Development and validation of a risk prediction model for social isolation in older adults

Ya-Qin Li
School of Nursing, Jinan University
Ying-Yin Long
School of Nursing, Jinan University
YuTing Huang
School of Nursing, Jinan University
Yu Wang
hulibuwangyu@126.com

First Affiliated Hospital of Jinan University

Research Article

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Abstract

Background: Older people are at high risk of social isolation (SI), which can have adverse effects on their health. The extent of SI amongst older people has emerged as a major concern for health and social policy. The objective of this study was to develop a risk prediction model for SI in older adults.

Methods:A total of 4817 participants aged 60 and over were selected from the 2018 wave of the Chinese Longitudinal Healthy Longevity Survey (CLHLS). Participants were randomly assigned to the training set and the validation set at a ratio of 70 to 30%. LASSO regression analysis was used to screen the predictors. Then, identified predictors were included in multivariate logistic regression analysis and used to construct model nomogram. The performance of the model was evaluated by area under the receiver operating characteristic (ROC) curve (AUC), calibration curves and decision curve analysis (DCA).

Results: Out of 4817 participants, 1175 were in a state of SI. Multivariate logistic regression analysis showed that gender, age, living arrangements, ADL, cognitive function, exercise, medical insurance, community services, intergenerational economic support and homeownership were predictors of SI in older adults. Using these factors, a nomogram model was constructed. The AUC values for the training and validation sets of the predictive model were 0.861 (95% CI= 0.846-0.875) and 0.864 (95% CI= 0.843-0.886), respectively. Calibration curves demonstrated that the predicted values of the nomogram were in good agreement with the observed data. DCA showed that the model had good clinical validity.

Conclusion: The nomogram constructed in this study is a useful tool for evaluating the SI risk of elderly individuals, which can help community healthcare workers identify high-risk individuals. The variables used in the model are easy to obtain, and the performance of the model is good, making it easy to use and promote in the community.

1 Background

According to data from China's seventh national census, people aged 60 and over account for 18.70% of the total population, approximately 264 million people. By 2050, this proportion is expected to increase to 26.9%[1]. Therefore, the elderly are a high-risk group for social isolation. Social isolation (SI) was first proposed by Berkman[2], who defined it as the irreversible loss of social attachment and community relationships, and is a key aspect of the aging process of older adults. Currently, Most of the current literature defines social isolation as a state in which individuals have less contact with the outside world, lack of social belonging and social satisfaction, and decline in relationship quality.

From an international perspective, the prevalence of SI among the elderly in the United States, the Japan, and South Korea stands at 24%[3], 25%[4], and 17.8%[5], respectively. However, in some developing countries, the proportion of elderly individuals living in SI is even higher, reaching 49.8% in Malaysia[6]. Qiao Wu et al.[7] included 20 studies for meta-analysis and found that the incidence of SI among the elderly in China was 27.54%. Numerous studies have shown that SI adversely affects health, leading to an increased risk of falls[8], cardiovascular diseases[9], and dementia[10]. Moreover, previous studies have shown that SI is an independent predictor of death, with a risk equal to or greater than traditional risk factors such as alcohol consumption, smoking and obesity[11]. In conclusion, SI has emerged as a major global public health issue, posing a significant threat to the lifelong health of elderly people.

In 2002, the World Health Organisation's (WHO) “Active Ageing Initiative” highlighted the importance of reducing SI[12] and identified it as one of the four key areas for action in the “Healthy Ageing Decade Strategy (2021–2030)”[13]. However, SI often goes undetected because it is not routinely assessed in primary care, and there is currently no research on predictive models of SI in older people. The aim of this study is to identify and incorporate factors related to SI and to construct a nomogram based on a model for predicting SI in the elderly.

