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Using machine learning models to identify severe subjective cognitive decline and related factors in nurses during the menopause transition: a pilot study

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Abstract

Objective: This study aims to develop and validate a machine learning model for identifying individuals within the nursing population experiencing severe subjective cognitive decline (SCD) during the menopause transition, along with their associated factors.

Methods: A secondary analysis was performed using cross-sectional data from 1,264 nurses undergoing the menopause transition. The data set was randomly split into training (75%) and validation sets (25%), with the Bortua algorithm employed for feature selection. Seven machine learning models were constructed and optimized. Model performance was assessed using area under the receiver operating characteristic curve, accuracy, sensitivity, specificity, and F1 score. Shapley Additive Explanations analysis was used to elucidate the weights and characteristics of various factors associated with severe SCD.

Results: The average SCD score among nurses in the menopause transition was (5.38 ± 2.43). The Bortua algorithm identified 13 significant feature factors. Among the seven models, the support vector machine exhibited the best overall performance, achieving an area under the receiver operating characteristic curve of 0.846, accuracy of 0.789, sensitivity of 0.753, specificity of 0.802, and an F1 score of 0.658. The two variables most strongly associated with SCD were menopausal symptoms and the stage of menopause.

Conclusions: The machine learning models effectively identify individuals with severe SCD and the related factors associated with severe SCD in nurses during the menopause transition. These findings offer valuable insights for the management of cognitive health in women undergoing the menopause transition.

Key Words: Machine learning, Nurse, Menopause transition, Subjective cognitive decline.

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The menopause transition refers to the period spanning from the late reproductive stage to postmenopause, signifying the transition from a reproductive phase to a nonreproductive phase in women. This transitional phase typically occurs within the age range of 40 to 60 years.[1] According to the Stages of Reproductive Aging Workshop+10 (STRAW+10), the menopause transition comprises three stages: the late reproductive stage, the menopause transition stage, and the early postmenopausal stage.[1] During this period, as ovarian function in women declines, there is a decrease in estrogen production, which subsequently elevates the release of gonadotropins.[2] This hormonal shift leads to a range of physiological and psychological symptoms, including hot flashes, night sweats, mood swings, sleep disturbances, and cognitive decline.[3,4] Cognitive decline is particularly concerning, as it not only affects women's quality of life but also may indicate a higher risk of severe neurodegenerative diseases, such as Alzheimer's disease.[5-7]

Subjective cognitive decline (SCD) refers to an individual's self-perceived decline in memory or other cognitive functions, which may not be objectively measurable through standardized neuropsychological tests, that is, there's no objective cognitive impairment.[8] Given the potential implications, it becomes crucial to explore which groups may be especially vulnerable to SCD and why. Research shows that nurses, a group often experiencing high occupational stress, are prone to SCD during the menopause transition.[9] As crucial members of the healthcare system, nurses' health and job performance directly impact patient outcomes and overall healthcare quality. However, due to the high-intensity physical and mental demands of their work, long-term irregular schedules, and the physiological and psychological changes brought about by menopause, nurses face particularly pronounced challenges during this transition.[10] SCD can adversely affect their work efficiency and quality of care, potentially impacting the sustainability of their careers. Therefore, identifying SCD and related factors in nurses during the menopause transition at an early stage is of great practical significance.

Previous evidence indicates that certain relevant factors can increase the risk of cognitive decline, with common examples including aging, hypertension, obesity, depression, and so on.[11] The interplay of these factors can significantly elevate an individual's risk of cognitive deterioration.[12] Currently, most models for cognitive health are centered around dementia.[13,14] However, dementia is an incurable disease, and once the

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condition progresses to a severe stage, clinical intervention is highly limited.[15] In contrast, SCD has received growing attention in recent years. Although SCD does not always predict long-term cognitive changes or dementia, some studies suggest that SCD may be associated with an increased risk of future cognitive decline, including Alzheimer's disease.[6] Moreover, predictive models for cognitive impairment vary widely in terms of variables, with most models typically incorporating various laboratory indicators such as blood glucose, blood lipids, and brain imaging.[16,17] However, the complexity and high cost of these models pose challenges for their practical application, making it difficult to implement them quickly and broadly in clinical and community settings.[14] In comparison, questionnaire-based models offer a simpler and more cost-effective alternative. These models rely on structured questionnaires or psychological scales, which can identify the risk of SCD by assessing an individual's subjective experiences, lifestyle, and psychological state, among other nonbiological factors.[18] Especially for nurses during the menopause transition, questionnaire-based models can effectively reflect the impact of their lifestyle habits and occupational stress on SCD.

Based on existing studies, a thorough literature review was conducted to identify independent variables influencing SCD during the menopause transition, particularly within the nursing population. Variables were categorized into five categories: sociodemographic, work-related, menstrual-related, lifestyle-related, and mental health-related, chosen for their established or hypothesized links to cognitive health. Sociodemographic factors like age,[19] body mass index (BMI),[19] educational attainment,[20,21] marital status,[22] socioeconomic status,[21,23] major life events,[24] and chronic diseases[23] are known to impact cognitive function. Work-related factors such as department, job title, and shift patterns were included, considering how nursing roles may affect cognitive load and stress levels. Emerging evidence supports the inclusion of menstrual-related factors, including menopausal symptoms,[19,25,26] age at menarche,[21] menopausal stage,[27] and hormone therapy.[28,29] Lifestyle-related variables, such as sleep and physical activity, were included due to their strong links to overall cognitive health.[30-32] Sleep disturbances have been recognized as a significant factor contributing to cognitive decline, while regular physical activity is known to promote brain health and cognitive function. Lastly, mental health variables like neuroticism, resilience, and emotional states are essential, as they affect cognitive processing and stress management. Research indicates that individuals imbued with resilience and positive emotion are less prone to severe cognitive decline.[33-35] In investigations examining various interrelated factors, while traditional regression analysis offers valuable insights, it is constrained in its ability to assess the relative impact of various factors. In contrast, machine learning techniques offer enhanced capabilities for data analysis, which has attracted more and more attention in recent years.

