Comparison of logistic regression and machine learning methods for predicting depression risks among disabled elderly individuals: results from the China Health and Retirement Longitudinal Study

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Abstract

Background

Given the accelerated aging population in China, the number of disabled elderly individuals is increasing, depression has been a common mental disorder among older adults. This study aims to establish an effective model for predicting depression risks among disabled elderly individuals.

Methods

The data for this study was obtained from the 2018 China Health and Retirement Longitudinal Study (CHARLS). In this study, disability was defined as a functional impairment in at least one activity of daily living (ADL) or instrumental activity of daily living (IADL). Depressive symptoms were assessed by using the 10-item Center for Epidemiologic Studies Depression Scale (CES-D10). We employed SPSS 27.0 to select independent risk factor variables associated with depression among disabled elderly individuals. Subsequently, a predictive model for depression in this population was constructed using R 4.3.0. The model's discrimination, calibration, and clinical net benefits were assessed using receiver operating characteristic (ROC) curves, calibration plots, and decision curves.

Results

In this study, a total of 3,107 elderly individuals aged ≥ 60 years with disabilities were included. Poor self-rated health, pain, absence of caregivers, cognitive impairment, and shorter sleep duration were identified as independent risk factors for depression in disabled elderly individuals. The XGBoost model demonstrated better predictive performance in the training set, while the logistic regression model showed better predictive performance in the validation set, with AUC of 0.76 and 0.73, respectively. The calibration curve and Brier score (Brier: 0.20) indicated a good model fit. Moreover, decision curve analysis confirmed the clinical utility of the model.

Conclusions

The predictive model exhibits outstanding predictive efficacy, greatly assisting healthcare professionals and family members in evaluating depression risks among disabled elderly individuals. Consequently, it enables the early identification of elderly individuals at high risks for depression.

Background

Research indicates that the population of disabled elderly individuals in China has exceeded 40 million, making up over 16% of the elderly population. Projections anticipate that the number will reach 65 million by 2030 [1]. Depression is a prevalent mental health disorder among the elderly population, impacting around 7% of them worldwide [2, 3]. Both disability and depression have emerged as notable social concerns. Disability encompasses physical, psychological, and social aspects and pertains to the impaired capacity of older individuals to engage in fundamental activities of daily living autonomously. This decline in functional abilities hampers their adaptation to environmental changes. Depression is a common psychological issue characterized by a chronic trajectory and a high likelihood of recurrence [4]. It is associated with various adverse outcomes, such as reduced quality of life, amplified healthcare burden, and heightened incidence and mortality rates [5]. Both disability and depression impose substantial burdens on individuals as well as society.

Late-life depression is closely associated with disability, particularly when it hinders self-care and social participation [6]. Research indicates that the likelihood of depression in the population with physical disabilities is at least three times higher compared to normal individuals [7]. Moreover, there is a potential direct causal link between disability among older adults and the occurrence of depression. There could exist a direct causal relationship between disability and depression in the older adult population [8, 9].

Previous research has indicated that several significant factors are associated with the onset and persistence of depression in older adults, including being female, having a low educational level, experiencing spousal loss, cognitive decline, physical illness, and functional impairment [10]. Currently, the relationship between disability in elderly individuals and depression is still the subject of ongoing investigations, and interventions for depression among disabled older adults are considered essential for healthcare services.

Clinical risk prediction models have become widely prevalent in various medical fields in recent years. These models aim to utilize individual-level information to predict clinically relevant outcomes [11]. By employing clinical prediction models, the efficiency of healthcare processes and self-management can be enhanced while reducing the workforce costs associated with healthcare [12].

In certain studies, relevant biochemical indicators such as HDL-C, fasting blood glucose, triglycerides, and other metabolic markers are integrated into prediction models [13]. However, the process of collecting data for these indicators is invasive or costly, necessitating well-trained experts and controlled experimental environments, often rendering them impractical in community settings. While the inclusion of biochemical indicators may enhance the predictive performance of risk models, it may also diminish their practicality [14]. Primary healthcare demands more straightforward tools [15]. In primary healthcare settings, risk prediction models based on readily accessible data concerning risk factors associated with depression in disabled elderly individuals prove to be more suitable and feasible [16].

We constructed a clinical prediction model for depression among disabled elderly individuals by analyzing data from the 2018 China Health and Retirement Longitudinal Study (CHARLS) to identify the relevant factors associated with depression in this population. By utilizing commonly available predictive factors in the community environment, we developed a practical prediction system for assessing the risks of depression among disabled elderly individuals. This system aims to assist healthcare professionals in measuring the probability of depression in this population and facilitate to identify the risk of depression at an early stage among these individuals.

Methods

Study design and participants

The data was derived from the China Health and Retirement Longitudinal Study (CHARLS). CHARLS is conducted every two years (2011, 2013, 2015, 2018), with each wave adding new participants. The CHARLS participants were sampled using a multistage probability sampling strategy and probability proportionate to the size sampling method. It covered 150 counties of 28 provinces, municipal cities, and autonomous regions of China [17]. The CHARLS was approved by the Ethical Review Committee at Peking University, and all participants signed informed consent before participation.

We employed the baseline data from 2018 to develop a practical risk prediction model for depressive symptoms among disabled older adults. In the longitudinal CHARLS cohort, disability is classified into two dimensions: Activities of Daily Living (ADL) and Instrumental Activities of Daily Living (IADL). To assess disability, this study utilized the PSMS scale and Lawton scale, each comprising six sections[18]. In the present study, participants who acknowledge difficulties by responding with “yes, I have difficulty and need assistance”, or express an inability with “I cannot do it” in the context of any given project, are regarded as functionally impaired[19, 20]. Participants were considered disabled if any section was classified as such. The 2018 baseline survey included a total of 19,817 participants. After excluding individuals with missing or abnormal data, the final analytical sample consisted of 3,107 disabled older adults aged 60 years and above. Figure 1 illustrates the flowchart for selecting and following up on all eligible study subjects.

Measures

Depressive symptoms

In the CHARLS cohort, depression is measured by using the 10-item Center for Epidemiologic Studies Depression Scale (CESD-10) administered through the survey [21]. This scale consists of 10 components: "feeling down," "feeling afraid," "feeling lonely," "having poor sleep," "having difficulty in completing tasks," "being irritable over minor matters," "having trouble concentrating" and "feeling unable to continue with life." The items "I have hope for the future" and "I feel happy" in this scale are scored inversely. Each question offers four response options: Rarely or none of the time (< 1 day), Some or a little of the time (1–2 days), Occasionally or a moderate amount of the time (3–4 days), and most or all of the time (5–7 days).The overall scale score ranges from 0 to 30, with a threshold of 10 points indicating a tendency towards depression.