2 Methods

2.1 Study participants

The data in the present study was derived from the seventh wave of the Chinese Longitudinal Health Longevity Survey (CLHLS) in 2018[14]. CLHLS is a nationally representative survey that includes samples of elderly people from 22 provinces in China. The ethics review was approved by the Ethics Committee of Peking University (approval number: IRB00001052-13074). All the participants gave their written informed consent at his or her enrollment. Inclusion criteria for this study: (1) age ≥ 60 years; (2) Complete SI information. Participants living in nursing homes and those with missing variables were excluded. Finally, 4817 eligible participants were selected to construct the prediction model.

2.2 Assessment of social isolation

The social network index was used to evaluate the SI of the elderly, which included four indicators: marital relationships, intimate relationships, belief and organizational participation[15]. Marital relationships are categorized into two types: married (1 point) and unmarried (0 point). Intimacy is assessed based on the frequency of visits and communications with siblings and children. Frequent visits or communications are assigned a score of 1. Since belief was not measured in CLHLS, this study used social activities for evaluation based on other similar studies in China[16, 17]. There are four social activities including Tai Chi, square dancing, visiting with friends, playing cards or mahjong, and participation in any of them is awarded 1 point. Respondents also scored one point for participating in organized social activities. The total score range for this index is 0–4 points and a score of 0 or 1 is considered to be SI.

2.3 Predictors

2.3.1 Sociodemographic data and economic factors

Sociodemographic factors included age, sex, pre-retirement occupation, residential area, territory and living arrangements. Territory was divided into eastern, central, and western regions according to the China Health Statistics Yearbook. Living arrangements was classified as living alone or living with others. Economic factors included economic sources, living standard, homeownership, economic status and medical burden. The standard of living was evaluated in the CLHLS questionnaire with the question "Does all of your financial support sufficiently pay your daily costs?" The ownership of the house was evaluated by the question "Under whose name was your current house/apartment purchased/self-built/inherited?" Answering self or spouse was defined as having ownership of the house. Economic status was classified as "rich", "fair", and "poor". Medical burden was the participants' total outpatient and inpatient costs in the last year.

2.3.2 Behavioral factors

Behavioral factors included drinking, smoking, exercise and sleep. Currently drinking and smoking were classified as "yes" and "no". Exercise was determined by the question "Do you do exercises regularly at present?". Sleep was categorised into three groups according to the duration of the participants' sleep each day: short sleep (≤ 6 hours), long sleep (≥ 9 hours) and normal sleep (7–8 hours).

2.3.3 Physical health factor

Based on previous research and our expertise[18–20], the factors selected as potential predictors of SI were morbidity, self-rated health, vision, hearing, tooth, dentures, Activity of Daily Living (ADL), cognitive function and depression.

Morbidity was defined as the presence of two or more chronic diseases, based on the sum of self-reported chronic disease numbers. Self-rated health was divided into "good" and "bad". Vision and hearing were divided into "impaired" and "normal". Tooth (excluding dentures) and dentures were divided into "with" and "without" based on the current situation of the respondents. The CLHLS questionnaire includes six ADL activities, such as bathing, dressing, eating, and so on. Any item that cannot be completed independently is defined as "ADL damaged"[21].

Cognitive function was measured by the Chinese version of the Mini-Mental State Examination (MMSE), which included six aspects: orientation, registration, naming, attention and calculation, recall, and language. The MMSE score ranged from 0 to 30, and a higher score indicated better cognitive function. This scale has been used in Chinese population and has good reliability and validity[22].

In this study, the Center for Epidemiologic Studies Depression Scale (CES-D) was used to assess depression, which is applicable to Chinese elderly people[23]. CES-D consists of ten items, and the answer "always", "often", "sometimes", "rarely" and "never" are assigned a score of 1–5 from positive to negative. Calculate the scores for all options, with higher scores indicating higher levels of depression.

2.3.4 Social support factors

Social support factors included pension, endowment insurance, medical insurance, community services, social security, intergenerational economic support and living offspring. Pensions, endowment insurance, medical insurance, social security and intergenerational economic support were all classified as "yes" or "no" according to the respondents' answers. In the CLHLS questionnaire, community services includes 8 items such as home visits, daily shopping, and social and recreation activities, and so on. If any item is provided by the community, it is classified as "Yes".