Machine learning, as an advanced data analysis technique, has shown tremendous potential in the field of cognitive health in recent years.[36] By mining patterns and trends from large datasets, machine learning can construct accurate models and automate the handling of complex variable relationships. Compared with traditional statistical methods, machine learning is capable of processing more complex, multidimensional data and performing in-depth analyses, thus enhancing the accuracy and reliability of identification.[37]

This study aims to develop a machine learning model for identifying individuals within the nursing population experiencing severe SCD during the menopause transition, along with their associated factors. By performing a secondary analysis of existing cross-sectional data, the research will integrate multidimensional data collected from questionnaires, encompassing sociodemographic information, work-related factors, menstrual-related factors, lifestyle, and mental health indicators. This comprehensive model will be built using seven distinct machine learning algorithms, with the optimal model being identified through a comparison of various performance metrics. To further enhance the model's interpretability, Shapley Additive Explanations (SHAP) analysis will be conducted to examine the contributions and relationships of different factors on the identification of severe SCD.[38] This preliminary pilot study seeks to identify factors associated with severe SCD in women undergoing the menopause transition, providing insights for understanding the cognitive health of this population and serving as a reference for the design of future longitudinal studies.

METHODS

Participants

A cross-sectional survey was conducted across 16 hospitals located in Shandong Province. Participants were recruited using the convenience sampling method. Considering the definition of SCD, the inclusion criteria of this study are as follows: (1) nurses between the age of 40 and 60; (2) reporting changes in menstrual cycles; (3) absence of measurable objective cognitive impairment; and (4) voluntarily attend the study. The exclusion criteria included: (1) severe diseases such as malignant tumors or kidney failure; (2) diseases and relevant treatments affecting ovarian function, such as breast cancer or endometrial cancer; (3) history of ovariectomy or hysterectomy; and (4) mental disorder, including anxiety, depression, or substance abuse. In total, 1,335 eligible nurses participated in the study. Out of 1,335 eligible nurses, 1,264 were ultimately included in the analysis after removing 71 incomplete questionnaires. Recruitment took place within hospital departments, where participants were provided with comprehensive study details, including eligibility, the voluntary nature of participation and withdrawal, and a link to the online survey. By completing the questionnaire, participants gave their consent to participate, as clearly stated in the survey. The study was approved by the University's Ethical Review Committee.

Sample size

Sample size is calculated using the formula $N = deff[\mu^2 p(1-p)/\delta^2]$, where μ represents its value within the context of a specified confidence interval. For this study, $\mu = 1.96$ (95% confidence level). The parameter p represents the estimated prevalence of a specific characteristic or behavior within the studied population. In this context, it denotes the prevalence of SCD among the Chinese population, which has been estimated at approximately 11.1% based on previous research ($P = 0.111$).[39] δ stands for the expected margin of error, set as $\delta = 0.03$ for this study. The deff value is determined to be 1.5. Substituting these values into the formula yields a calculated sample size N of 632 cases. After considering a 20% rate of invalid questionnaires, the final determined sample distribution consists of 790 cases. Initially, a total of 1,335 questionnaires were distributed for this study, resulting in 1,264 complete and valid responses.

Measures

Outcome variable

SCD was measured employing the self-reported SCD-Q9, a 9-item questionnaire developed based on the SCD-Q57 items scale.[40] This questionnaire was condensed into two components: overall functional memory and time comparison (four items), and activities of daily living (five items). Each item was scored from 0 to 1, yielding a total score between 0 and 9, with higher scores reflecting greater SCD severity. Based on previous research, the 75th percentile of the continuous variable was used to define SCD levels as either mild or severe, with a cutoff score of 7.5 distinguishing these levels.[41,42] In this study, SCD-Q9 scores ≥7.5 were considered indicative of severe SCD. The Cronbach's α of SCD in this study was 0.841.

Independent variables

Based on previous literature, the study identified a total of 24 potential independent variables, comprising 9 sociodemographic variables, 3 work-related variables, 5 menstrual-related variables, 3 lifestyle-related variables, and 4 mental health-related variables.

Sociodemographic variables included age, BMI, waist-to-hip ratio, educational level, marital status, number of children, economic conditions, major life events, and presence of chronic diseases (eg, hypertension, hyperglycemia, digestive system diseases, and so on).

Work-related factors included department, title, and shift situation.

Menstrual-related variables included age at menarche, menopause transition stage, use of hormone therapy, presence of gynecological diseases (such as uterine fibroids, endometrial thickening, vaginitis, cervicitis, etc), and menopausal symptoms. The Menopause Rating Scale was utilized to assess the presence and severity of 11 menopausal symptoms, covering three domains: the somato-vegetative domain (including vasomotor symptoms, heart discomfort, sleep problems, and muscle and joint discomfort), the psychological domain (covering depressive mood, irritability, anxiety, and physical/mental exhaustion), and the urogenital domain (addressing sexual problems, bladder complaints, and vaginal dryness).[43] Each symptom was rated on a scale from 0 (absent) to 4 (very severe). In the present study, the Cronbach's α of Menopause Rating Scale was 0.893.