Variables

Considering the accuracy and practicality of the risk prediction model, we have incorporated variables related to depression among disabled older adults based on a review of existing evidence [6, 9, 22, 23].

Relevant information was collected through structured questionnaires, including sociodemographic factors (age, gender, place of residence, educational level, marital status, etc), health behaviors (smoking, drinking history, sleep, etc.), cognitive status and social support.

Statistical analysis

Data cleaning, preprocessing and merging were conducted using the STATA 17.0 software. The analysis of influencing factors and determining important predictive factors were performed on the sample using SPSS 27.0. The chi-square test for categorical variables was employed to compare the influencing factors of depression among disabled older adults and select variables with statistical significance. Important predictive factors related to depression among disabled older adults were selected based on expert opinions and through univariate and multivariate logistic regression analysis using the forward stepwise selection method. The statistical significance level was set at 0.05 for two-tailed tests.

Model construction and evaluation

A depression risk prediction model was constructed for elderly individuals with disabilities through the utilization of logistic regression and four machine learning algorithms: Support Vector Machine (SVM), Random Forest (RF), XGBoost, and Decision Tree. During the modeling process, conducting 10-fold cross-validation ensures the performance and stability of the model. The model's development was facilitated using R version 4.3.0.

Create the receiver operating characteristic (ROC) curve to evaluate the predictive capability of the prediction model, where an area under the curve (AUC) value of ≥ 0.70 is considered appropriate [24]. The calibration curve visualizes the consistency assessment between the average predicted risk occurrence rate and the actual observed event occurrence rate. If the solid line (representing the performance of the predictive model) is closer to the diagonal dashed line (representing the perfect prediction of an ideal model), it indicates better consistency [25, 26]. A Brier score of less than 0.25 indicates that the overall performance evaluation of discrimination and calibration is acceptable [27]. The decision curve evaluates the clinical utility by assessing the net benefit at different threshold probabilities [28].

Model interpretation

SHAP, an acronym for Shapley Additive exPlanations, was introduced by Lundberg and Lee in 2017[29]. It constitutes a framework employed for explicating the predictions made by machine learning models to elucidate each feature's contribution[30]. Shapley values, originating from cooperative game theory, serve as an equitable approach for allocating gains in cooperative games. About participants in cooperative games, Shapley values contemplate the marginal contributions of each participant, thereby ensuring a judicious distribution of benefits[31]. In machine learning, features can be construed as participants in a cooperative game, with the model's output representing the dividends of the game[32].

Results

Participant characteristics

A total of 3,107 disabled elderly individuals were included in this study. Among them, 1,774 (57.1%) had depression, making up 57.1% of the total sample of disabled elderly individuals. Within the training set, 56.66% (1233/2176) of individuals exhibited depression, whereas in the validation set, the proportion was 58.11% (541/931). Characteristics of the study population are given in Table 1.

Table 1
Characteristics of the participants at baseline

Variable	Total	Non-depressive	depression	x^2	p
	n = 3107	n = 1333	n = 1774		
Gender (%)	1278(41.13)	623(46.74)	655(36.9)	30.28	< 0.001
male	1829(58.87)	710(53.26)	1119(63.08)		
female					
Age, years	1726(55.55)	711(53.34)	1015(57.22)	11.867	0.003
60–69	1101(35.44)	476(35.71)	625(35.23)		
70–79	280(9.01)	146(10.95)	134(7.55)		
≥ 80					
Residence	2460(79.18)	1013(75.99)	1447(81.57)	14.34	< 0.001
village	647(20.82)	320(24.01)	327(18.43)		
non-rural					
Education level	1143(36.79)	462(34.66)	681(38.39)	22.386	< 0.001
illiteracy	1429(46.00)	597(44.79)	832(46.90)		
elementary school level	405(13.04)	198(14.85)	207(11.67)		
junior high school level	130(4.18)	76(5.70)	54(3.04)		
high school and above					
Health self-assessment					
good	340(10.94)	234(17.55)	106(5.98)	232.416	< 0.001
common	1238(39.85)	638(47.86)	600(33.82)		
poor	1529(49.21)	461(34.58)	1068(60.20)		
pains	668(21.50)	424(31.81)	244(13.75)	244.266	< 0.001
none	1339(43.10)	619(46.44)	720(40.59)		
occasionally	1100(35.40)	290(21.76)	810(45.66)		
often					
Sleep at night	1454(46.80)	462(34.66)	992(55.92)	138.99	< 0.001
< 6h	1328(42.74)	707(53.04)	621(35.01)		
6-8h	325(10.46)	164(12.30)	161(9.08)		
> 8h					

Variable	Total	Non-depressive	depression	x^2	p
Social activities	1689(54.36)	680(51.01)	1009(56.88)	10.55	< 0.001
no	1418(45.64)	653(48.99)	765(43.12)		
yes					
Caregiver	2094(67.40)	1004(75.32)	1090(61.44)	66.69	< 0.001
yes	1013(32.60)	329(24.68)	684(38.56)		
no					
Work	965(31.06)	541(40.59)	424(23.90)	100.67	< 0.001
no problem	1250(40.23)	477(35.78)	773(43.57)		
short time	892(28.71)	315(23.63)	577(32.53)		
unable					
Cognitive impairment	1357(43.68)	644(48.31)	713(40.19)	20.402	< 0.001
no	1750(56.32)	689(51.69)	1061(59.81)		
yes					
Deposit	2615(84.16)	1068(80.12)	1547(87.20)	28.658	< 0.001
≤ 5000	492(15.84)	265(19.88)	227(12.80)		
> 5000					

Variable selection results

Table 1 presents the influencing factors of depression in disabled elderly. Univariate logistic regression and multivariate logistic regression were employed to identify independent risk factors for depression among disabled elderly, resulting in the selection of five significant predictive factors for constructing a depression prediction model in disabled elderly, as shown in Tables 2 and 3. " poor self-rated health", "pain", " shorter sleep duration at night", "lack of caregivers" and "cognitive impairment" emerged as independent risk factors in the logistic regression analysis.