2.4 Statistical analysis

Statistical analysis was conducted with R software. Two-tailed were used in all tests, and significance level was $P < 0.05$. Categorical variables were presented as frequencies and percentages, while continuous variables were reported as mean ± standard deviation (SD) or median with interquartile range (IQR). Group comparisons were conducted using t-tests, chi-square tests, and nonparametric tests as appropriate. The dataset was randomly split into a training set (n = 3371) and a validation set (n = 1446) in a 7:3 ratio[24].

First, the least absolute shrink age and selection operator (LASSO) regression analysis was conducted on the training dataset to identify predictors of SI[25]. Ten-fold cross-validation was utilized to identify the optimal tuning parameters (λ) for the LASSO regression, and important features were selected. Subsequently, the predictive factors were incorporated into the multivariate logistic regression analysis. Lastly, predictive factors with p-value < 0.05 were used to develop the nomogram.

The area under the receiver operating characteristic (ROC) curve (AUC) was used to assess the prediction accuracy. Calibration curves and the Hosmer-Lemeshow goodness-of-fit test were employed to evaluate the agreement between predicted and observed values in the nomogram. Furthermore, the clinical benefit of predictive nomogram was evaluated by decision curve analysis (DCA).

3 Results

3.1 Participant characteristics

A total of 4,817 older adults participated in the study, and the prevalence of SI was 24.4%(1,175/4,817), with 2,027 (42%) males and 2,790 (58%) females. Table 1 presents the demographic and clinical characteristics of the participants. A comparison of the distribution of variables between the training and the validation sets is provided in Table 2 of the supplementary file, and no significant differences in variables were found between the two groups except for the residential area.

3.2 Selection of variables as predictors and derivation of the prediction model

With LASSO regression, 24 variables were selected. All 24 variables were then analyzed with the logistic regression model (shown in Fig. 1). The variance inflation factor (VIF) test was performed, and VIF values for all variables were < 4. There were 10 variables that remained in the model: gender, living arrangements, ADL, exercise, community services, medical insurance, intergenerational economic support, homeownership, age and cognitive function. Logistic analysis showed that the association between these 10 factors and SI was statistically significant and could be considered as an independent risk factor (Table 3). By combining these independent predictors, a model was built and presented as a nomogram (shown in Fig. 2). Use the appropriate scale of the nomogram to calculate an individual score for each risk factor and subsequently aggregate the scores. By comparing the corresponding percentages at the bottom, the predicted risk of SI in older adults can be determined.

3.3 Evaluation of the prediction model

The AUC of the training set was 0.861 (0.846–0.875), and the AUC of the validation set was 0.864(0.843–0.886) (Fig. 3). These data indicate the nomogram has good discriminative ability, being able to correctly identify SI and non-SI participants. The nomogram was assessed through calibration plots and the Hosmer-Lemeshow goodness-of-fit test. The HL test results show that the model has a good fit to both the training set (χ^2 = 7.534, p = 0.5817) and the validation set (χ^2 = 15.690, p = 0.0736). The calibration curves of the training and validation sets show that the predicted values differ little from the actual values (Fig. 4). The DCA curve shows that this nomogram has good clinical application value (Fig. 5).

4 Discussion

By incorporating important variables such as gender, age, living arrangements, ADL, cognitive function, exercise, medical insurance, community services, intergenerational economic support and homeownership, we established a nomogram model to provide a simple and statistically sound method for predicting SI among the elderly. Using ROC curves, calibration plots, Hosmer-Lemeshow tests, and DCA validation, our model has an excellent ability to distinguish, calibrate and validate predictions of SI in the olderly.