Lifestyle-related variables included the average total sleep duration per night over the past month, sleep satisfaction, and physical activity. Sleep satisfaction was evaluated using a single item "How satisfied are you with your sleep?" as well. The answer was rated from 1 (very satisfied) to 5 (2 = fairly satisfied; 3 = moderate satisfied; 4 = fairly unsatisfied; 5 = very unsatisfied). Physical activity was assessed using the International Physical Activity Questionnaire, a 7-item scale evaluating three dimensions: intensity (low, moderate, and vigorous), frequency (days per week), and duration (minutes per day).[44] According to activity intensity, a metabolic equivalent of task (MET) score was allocated to different activities (eg, walking = 3.3, moderate activities = 4, vigorous activities = 8), and a 7-day activity score was computed in MET-minutes per week. Moreover, the International Physical Activity Questionnaire categorized participants into three physical activity levels—low, moderate, and high—based on these parameters.[45]

Mental health-related variables included neurotic personality, positive emotion, negative emotion, and resilience. The neuroticism dimension of the Big Five Inventory-44 was used to measure neuroticism, comprising eight items rated on a 5-point Likert scale from 1 (strongly disagree) to 5 (strongly agree), with higher scores reflecting greater neuroticism.[46] The scale demonstrated good validity, with a Cronbach's α of 0.836. Positive and negative emotion were assessed using the Positive and Negative Affect Scale (PANAS), which includes 20 items divided into two subscales: positive affect (10 items) and negative affect (10 items), assessing emotional states over the past 1-2 weeks.[47] Each item was rated on a 5-point Likert scale ranging from 1 (very slightly or not at all) to 5 (extremely), with summed scores indicating higher levels of positive or negative emotion. In this study, Cronbach's α values for the two dimensions were 0.923 and 0.930, respectively. The 10-Item Connor-Davidson Resilience Scale, a shorter version of the 25-item CD-RISC, measured resilience by assessing the ability to cope with adversity.[48,49] Respondents rated items on a scale from 0 (not true at all) to 4 (true nearly all the time), with higher total scores indicating greater resilience. The 10-Item Connor-Davidson Resilience Scale showed strong reliability in this study, with a Cronbach's α of 0.960.

Data analysis

All analyses were conducted using the IBM SPSS version 26.0 (IBM Corp, Armonk, NY) and R software version 4.2.3 (R Foundation for Statistical Computing, Vienna, Austria), with statistical significance set at $P < 0.05$ (two-tailed). Descriptive analysis of 24 independent variables and one outcome variable was conducted to understand the basic characteristics of the sample. Continuous variables were presented as means (M) and standard deviations (SD), whereas categorical variables were summarized as frequencies (N) and percentages (%). The dataset was randomly split into 75% for the training set and 25% for the validation set. To evaluate the effectiveness of this division, a comparative analysis of the basic characteristics between the two sets was carried out using t tests or Mann-Whitney U tests for continuous variables and χ^2 tests for categorical variables.

In the machine learning model construction phase, a correlation analysis of the 24 initial independent variables was performed to ensure that all correlation coefficients were below 0.8. Next, the Bortua algorithm was used for feature selection, ultimately identifying 13 independent variables with significant value.[50] These variables were used to construct seven machine learning models: logistic regression, random forest, support vector machine (SVM), extreme gradient boosting, multilayer perceptron, k-nearest neighbors, and elastic net. Each model was built following a standardized process to ensure the comparability of the results. To achieve optimal performance, each model underwent five repetitions of 5-fold cross-validation, followed by further optimization through parameter tuning. The optimized models were evaluated on both the training and validation sets using metrics such as area under the receiver operating characteristic curve (AUC), accuracy, sensitivity, specificity, and F1 score. These metrics comprehensively assessed the models' classification ability and stability, ensuring consistent performance across different datasets. By comparing the performance of the different models, the best-performing model was selected as the final model for further analysis. For model calibration, calibration curves were plotted to analyze the consistency between identified probabilities and actual incidence rates, ensuring greater reliability of the model's output. Finally, employing the SHAP method to investigate the relationship between independent variables and SCD. SHAP values quantitatively assessed the contribution of each feature to the model's identifications and visualized the importance and direction of influence of the variables, further enhancing the model's interpretability. The specific research design flowchart is shown in Figure 1.

RESULTS

General information

This study included 1,264 nurses undergoing the menopause transition, with a mean SCD score of 5.38 ± 2.43. According to the SCD-Q9 criterion of ≥7.5, 340 nurses were identified as having severe SCD. The average age of the participants was 46.17 ± 4.18 years, and the mean BMI was 23.28 ± 2.65 kg/m^2. Additionally, 60.2% of the nurses had a waist-to-hip ratio of ≤0.8, and the majority had attained a bachelor's degree or higher. Most of the nurses (96.2%) were currently married, whereas only 51 reported financial difficulties. Furthermore, 78.2% of the participants had one child, 238 had experienced significant life events in the past 12 months, and 24.9% were living with a chronic illness. Additional details are provided in Table 1.