Table 2
Results of univariate logistic regression analysis

	B	S.E	Wald	df	Sig.	Exp(B)	95%C.I.for EXP(B)
Gender	-0.510	0.088	33.618	1	< 0.001	0.600	0.505–0.713
Age			8.370	2	0.015		
60–69 vs. >=80	0.444	0.154	8.256	1	0.004	1.558	1.151–2.109
70–79 vs. >=80	0.350	0.161	4.753	1	0.029	1.419	1.036–1.994
Residence	0.413	0.106	15.294	1	< 0.001	1.512	1.229–1.859
Education level			25.552	3	< 0.001		
illiteracy vs. high school and above	0. 978	0.229	18.244	1	< 0.001	2.660	1.698–4.166
elementary school level vs. high school and above	0.910	0.227	16.111	1	< 0.001	2.483	1.593–3.872
junior high school level vs. high school and above	0.553	0.248	4.971	1	0.026	1.738	1.069–2.825
Health self-assessment			162.176	2	< 0.001		
good vs. poor	-1.534	0.154	98.787	1	< 0.001	0.216	0.159–0.292
common vs. poor	-1.004	0.095	110.951	1	< 0.001	0.367	0.304–0.442
Pain			178.705	2	< 0.001		
none vs. often	-1.669	0.127	172.755	1	< 0.001	0.188	0.147–0.242
Occasionally vs. often	-0.942	0.106	79.041	1	< 0.001	0.390	0.317–0.480
Sleep at night			86.648	2	< 0.001		
< 6h vs. >8h	0.726	0.148	24.217	1	< 0.001	2.067	1.548–2.761
6-8h vs. >8h	-0.126	0.147	0.733	1	0.392	0.882	0.662–1.176
Social activities	-0.249	0.087	8.219	1	0.004	0.779	0.657–0.924
Caregiver	-0.592	0.095	38.790	1	< 0.001	0.553	0.459–0.666

	B	S.E	Wald	df	Sig.	Exp(B)	95%C.I.for EXP(B)
Work			75.693	2	< 0.001		
no problem vs. unable	-0.899	0.114	61.785	1	< 0.001	0.407	0.325–0.509
short time vs. unable	-0.138	0.108	1.633	1	0.201	0.871	0.705–1.076
Cognitive impairment	0.291	0.088	11.046	1	< 0.001	1.338	1.127–1.588
Deposit	0.504	0.116	18.742	1	< .0001	1.655	1.317–2.079

Table 3
Results of multivariate logistic regression analysis

	B	S.E	Wald	df	Sig.	Exp(B)	95%C.I.for EXP(B)
Health self-assessment			53.612	2	< 0.001		
good vs. poor	-0.985	0.171	33.025	1	< 0.001	0.373	0.267–0.522
common vs. poor	-0.671	0.107	39.278	1	< 0.001	0.511	0.414–0.630
Pain			60.979	2	< 0.001		
none vs. often	-1.088	0.141	59.651	1	< 0.001	0.337	0.256–0.444
Occasionally vs. often	-0.580	0.114	25.746	1	< 0.001	0.560	0.447-0.700
Sleep at night			36.563	2	< 0.001		
< 6h vs. >8h	0.497	0.162	9.427	1	< 0.002	1.644	1.197–2.257
6-8h vs. >8h	-0.110	0.161	0.469	1	0.494	0.895	0.653–1.228
Caregiver	-0.597	0.104	32.638	1	< 0.001	0.551	0.449–0.676
Cognitive impairment	0.222	0.101	4.859	1	< 0.028	1.249	1.025–1.522

Predictive performance of disabled elderly

Table 4 and Fig. 2 showed that except for decision trees, the use of LR and ML techniques for predicting depression among disabled elderly individuals is deemed acceptable. In the training set, XGBoost exhibited good predictive performance (AUC = 0.76). In the validation set, traditional LR showed better predictive performance (AUC = 0.73). Decision trees produced inconclusive results in both the training and validation sets (AUC < 0.70); however, the other models did not show significant differences in AUC. The overall predictive performance, as proved by the Brier score, demonstrated favorable outcomes. Figure 3 illustrated the calibration plot, showing good consistency between the predicted probabilities of LR and XGBoost and the actual observations. In Fig. 4, within the threshold probability range of 0.15 to 0.89 for depression among disabled elderly individuals, implementing a selective intervention strategy yielded higher net gains than the default approach of intervention or non-intervention with all patients.

Table 4
Comparison of Predictive Model Performance

Model	AUC	Accuracy	Sensitivity	Specificity	PPV	NPV	precision	recall	Brier-score
Training set									
LR	0.73	0.67	0.79	0.53	0.69	0.66	0.74	0.59	0.20
RF	0.74	0.69	0.80	0.55	0.70	0.67	0.70	0.79	0.21
SVM	0.72	0.68	0.78	0.53	0.68	0.65	0.68	0.82	0.22
DT	0.67	0.67	0.79	0.52	0.68	0.65	0.68	0.82	0.22
XGB	0.76	0.69	0.78	0.58	0.71	0.67	0.71	0.79	0.20
Validation set									
LR	0.73	0.67	0.78	0.52	0.69	0.63	0.76	0.62	0.20
RF	0.72	0.66	0.76	0.51	0.68	0.61	0.73	0.79	0.21
SVM	0.72	0.67	0.78	0.53	0.69	0.63	0.69	0.83	0.22
DT	0.65	0.66	0.74	0.51	0.69	0.62	0.69	0.80	0.21
XGB	0.71	0.65	0.74	0.52	0.68	0.59	0.73	0.80	0.21

Visualization by SHAP

We were using the SHAP algorithm to intuitively display the independent risk factors for predicting depression among functionally impaired older adults using the XGBOOST model. (Fig. 5A, B) demonstrated the ranking of the importance of risk factors in descending order. Self-rated health has the most vital predictive ability, followed by pain and shorter sleep duration at night. (Fig. 5C) SHAP provides feature interaction diagrams to identify features suitable for combination. We also provide two typical examples, one predicting no depression (Fig. 5D) and the other predicting depression (Fig. 5E), to demonstrate the interpretability of the model.

