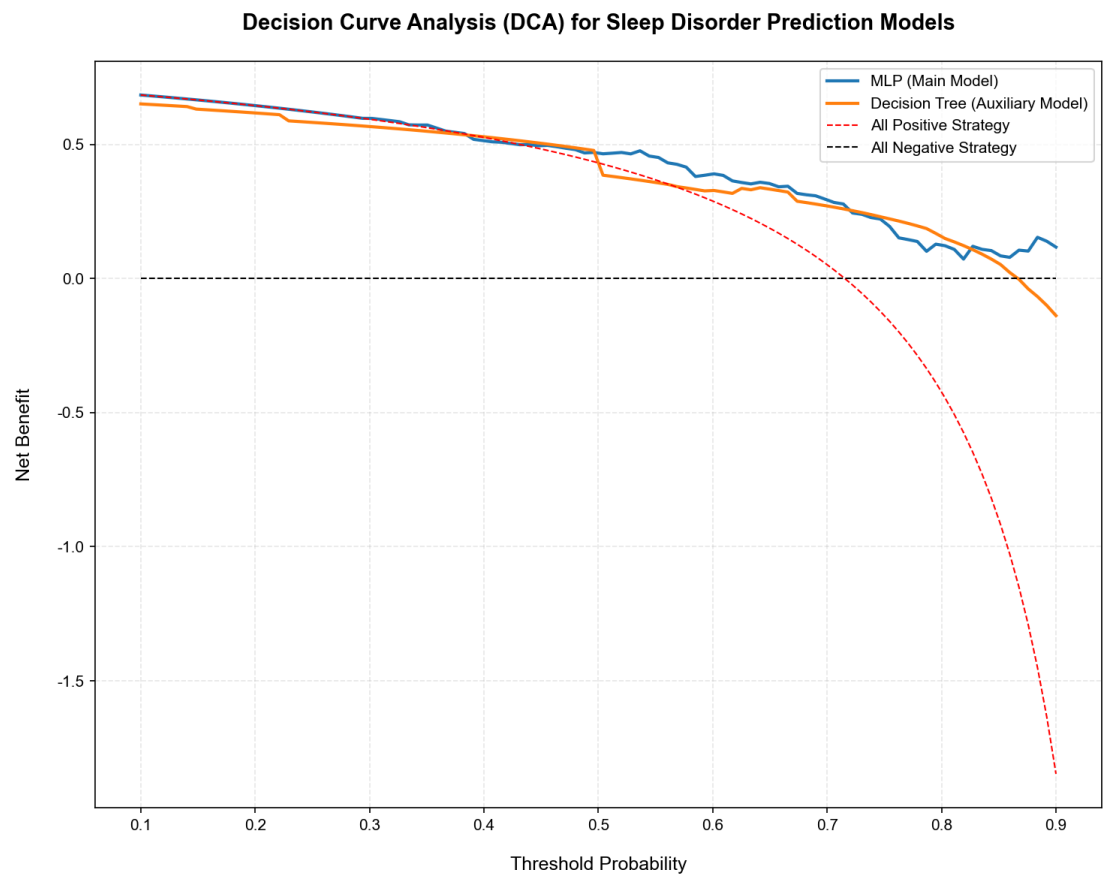


Figure 8. DCA diagram for the screening model.

## Supplementary Files

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