Feature selection

The Bortua algorithm was used to refine the selection of 24 features, and 13 were identified as having significant value, marked in green as "acceptable" in Supplemental Figure 1 (http://links.lww.com/MENO/B352). These included four sociodemographic variables (economy, age, major life events, chronic diseases), three menstruation-related variables (menopause symptoms, menopause transition stage, hormone therapy), two lifestyle-related variables (sleep satisfaction, total sleep duration), and four mental health-related variables (negative emotion, resilience, neurotic personality, positive emotion). These 13 features were then used for subsequent model development and validation. The training set included 948 nurses, and the validation set included 316 nurses. A comparison between the training and validation sets showed a significant difference only in total sleep duration ($\chi^2 = 10.055$, $P = 0.007$), with no significant differences observed in the other features.

Model construction and performance comparison

Models for severe SCD in nurses undergoing the menopause transition were developed using 13 selected features as independent variables and the presence of severe SCD as the dependent variable. The models included logistic regression, random forest, SVM, extreme gradient boosting, multilayer perceptron, k-nearest neighbors, and elastic net. The coding of classification variables is detailed in Table 2, with the

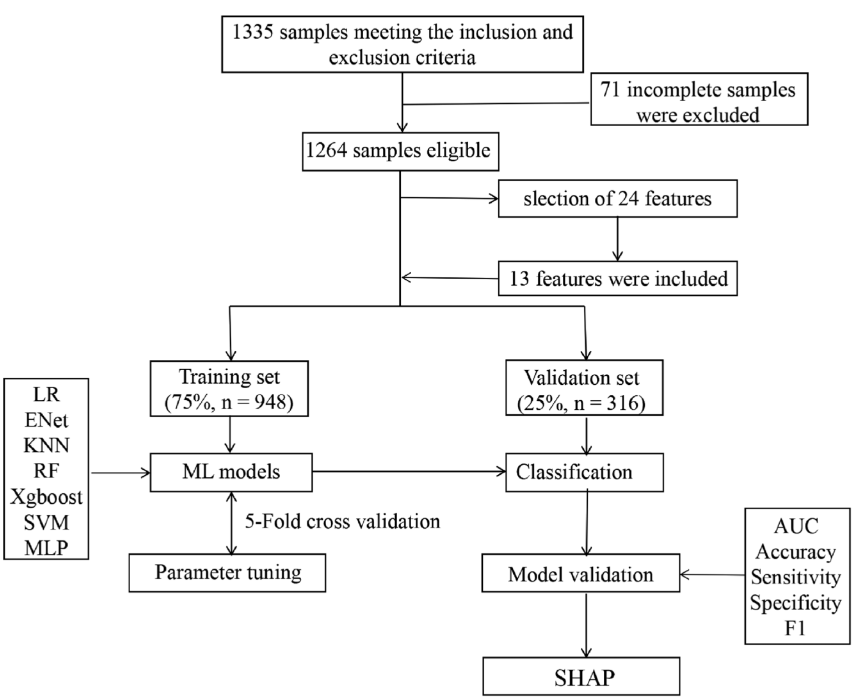

FIG. 1. Flowchart of the study design. AUC, area under the receiver operating characteristic curve; ENet, elastic net; KNN, K-nearest neighbors; LR, logistic regression; ML, machine learning; MLP, multilayer perceptron; RF, random forest; SHAP, Shapley Additive Explanations; SVM, support vector machine; Xgboost, extreme gradient boosting.

TABLE 1. General information of participants (n = 1,264)

Characteristics	N (%)/M ± SD	Severe SCD		Z/χ²	*P*
		No (924 [73.10%])	Yes (340 [26.90%])		
Sociodemographic variables					
Age, y	46.17 ± 4.18	45.97 ± 4.20	46.69 ± 4.07	2.848	0.004
BMI (kg/m²)	23.28 ± 2.65	23.22 ± 2.67	23.42 ± 2.59	1.213	0.225
Waist-to-hip ratio				0.183	0.669
≤0.8	761 (60.20%)	553 (59.80%)	208 (61.20%)		
>0.8	503 (39.80%)	371 (40.20%)	132 (38.80%)		
Educational level				3.448	0.063
Junior college or below	154 (12.20%)	103 (11.10%)	51 (15.00%)		
Bachelor's degree or above	1,110 (87.80%)	821 (88.90%)	289 (85.00%)		
Marital status				0.480	0.488
Married	1,216 (96.20%)	891 (96.40%)	325 (95.60%)		
Other (divorced/widowed)	48 (3.80%)	33 (3.60%)	15 (4.40%)		
Economy				26.618	<0.001
Insufficient	51 (4.00%)	28 (3.00%)	23 (6.80%)		
Sufficient for essentials	580 (45.90%)	396 (42.90%)	184 (54.10%)		
More than sufficient	633 (50.10%)	500 (54.10%)	133 (39.10%)		
Number of children				1.242	0.537
None	27 (2.10%)	22 (2.40%)	5 (1.50%)		
One child	989 (78.20%)	718 (77.70%)	271 (79.70%)		
Above two children	248 (19.60%)	184 (19.90%)	64 (18.80%)		
Major life events				10.510	0.001
Yes	238 (18.80%)	154 (16.70%)	84 (24.70%)		
None	1,026 (81.20%)	770 (83.30%)	256 (75.30%)		
Chronic diseases				34.870	<0.001
Yes	315 (24.90%)	190 (20.60%)	125 (36.80%)		
No	949 (75.10%)	734 (79.40%)	215 (63.20%)		
Work-related variables					
Department				7.589	0.180
Internal medicine	265 (21.00%)	198 (21.40%)	67 (19.70%)		
Surgery	242 (19.10%)	188 (20.30%)	54 (15.90%)		
Gynecologic	100 (7.90%)	75 (8.10%)	25 (7.40%)		
Pediatrics	59 (4.70%)	37 (4.00%)	22 (6.50%)		
Operating room	136 (10.80%)	95 (10.30%)	41 (12.10%)		
Other	462 (36.60%)	331 (35.80%)	131 (38.50%)		
Title				8.933	0.011
Junior	27 (2.10%)	21 (2.30%)	6 (1.80%)		
Intermediate	812 (64.20%)	571 (61.80%)	241 (70.90%)		
Senior	425 (33.60%)	332 (35.90%)	93 (27.4%)		
Shift				0.842	0.359
Long day shift mainly	1,066 (84.30%)	774 (83.8%)	292 (85.90%)		
Shift mainly	198 (15.70%)	150 (16.20%)	48 (14.10%)		
Menstruation-related variables					
Menopause transition stage				67.448	<0.001
Premenopause	777 (61.50%)	628 (68.00%)	149 (43.80%)		
Menopause	359 (28.40%)	229 (24.80%)	130 (38.20%)		
Postmenopause	128 (10.10%)	67 (7.30%)	61 (17.90%)		
Menophania, y				0.759	0.684
≤12	219 (17.30%)	161 (17.40%)	58 (17.10%)		
13–16	992 (78.50%)	727 (78.70%)	265 (77.90%)		
≥17	53 (4.20%)	36 (3.90%)	17 (5.00%)		
Gynecological diseases				14.131	<0.001
Yes	358 (28.30%)	235 (25.40%)	123 (36.20%)		
None	906 (71.70%)	689 (74.60%)	217 (63.80%)		