Construction of nomogram

Based on the logistic regression analysis results, a nomogram is constructed for the independent risk factors mentioned above. As shown in Fig. 6, each axis represents a specific variable, and the corresponding values for each variable are found along the axis, typically marked with scales. Then, summing these values yields a total score corresponding to the predicted probability, indicating the higher the total score, the greater the likelihood of depression among disabled elderly individuals.

Discussion

We investigated the contributing factors between disability among elderly individuals and depression using cross-sectional data from a representative Chinese population. The predictive factors consisted of " health self-assessment", "pain", " sleep at night", "caregiver" and "cognitive impairment." This study was the first to predict the risk of depression in disabled individuals aged 60 years or older in China, and it also compared various machine learning techniques with traditional logistic regression.

All models, except for decision trees, demonstrate acceptable discriminative capability; however, their performance falls short of the desired threshold (AUC ≥ 0.9) [33]. This may be because the concept of depressive tendencies involves multiple aspects and diagnostic approaches, and currently, there are no valuable biomarkers or biological screening tests in clinical practice [34]. Conversely, prediction models have demonstrated good performance in diseases characterized by well-defined conditions, such as stroke and diabetes [35, 36]. It is worthwhile to consider some depression-related risk factors [34]. Therefore, it is of practical significance to predict depression in disabled elderly individuals by identifying crucial predictive factors [37, 38]. Risk prediction models for depression, integrating variables such as cognitive assessments and self-rated health, achieve satisfactory performance when applied to cross-sectional data.

The sensitivity values of all models (ranging from 0.74 to 0.80) are higher compared to the specificity values (ranging from 0.51 to 0.58). Greater sensitivity contributes to a lower false-negative rate, facilitating the identification of a larger proportion of elderly individuals exhibiting depressive tendencies. This enhances the awareness of primary healthcare workers toward disabled older adults with depressive tendencies and allows for early prevention strategies targeting this specific population group. Furthermore, the results of DCA indicate that all models can be used in clinical practice within a reasonable range of threshold probabilities[28]. Predictive models built using readily accessible variables will be employed in diverse scenarios for the identification of individuals at risk of depression and the implementation of preventive interventions[39, 40].

"Poor self-rated health," "pain," " shorter sleep duration at night," " absence of caregivers," and "cognitive impairment" are high-risk factors for depression in disabled elderly individuals. The most prominent risk factor identified in this study is "poor self-rated health," which measures self-perceived health. Previous research has confirmed the correlation between self-rated health and depression.[41, 42]. For individuals with impaired functioning, perceiving oneself as physically unhealthy is more likely to trigger severe depressive symptoms than perceiving oneself as physically healthy. This finding implies that the elderly population's perception of health may exert a more substantial influence on their depressive symptoms.

Depression and pain share significant pathophysiological overlap, with a higher prevalence of depression observed in patients with chronic pain compared to those without pain[43]. Furthermore, the simultaneous presence of pain and depressive symptoms adversely affects individuals[44]. Over 60% of individuals with depression experience chronic pain symptoms[45]. The comorbidity between pain and depression holds particular significance in clinical settings, as the simultaneous presence of chronic pain and depression in older adults presents treatment challenges[46]. Furthermore, depression and pain have a bidirectional relationship where they can act as risk factors for each other[47].

Short sleep duration may increase daytime fatigue, which can lead to adverse events and emotions caused by fatigue, ultimately resulting in depression[48].In addition, research has shown that longer sleep duration is associated with lower levels of physical activity, which is beneficial for reducing the risk of depression[49]. Through elevation of neurotransmitter levels, specifically dopamine and serotonin, and enhancement of brain noradrenergic synaptic transmission[50], this mechanism promotes endorphin secretion[51], diminishes stress stimuli[52], and enhances self-efficacy and self-esteem. A longitudinal study revealed a robust correlation between depression scores and sleep duration, indicating a substantial impact of inadequate sleep on depression[53]. Furthermore, another prospective study showed that shorter sleep duration is associated with increased severity of depressive symptoms[54]. There is a strong bidirectional relationship between sleep and depression, where reduced sleep duration serves as the strongest predictor for increased acute depressive symptoms. Moreover, more than 80% of individuals with depression experience disturbances in their sleep patterns.

Inadequate social support has a detrimental impact on mental health[55], whereas sufficient social support exerts a positive influence on the well-being of individuals experiencing depression. Previous studies have consistently identified spousal care for elderly individuals as a protective factor against depression. This is especially true for males, as poor marital relationships or the absence of a partner at home are related to depression in elderly individuals[56]. Caregivers can provide accommodation and meals, thereby reducing the need for hospitalization. They can also make more use of social networks and provide support by accompanying individuals during treatment. Insightful family members or close friends can serve as an "early warning system," enabling early intervention for individuals who may be at risk of depression[57]. Compared to elderly individuals with caregivers, empty nesters show a significantly higher tendency towards depression than non-empty nesters[58]. Studies have demonstrated a prevalence rate exceeding 70% for depression or depressive symptoms among empty nesters in China[59, 60].

Depression may co-occur with or even precede dementia, which is characterized by diffuse cognitive impairment[61]. Studies have indicated an association between cognitive dysfunction and late-life depression, as well as adverse reactions to antidepressant medications[62]. Furthermore, cognitive impairment plays a significant role in the development of depression[63]. Cognitive impairments are observed in individuals at the onset of depression. Recurrent episodes of depression exhibit more significant cognitive impairments compared to single episodes, particularly in processing speed, executive function, language learning, and memory[64].

We have developed a risk prediction model for depression among disabled elderly individuals. By incorporating five high-risk factors: " health self-assessment", "pain", " sleep at night", "caregiver" and "cognitive impairment." We have developed a web-based clinical support system that is user-friendly and community-oriented. This system will facilitate the early identification of elderly individuals with depressive tendencies by themselves and caregivers, promoting proactive care and enhancing healthcare allocation through targeted interventions for disease prevention and management.

Strengths and limitations

To our knowledge, this is the first nomogram constructed based on the Chinese elderly population to predict depression among disabled older adults. This nomogram accurately identifies individuals with high-risks by incorporating selected independent risk factors. This tool will assist caregivers and healthcare practitioners in implementing timely intervention strategies to prevent depression among disabled older adults.

Inevitably, this study has some limitations. Firstly, caution should be exercised when extrapolating the findings of this study to other countries as it is solely based on the Chinese population. Secondly, the presence of biases induced by missing data must be acknowledged. To ensure the robustness of the predictive model for depression among disabled elderly individuals, participants with missing data or abnormal values were excluded from the analysis. Thirdly, we could not obtain other important predictive factors, such as specific diets and physical activity, that were not collected in the CHARLS dataset[65].