The findings of this study revealed that demographic factors such as age and gender significantly impacted SI among the elderly. The older the respondents, the greater the risk of social isolation, which is consistent with the research findings of Yanwei Lin et al[26]. The reason may be that as individuals age, their social and familial roles shift. Moreover, the elderly usually experience more negative life events, such as bereavement, physical weakness and disability, which have a negative impact on the social participation of the elderly and the harm they cause is difficult to rectify[27]. Elderly women is another group that warrants concern. Pawinee Iamtrakul et al.[28] also support this view. In traditional culture, women usually bear more family affairs and their social networks are more restricted, making them more susceptible to SI. Therefore, when formulating management strategies, it is important to focus on the key transition points in the life process of the elderly, establish their resilience to cope with significant changes in life, and prevent the occurrence of SI rather than treatment. In terms of economy, this study found that elderly people who owned houses had a lower risk of SI, with similar results reported by older Malaysians[6]. The possible reason is that elderly people with houses having fixed residences can reduce relocation, stabilize social networks, and have more opportunities to participate in community activities[29].

Currently, home care is still the most important and common way for the elderly in our country. This study indicated that elderly people living alone had twice the risk of developing SI compared to elderly people living with others, similar to the findings of Jon Barrenetxea et al[30]. According to social relationship theory[31], strong social relationships centered around relatives and friends are the main channels for elderly people to seek help. The elderly living alone spend most of their time in solitude, which may result in a lack of interaction with family and friends, impeding timely access to social support and leading to SI. Therefore, greater attention and family care should be provided to solitary and empty-nest elderly, along with extended services from social work institutions.

The function of the body is often the precondition for individuals to engage in social activities and maintain social networks[32]. This study found that factors such as impaired ADL and decreased cognitive function can increase the risk of SI in the elderly, which is consistent with the results of previous studies[19, 33, 34]. On the one hand, impaired ADL can lead to limited activity ability, reduced external contact, and decreased frequency of social activities in elderly people. On the other hand, elderly people with impaired ADL find it difficult to establish and maintain meaningful interpersonal relationships, thereby increasing their sense of loneliness. In terms of cognitive function, the higher the cognitive function score of elderly people, the less likely they are to be socially isolated. And Yanran Duan et al.[35] followed 9,367 participants and found that lower cognitive was associated with a more pronounced increase in SI over time. The reason may be that cognitive decline can affect the communication ability of elderly people, leading to social communication barriers. And another study has found that people with mild cognitive impairment tend to use avoiding social activities as a coping mechanism[36]. It can be seen that both physical and mental decline will limit the social participation and activities of the elderly, making them more likely to be in a state of SI, which is consistent with social selection theory[37]. Therefore, community health care workers should routinely assess the ADL and cognitive functions of the elderly in the community, conduct regular home follow-up visits for the elderly with abnormal functions, and actively guide them to complete activities of daily living independently.

Exercise as a behavioral factor that is easy to intervene in. This study found a higher correlation between lack of exercise and the risk of SI, which is consistent with previous research findings[38]. Similarly, a 3-year longitudinal study found a significant reduction in future social isolation among older adults who participated in sports[39]. The mechanism by which exercise affect social isolation can be achieved by reducing feelings of loneliness and stress. W Tang Watanasriyakul et al.[40] studied female prairie voles and found that social isolation increased neuroendocrine stress responses, with increased levels of stress-related corticosterone, which was weakened by exercise. This suggests that exercise has translational value for socially isolated individuals. In addition, exercise can increase the release of norepinephrine, dopamine, and serotonin, which can promote individuals to generate positive emotions, and in turn may be related to a reduction in loneliness[41]. In order to enhance the physical fitness of the people, the country has issued the "Healthy China 2030 Plan", which lists national fitness as a priority development action. The community should actively cooperate with this action by guiding elderly people to participate in sports activities, teaching them scientific and reasonable sports skills, and encouraging them to engage in outdoor activities.