(Continued on next page)

TABLE 1. *(Continued)*

Characteristics	N (%)/M ± SD	Severe SCD No (924 [73.10%])	Severe SCD Yes (340 [26.90%])	Z/χ^2	P
Hormone therapy				11.500	0.001
Yes	67 (5.30%)	37 (4.00%)	30 (8.80%)		
No	1,197 (94.70%)	887 (96.00%)	310 (91.20%)		
Menopausal symptoms	10.05 ± 7.32	8.22 ± 6.37	15.05 ± 7.41	14.777	<0.001
Lifestyle-related variables					
Physical activity				2.076	0.354
Low	349 (27.60%)	255 (27.6%)	94 (27.60%)		
Medium	585 (46.30%)	437 (47.30%)	148 (43.50%)		
High	330 (26.10%)	232 (25.10%)	98 (28.80%)		
Total sleep duration				48.962	<0.001
≤5 h	100 (7.91%)	49 (5.30%)	51 (15.00%)		
5~7 h	970 (76.74%)	706 (76.40%)	264 (77.60%)		
>7 h	194 (15.35%)	169 (18.30%)	25 (7.40%)		
Sleep satisfaction	2.63 ± 1.08	2.44 ± 1.03	3.15 ± 1.01	10.465	<0.001
Mental health-related variables					
Neurotic personality	22.27 ± 6.78	21.06 ± 6.58	25.56 ± 6.19	10.313	<0.001
Positive emotion	27.85 ± 7.42	28.83 ± 7.64	25.19 ± 6.03	−7.959	<0.001
Negative emotion	20.96 ± 7.02	19.68 ± 6.43	24.42 ± 7.39	10.297	<0.001
Resilience	25.41 ± 8.30	26.67 ± 8.12	22.00 ± 7.81	−9.357	<0.001

validation set data used for model validation. Supplemental Table 1 (http://links.lww.com/MENO/B352) summarizes the performance of the seven models, whereas Figure 2 displays their AUC curves for both the training and validation sets. Supplemental Figure 2 (http://links.lww.com/MENO/B352) shows the calibration curves for the models. All models demonstrated high accuracy. Based on the overall performance in both the training and validation sets, the SVM model demonstrated relatively superior performance, achieving an AUC of 0.846, accuracy of 0.789, sensitivity of 0.753, specificity of 0.802, and an F1 score of 0.658 in the training set.

Interpretation of the SVM model based on SHAP

SHAP plot of feature variables for the SVM model

The feature importance ranking plot for the SVM model (Fig. 3A) identifies the features related to severe SCD in nurses undergoing menopause transition, listed in descending order of correlation weight; the top five are as follows: menopause symptoms, menopause transition stage, economy, sleep satisfaction, and positive emotion. Figure 3B provides the SHAP summary plot for the SVM model's feature variables, with each point representing a sample. Blue indicates a higher feature value, whereas red indicates a lower value. The results highlight menopause symptoms as the most crucial factor related to severe SCD. Patients with higher menopause symptom scores (blue, representing more severe symptoms) are more likely to experience severe SCD compared to those with lower scores (red, representing milder symptoms).

SHAP dependence plots for the SVM model

SHAP dependence plots show the distribution of Shapley values for specific features across different individuals. Figure 4 illustrates dependence plots for the SVM model's features, with Figure 4A depicting categorical independent variables and Figure 4B displaying continuous ones. As demonstrated in Figure 4B, the effects of menopause symptoms, sleep satisfaction, positive emotion, negative emotion, resilience, neurotic personality, and age on severe SCD follow complex, nonlinear patterns. For instance, the relationship between SHAP values and menopause symptoms suggests that as the menopause symptom score increases, the risk of severe SCD initially rises gradually before stabilizing.