Conclusion

In the study, the logistic regression and XGBoost models demonstrated good discrimination, calibration, overall predictive performance, and clinical utility in predicting depression among disabled elderly individuals. A straightforward and efficient preliminary clinical support system was developed based on the logistic regression model, showing promise to significantly reduce the burden on users and help healthcare service providers manage depression.

Abbreviations

ADL	activity of daily living
IADL	instrumental activity of daily living
PSMS	physical self-maintenance scale
CESD-10	10-item Center for Epidemiologic Studies Depression Scale
ROC	receiver operating characteristic
AUC	area under the curve
DCA	decision curve analysis
SHAP	Shapley Additive exPlanations
XGBoost	eXtreme Gradient Boosting
HDL-C	high-density lipoprotein cholesterol
LR	logistic regression
ML	machine learning
SVM	support vector machine

Declarations

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Authors' contributions

Shanshan Hong conceptualized and planned the overall study, conducted data analysis, and drafted the manuscript. Bingqian Lu,Yan Jiang and Shaobing Wang critically reviewed the manuscript. All authors read and approved the final manuscript.

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Data Availability

The database was used from the China Health and Retirement Longitudinal Study. (http://charls.pku.edu.cn/).

Ethics approval and consent to participate

This study was conducted following the principles of the Helsinki Declaration and was approved by the Biomedical Ethics Committee of Peking University. All participants signed informed consent forms before their participation, which were approved by the Ethics Review Committee of Peking University (IRB00001052-11015).

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

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Figures

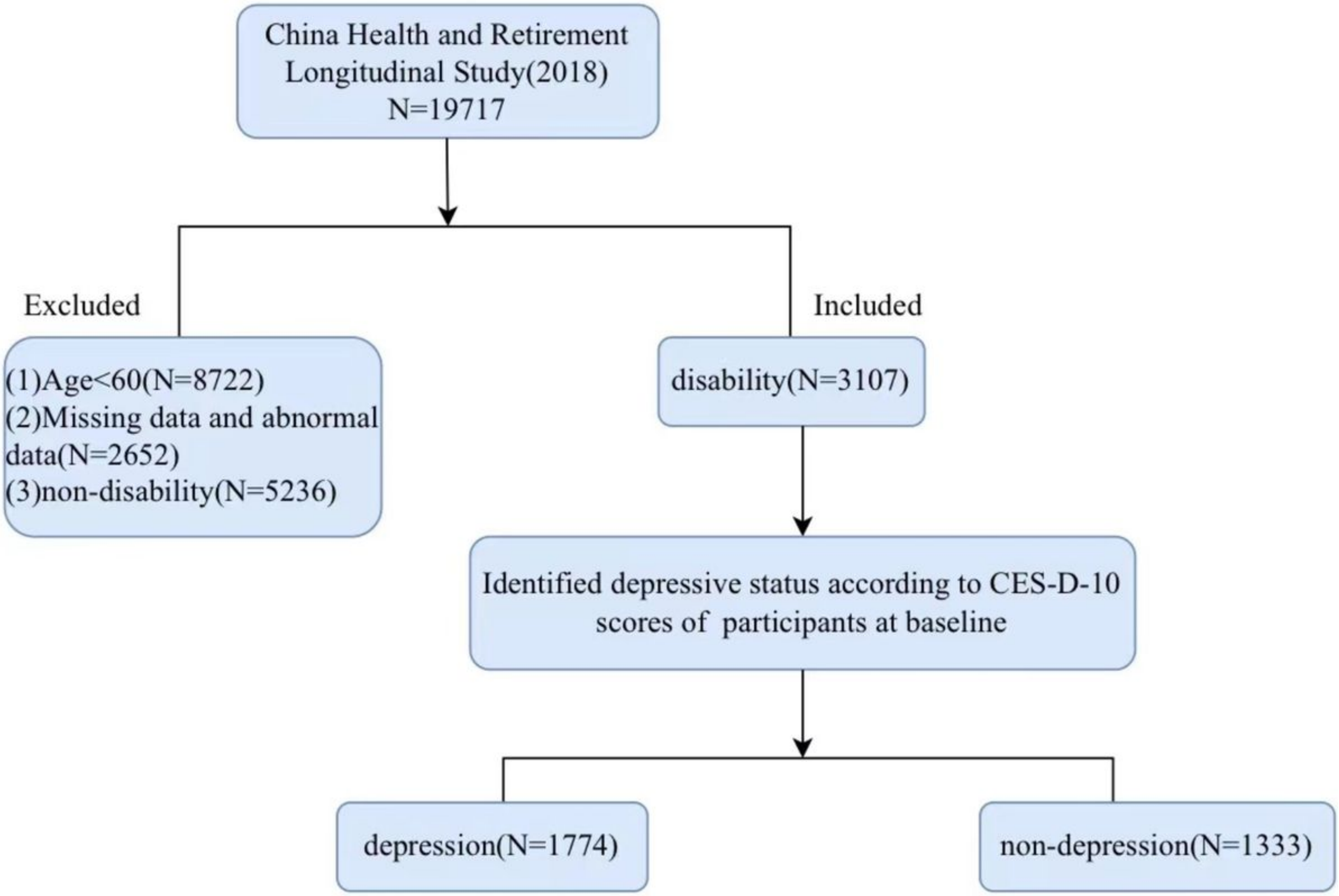
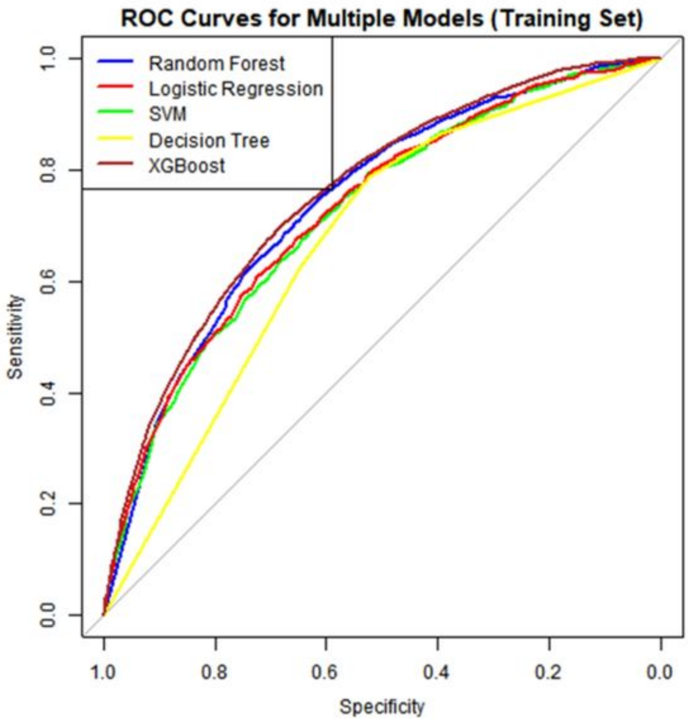