Older people with higher social support are less likely to experience SI. Both society and family are important sources of social support for the elderly. In this study, it was found that medical insurance, community services, and intergenerational economic support were protective factors for SI among the elderly. Medical insurance is an important support to resist medical economic risks[42]. When elderly people without medical insurance fall ill, they may encounter greater family medical risks, which will impact the social network based on mutual assistance, leading to their SI. Community services can effectively improve the disease status of the elderly and increase their social participation. For example, the community connector proposed by the UK is a structured support service where community volunteers provide services such as living, medical, and entertainment based on the needs of residents, effectively increasing social interaction among elderly people[43]. Descendants are the main providers of informal social support for the elderly, and can provide necessary help and resources for them. Elderly people with intergenerational economic support will improve their life satisfaction, reduce their burden, and obtain more resources to reduce the risk of social isolation[44]. In view of this, the country and government should truly implement medical insurance policies and expand medical insurance coverage. Community workers should actively build a "society-community-family" linked elderly support network to improve their social support level.

The advantages of this study are mainly reflected in several aspects. Firstly, this study constructed a predictive model using large sample data. Secondly, the variables used to construct the prediction model are simple and can be obtained at any time through consultation, making it highly practical in the community. In addition, as far as we know, this study is the first attempt to establish a risk prediction model for SI in the elderly, which can help community health care workers screen the elderly population to prevent the occurrence of SI at an early stage. However, this study also has some limitations. Firstly, due to data limitations, some key predictive factors such as community functionality[45] have not been included, which may affect predictive performance. Secondly, some variables in CLHLS are evaluated through self-report, which may be influenced by recall bias. In addition, our model is developed and validated based on population data from China and may not be able to be extended to other races.

5 Conclusion

This study established and validated a nomogram model for SI among the elderly. The nomogram model, which incorporates age, gender, living arrangements, ADL, cognitive function, exercise, medical insurance, community service, intergenerational economic support and homeownership, has been subjected to internal validation and has good predictive performance. This nomogram provides a convenient and reliable tool for predicting SI among elderly people in the community.

Abbreviations

CLHLS: Chinese Longitudinal Healthy Longevity Survey

ADL: activities of daily living

MMSE: Mini-Mental State Examination

OR: odds ratio; 95% confidence interval

ROC: Receiver operating characteristic

AUC: Area under the curve

DCA: Decision curve analysis

CI: Confidence interval

Declarations

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Contributions

YQL created the study protocol, performed the statistical analyses and wrote the manuscript draft. YYL and YTH assisted with the study design and performed data collection. YQL and YYL contributed to data interpretation and manuscript revision. YW, as senior author, reviewed and edited all versions of this manuscript. All authors read and approved the final manuscript.

Ethics declarations

Ethics approval and consent to participate

The data were obtained from CLHLS, which was conducted according to the guidelines of the Declaration of Helsinki. The ethics review was approved by the Ethics Committee of Peking University (approval number: IRB00001052-13074). All the participants provided written and informed consent.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

Availability of data and materials

All the data used in our study were obtained from a public database named Peking University Open Research Data. (https://opendata.pku.edu.cn/dataset.xhtml?persistentId=doi:10.18170/DVN/WBO7LK).