Additional analysis

Given the limited number of women in the postmenopausal stage, we reconducted the modeling analysis after excluding this population segment. The results revealed that only three variables—age, chronic diseases, and hormone therapy—were excluded from the model, which indicates a degree of reliability in our findings. For detailed results, please refer to the Supplemental Figures 3 and 4 (http://links.lww.com/MENO/B352). Furthermore, as the SVM model does not provide odds

TABLE 2. Coding scheme for continuous independent variables

Variable Name	Coding
Menopause transition stage	Premenopause = 1; menopause = 2; postmenopause = 3
Economy	Insufficient = 1; sufficient for essentials = 2; more than sufficient = 3
Total sleep duration	≤5 h = 1; 5~7 h = 2; >7 h = 3
Hormone therapy	Yes = 1; no = 0
Major life events	Yes = 1; no = 0
Chronic diseases	Yes = 1; no = 0

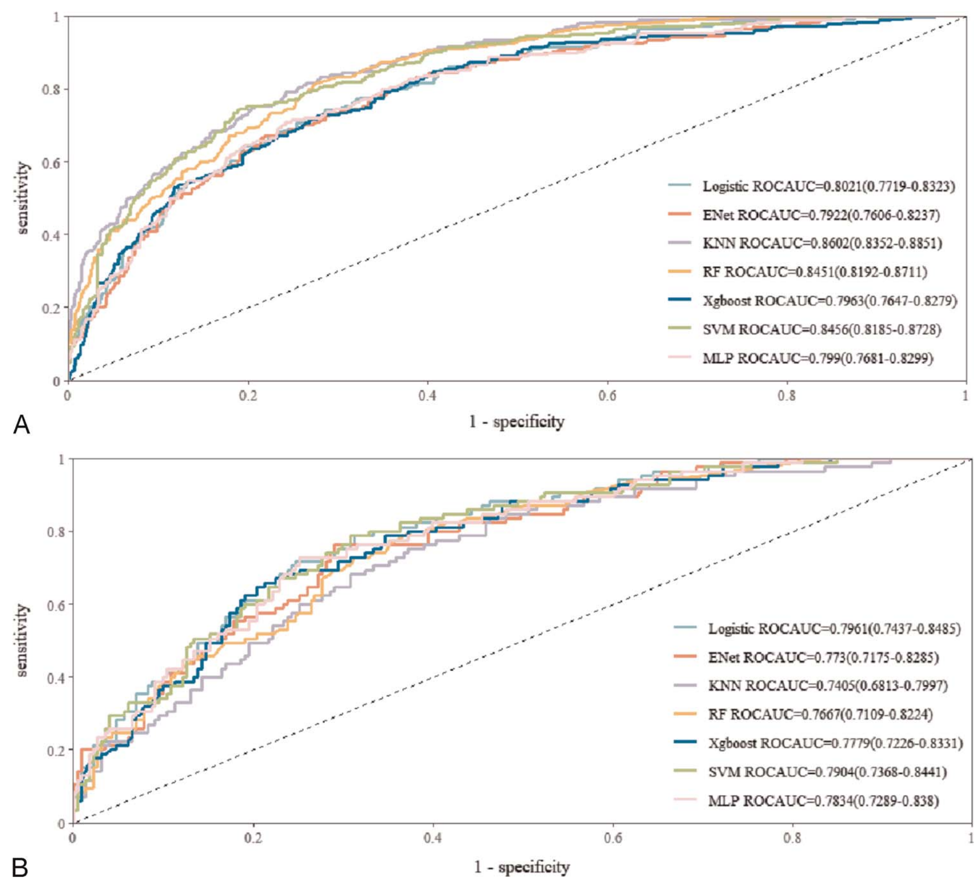

FIG. 2. Performance of models to identify severe SCD. (**A**) Area under the receiver operating characteristic curve of the 7 models in the training set. (**B**) Receiver operating characteristic curve area under the curve of the 7 models in the validation set. ENet, elastic net; KNN, K-nearest neighbors; MLP, multilayer perceptron; RF, random forest; SVM, support vector machine; Xgboost, extreme gradient boosting.

ratios or confidence intervals, we conducted an additional logistic regression analysis to present these values for each variable in the primary results; the specific results were shown in Supplemental Table 2 (http://links.lww.com/MENO/B352).

DISCUSSION

In this study, we performed a secondary analysis of data from nurses undergoing the menopause transition and developed machine learning–based models for severe SCD. The findings demonstrated that the SVM model performed well in identifying severe SCD among these nurses. Additionally, the SHAP value analysis highlighted the relative importance of various features and their patterns of influence, offering new insights into the cognitive decline experienced by women during the menopause transition and its underlying mechanisms.

Feature or variable selection is crucial to model development, as it directly impacts both model performance and clinical applicability.[51] In this study, we employed the Bortua algorithm to identify 13 features with significant value. Our findings are consistent with previous literature on factors such as socioeconomic status, age, major life events, chronic diseases, menopausal symptoms, menopause transition stage, hormone levels, sleep satisfaction, total sleep duration, negative emotions, resilience, neurotic personality traits, positive emotions, and cognitive status, confirming that the selected related factors are both valid and reliable.[52-60]

In this study, seven models were developed, with the SVM model showing the better performance on both the training and validation sets. The SVM model achieved an AUC of 0.846, an accuracy of 0.789, a sensitivity of 0.753, a specificity of 0.802, and an F1 score of 0.658. These metrics suggest that the SVM model possesses strong capabilities and can effectively identify patients with severe SCD. This performance not only highlights the SVM model's strength in handling complex classification problems but also provides a valuable reference for similar predictive tasks.