Figure 1

Participant selection flowchart in this study



(B)

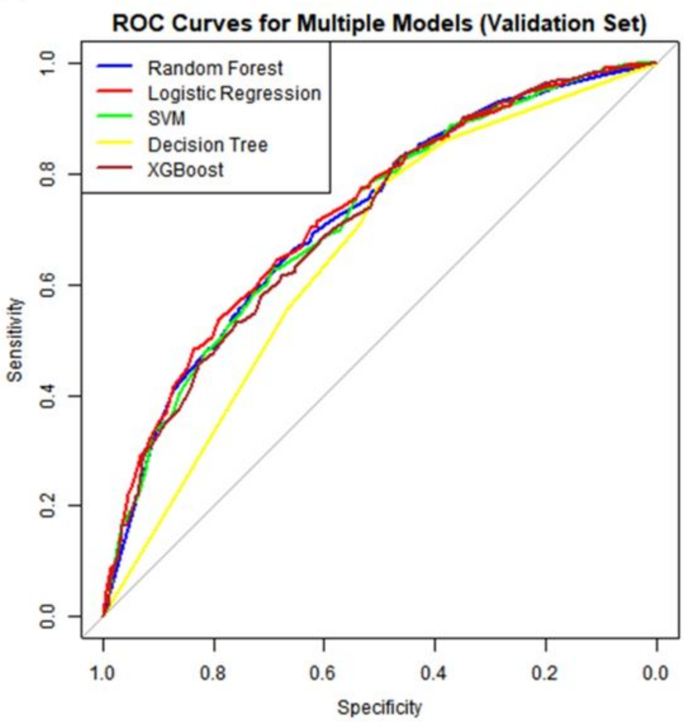
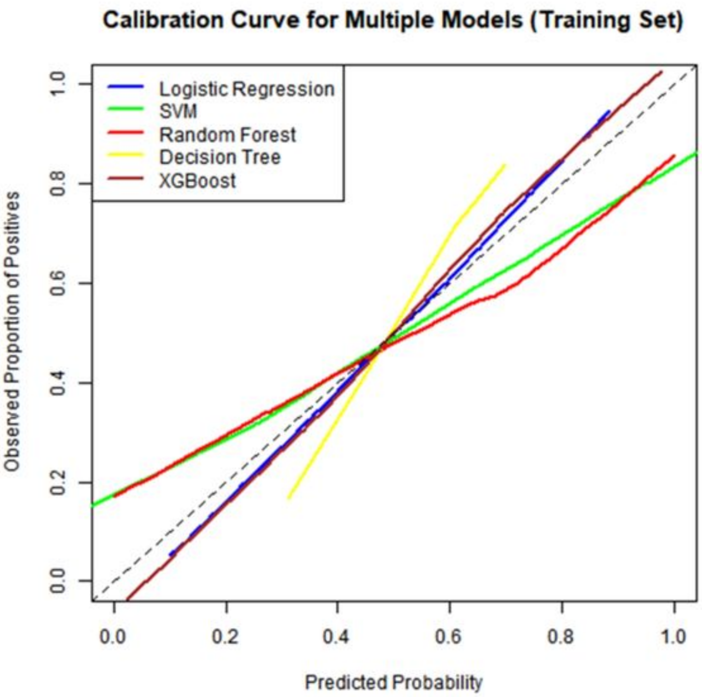


Figure 2

In the context of training set (A) and validation set (B), ROC curves were constructed to illustrate the predictive performance of the top five variables for depression among disabled elderly individuals using five distinct models. The x-axis denotes specificity, defined as the probability of a negative detection when depression is absent in disabled elderly individuals, while the y-axis represents sensitivity, indicating the probability of a positive detection when depression is present in disabled elderly individuals.



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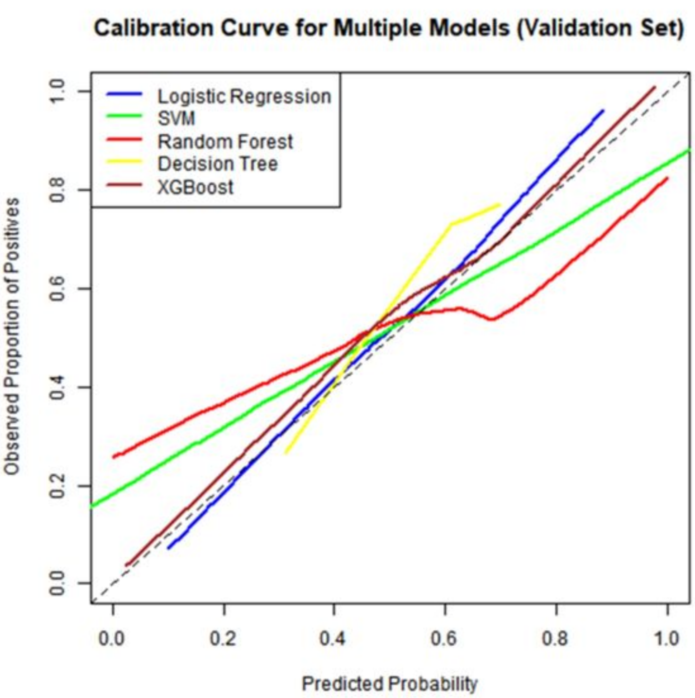
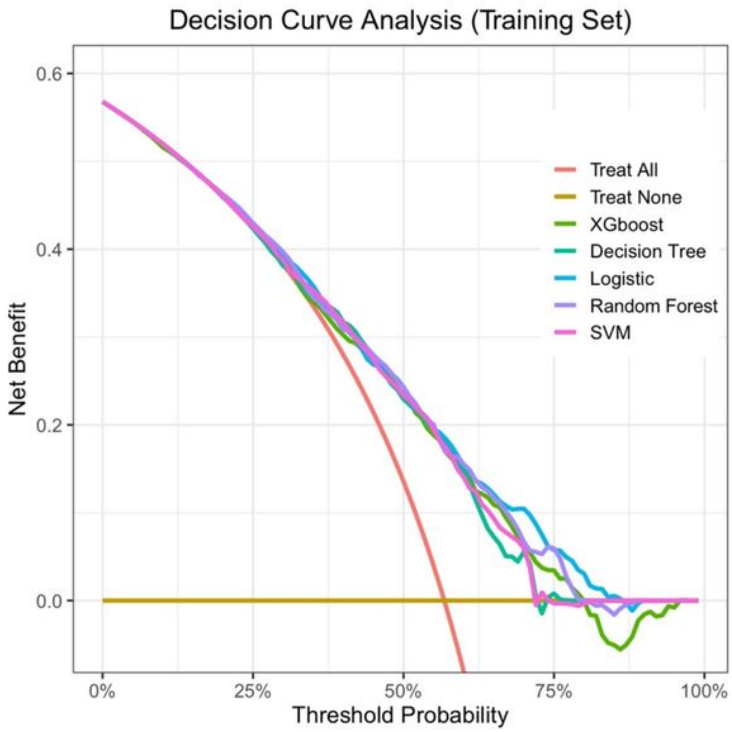