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Figures

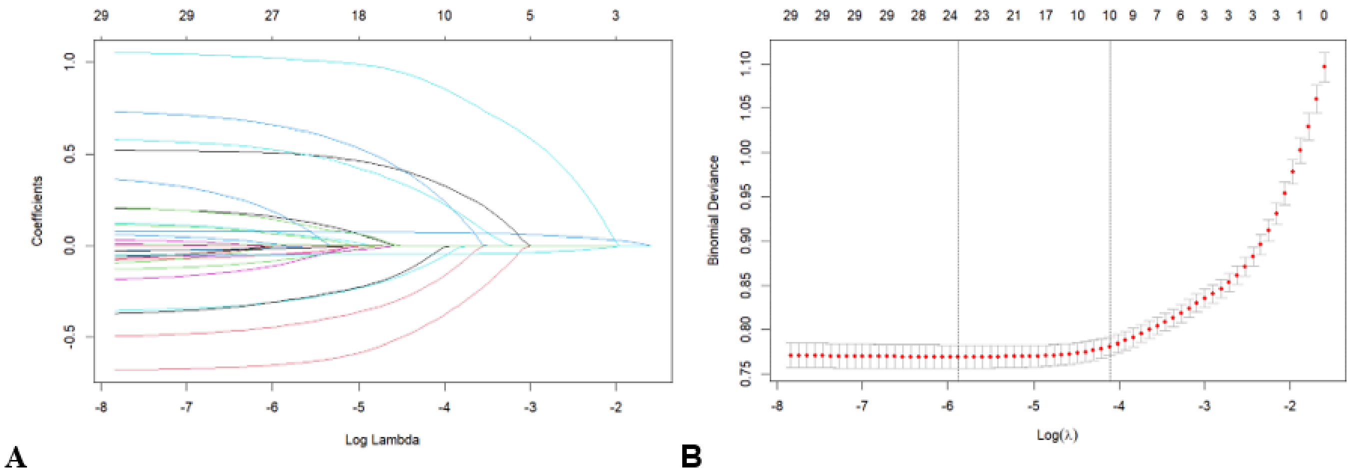

Figure 1

Demographic and clinical feature selection using the LASSO regression model.**A** LASSO coefcients profles (y-axis) of the 29 features. **B** Tenfold cross-validation for tuning parameter selection in the LASSO model