SHAP value analysis is a powerful tool for understanding a model's decision-making process.[61] In this study, SHAP analysis identified the key features associated with severe SCD and their interaction patterns. The results showed that menopausal symptoms, menopause transition stage, socioeconomic status, sleep satisfaction, and positive emotions were the most significant factors affecting severe SCD. Among these, menopausal symptoms had the greatest impact, exhibiting a notable nonlinear relationship. This pattern suggests that as menopausal symptoms worsen, the risk of severe SCD initially increases slowly and then stabilizes, possibly reflecting the cumulative effect of these symptoms on cognitive function, consistent with our previous findings.[41] In the early stages, mild menopausal symptoms may not be significantly associated with cognition,

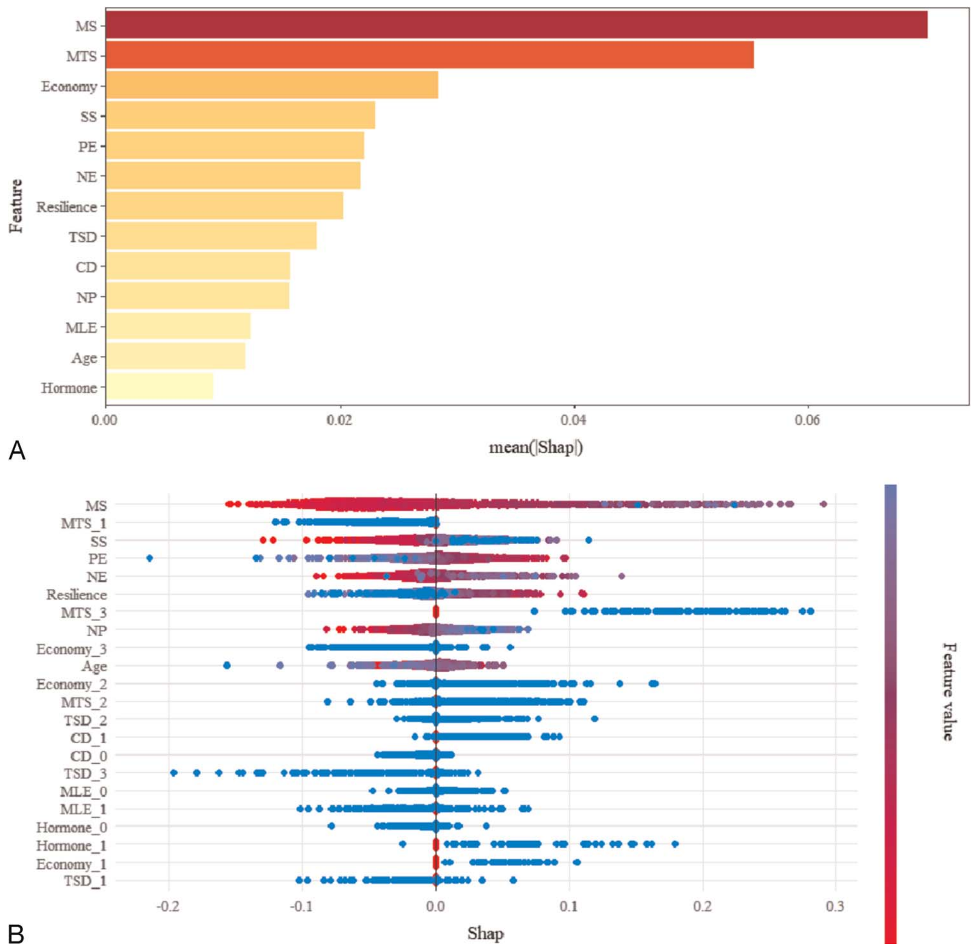

FIG. 3. The SHAP plots of feature variables for the SVM model. (**A**) The feature importance ranking plot for the SVM model. (**B**) The SHAP summary plot for the SVM model's feature variables. CD, chronic diseases; MLE, major life events; MS, menopause symptoms; MTS, menopause transition stage; NE, negative emotion; NP, neurotic personality; PE, positive emotion; SHAP, Shapley Additive Explanations; SS, sleep satisfaction; TSD, total sleep duration. The coding details for the feature variables are presented in Table 2.

but as symptoms become more intense—particularly with frequent or severe hot flashes, mood swings, and sleep disturbances—the risk of cognitive decline rises markedly. However, once menopausal symptoms reach a certain level of severity, their negative effects on cognition may plateau or be mitigated by other physiological or psychological factors, like coping mechanisms, hormonal adaptations, or resilience strategies.[51,62,63] Therefore, the severity of menopausal symptoms might be a crucial indicator of cognitive health, necessitating careful attention and monitoring in health management to facilitate early identification and intervention for potential cognitive decline. Furthermore, effective management and treatments of menopause symptoms can significantly mitigate the burden imposed by the SCD experienced by women during this transitional phase.