Figure 3

The figure below depicts the calibration curves for the training set (A) and validation set (B).



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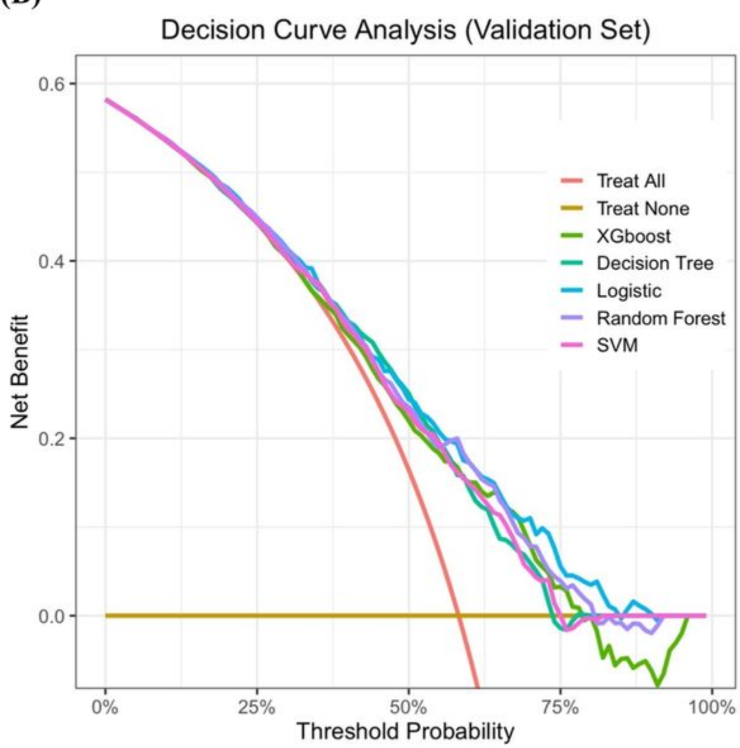

Figure 4

The following figure illustrates the decision curve analysis of five predictive models for depression in disabled elderly individuals within the training set(A) and validation set (B). The x-axis represents the threshold probability for depression, while the y-axis denotes the net benefit.