The menopause transition stage is a significant factor of severe SCD. Women at different stages of this transition face varying risks of cognitive decline, likely due to hormonal fluctuations, emotional changes, and physiological alterations.[25,64,65] Additionally, economic status, a critical sociodemographic factor, has a notable association with severe SCD. Nurses with poorer economic conditions may be more susceptible to cognitive decline because of prolonged psychological stress, lack of social support, or increased work burdens.[66,67] The effect of sleep satisfaction is also crucial. Nurses with poorer sleep quality are more likely to experience cognitive issues, as sleep disturbances can impair brain recovery and memory consolidation, thereby elevating the risk of cognitive decline.[68] The protective effect of positive emotions on cognitive function is well-established, with higher levels of positive emotions potentially reducing the risk of cognitive decline by alleviating stress and enhancing cognitive resilience.[57,69] Analyzing these key factors provides robust support for understanding the mechanisms underlying severe SCD and offers valuable insights for managing cognitive health in women undergoing the menopause transition.

Study limitations and strengths

Despite the valuable insights offered by this study, there are several limitations to address. First, the study sample is confined to nurses, which may limit the generalizability of the findings to other occupational groups. Expanding research to include women from diverse professions, age groups, and geographic regions could also enhance the generalizability of the results. Second, due to the constraints of sample size, this study may lack sufficient power to investigate the relationships between multiple independent and dependent variables, and some variables may show lower statistical power due to their

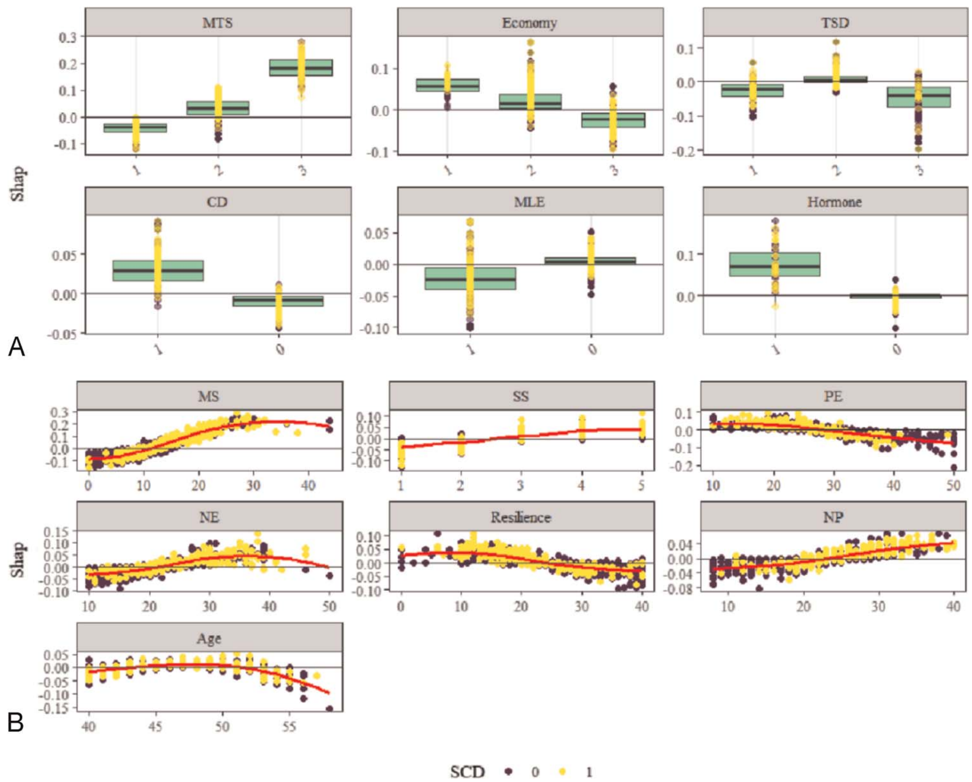

FIG. 4. SHAP dependence plots for the SVM model. (**A**) SHAP dependence plots of categorical independent variables. (**B**) SHAP dependence plots of continuous independent variables. CD, chronic diseases; MLE, major life events; MS, menopause symptoms; MTS, menopause transition stage; NE, negative emotion; NP, neurotic personality; PE, positive emotion; SHAP, Shapley Additive Explanations; SS, sleep satisfaction; SVM, support vector machine; TSD, total sleep duration. The coding details for the feature variables are presented in Table 2.

prevalence or rarity. Future research should aim to increase the sample size to improve model reliability. Third, the cross-sectional nature of the data prevents causal inferences; thus, incorporating longitudinal studies in future research is essential to explore the complex relationships among multiple variables. Fourth, cognition encompasses various dimensions, so relying on a single questionnaire for one-time evaluation may lack reliability. Future studies should employ multiple instruments for a comprehensive assessment of severe SCD. Additionally, this study relied solely on oral inquiries to assess objective cognitive impairment, which may introduce inaccuracies. Therefore, incorporating objective measurements in future investigations is crucial for enhancing the precision and validity of the results. Finally, considering genetic factors, social support, and lifestyle variables could provide a more holistic understanding of the mechanisms behind severe SCD.

The study's results hold significant clinical implications. The establishment and validation of a severe SCD model provide clinicians with a valuable basis for early identification of high-risk individuals and the customization of personalized intervention strategies. Additionally, SHAP value analysis has elucidated the complex effects of various factors on cognitive function, providing a theoretical foundation for designing more effective interventions.

CONCLUSIONS

In conclusion, this study employed machine learning and SHAP analysis to identify key factors influencing severe SCD in nurses undergoing the menopause transition, uncovering the complex relationships between these variables. These findings provide a novel guidance for interventions designed to preserve cognitive health in women undergoing the menopause transition. Future research should aim to further validate these results and investigate additional potential influencing factors to develop more effective strategies for promoting cognitive health during the menopause transition.

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