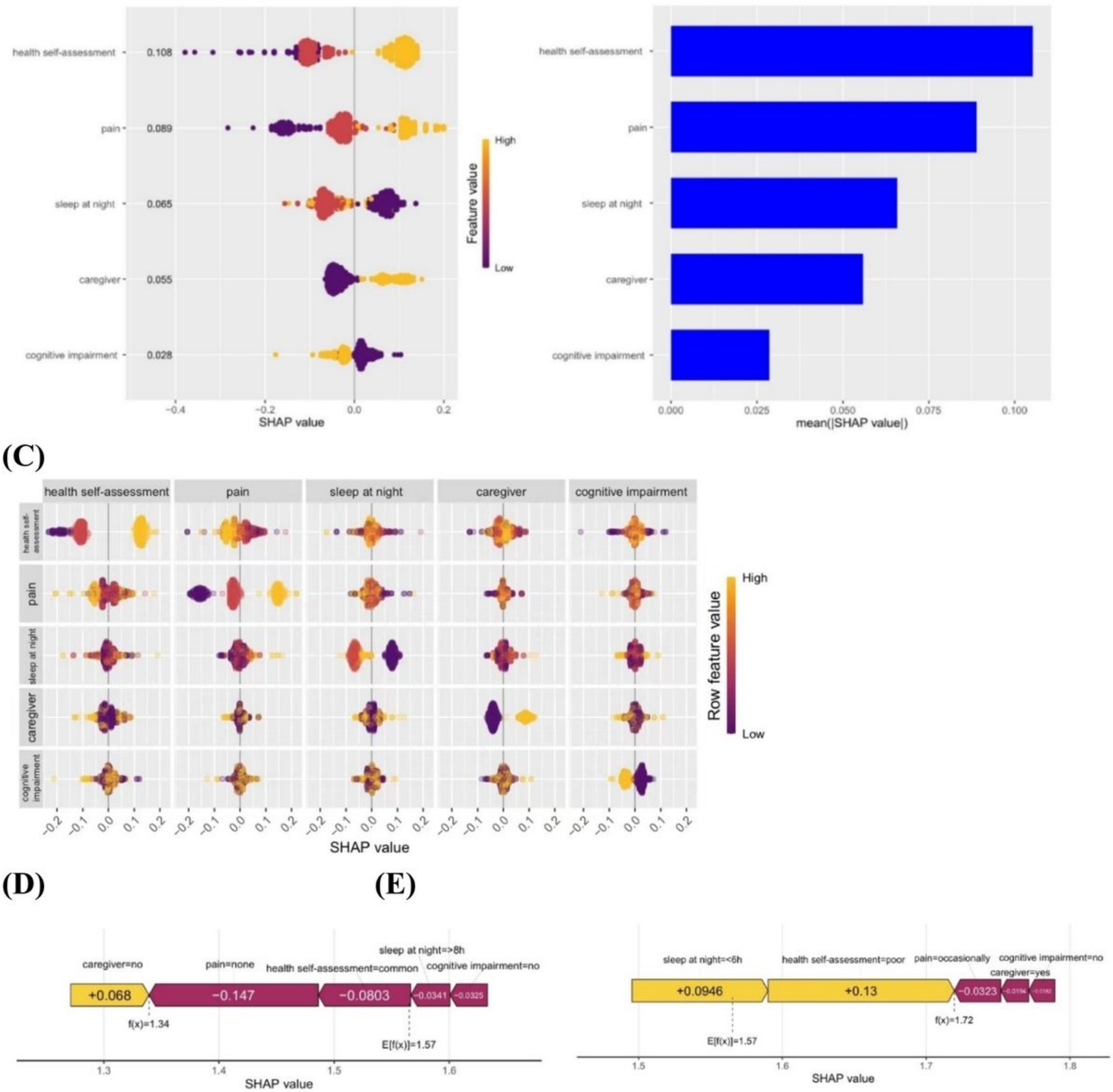

Figure 5

SHAP summary plot for the identified independent risk factors contributing to the XGBoost model. (**A**) In the figure, different colors represent levels of variable values—yellow indicates higher levels, while purple indicates lower levels. The thickness of the line, which is composed of individual dots, corresponds to the number of samples at a given value. The x-axis represents the influence of the variable on the outcome, where a positive SHAP value indicates an increase in risk, and a negative SHAP value indicates a decrease in risk. (**B**) SHAP feature importance is measured as the mean absolute Shapley values. This matrix chart illustrates the importance of independent risk factors in the development of the XGBoost model. (**C**)SHAP provides feature interaction plots to identify features suitable for combinations. Features highlighted in yellow and purple in the plot indicate that constructing cross-features can effectively enhance the model's performance. **(D)** SHAP prediction without depression. **(E)** SHAP prediction with depression. Yellow arrows indicate a higher risk of depression, while purple arrows indicate a lower risk of depression. The length of the arrows helps visualize the degree of influence of the features, so the longer the arrow, the more important the feature is to the outcome.

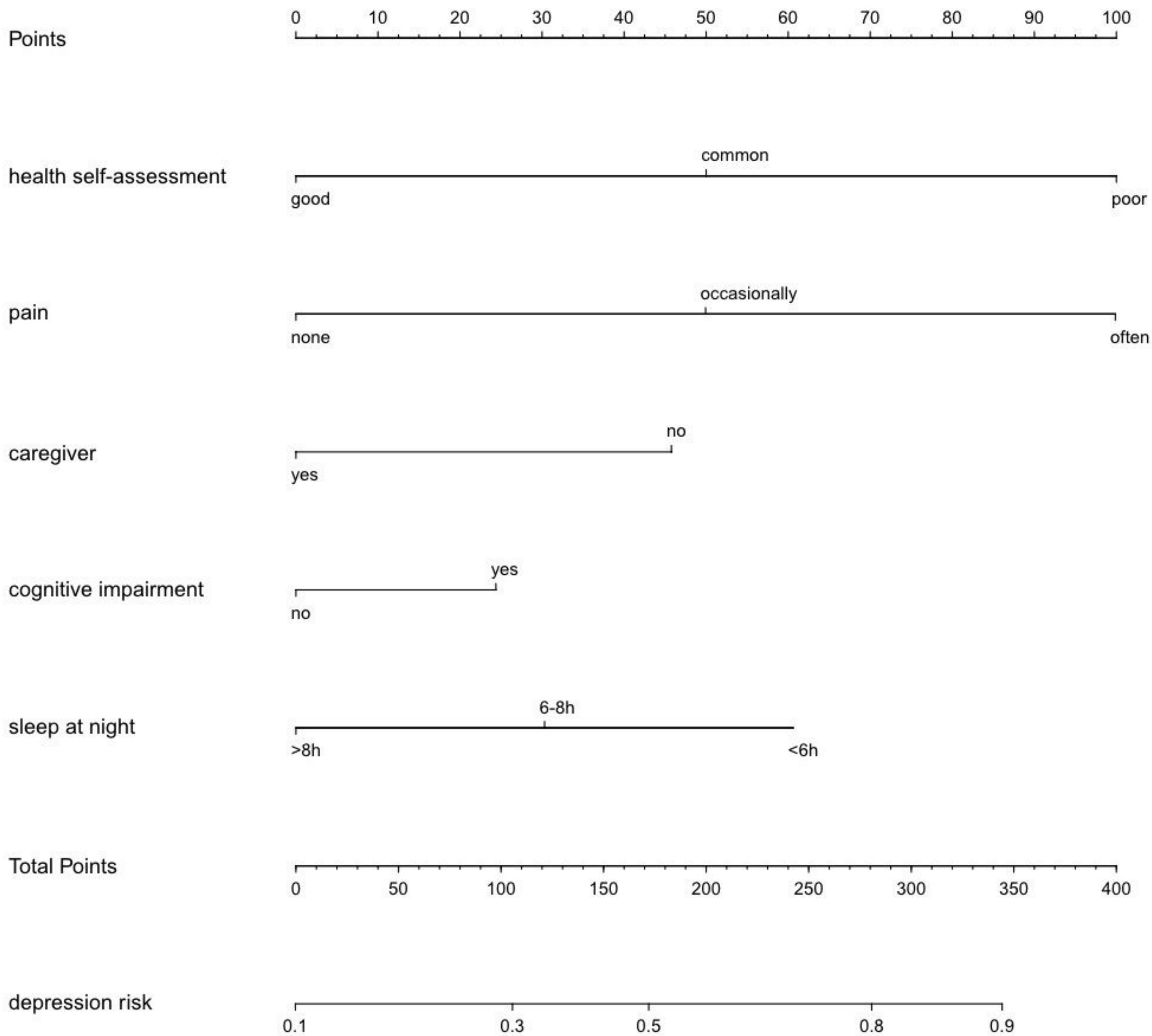

Figure 6

A nomogram was developed within the training dataset, incorporating health self-assessment, pain, caregiver, cognitive impairment, and sleep at night.