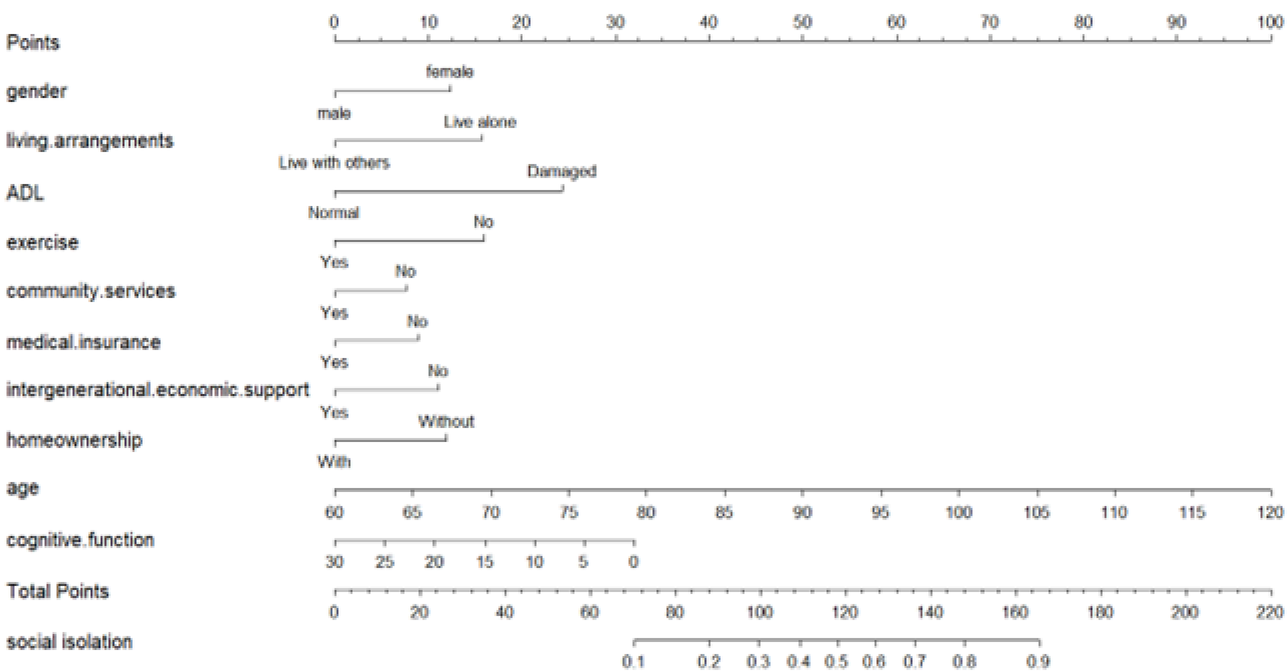

Figure 2

Nomogram

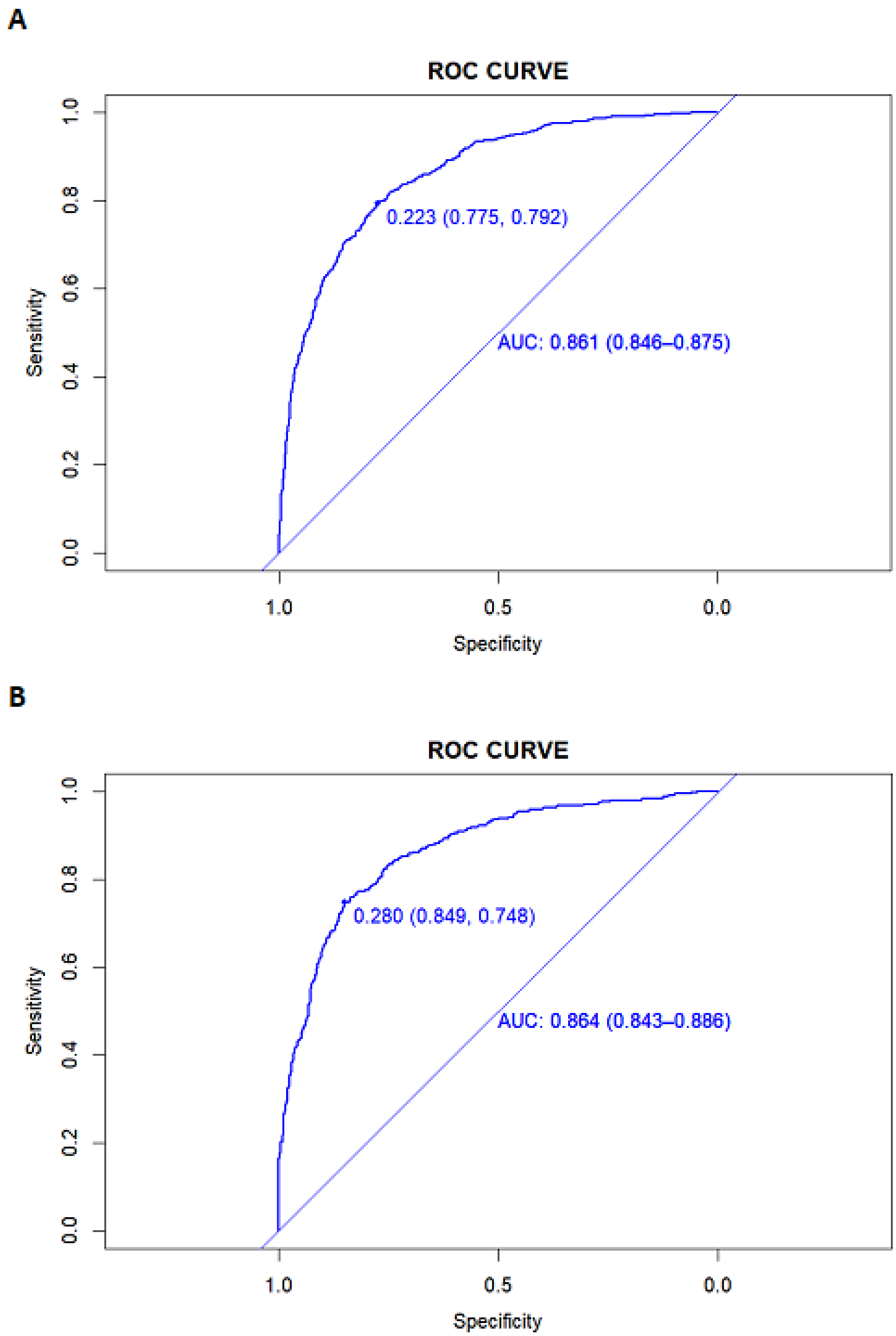

Figure 3

A Nomogram ROC curves generated from the training dataset. B Nomogram ROC curves generated using the validation dataset

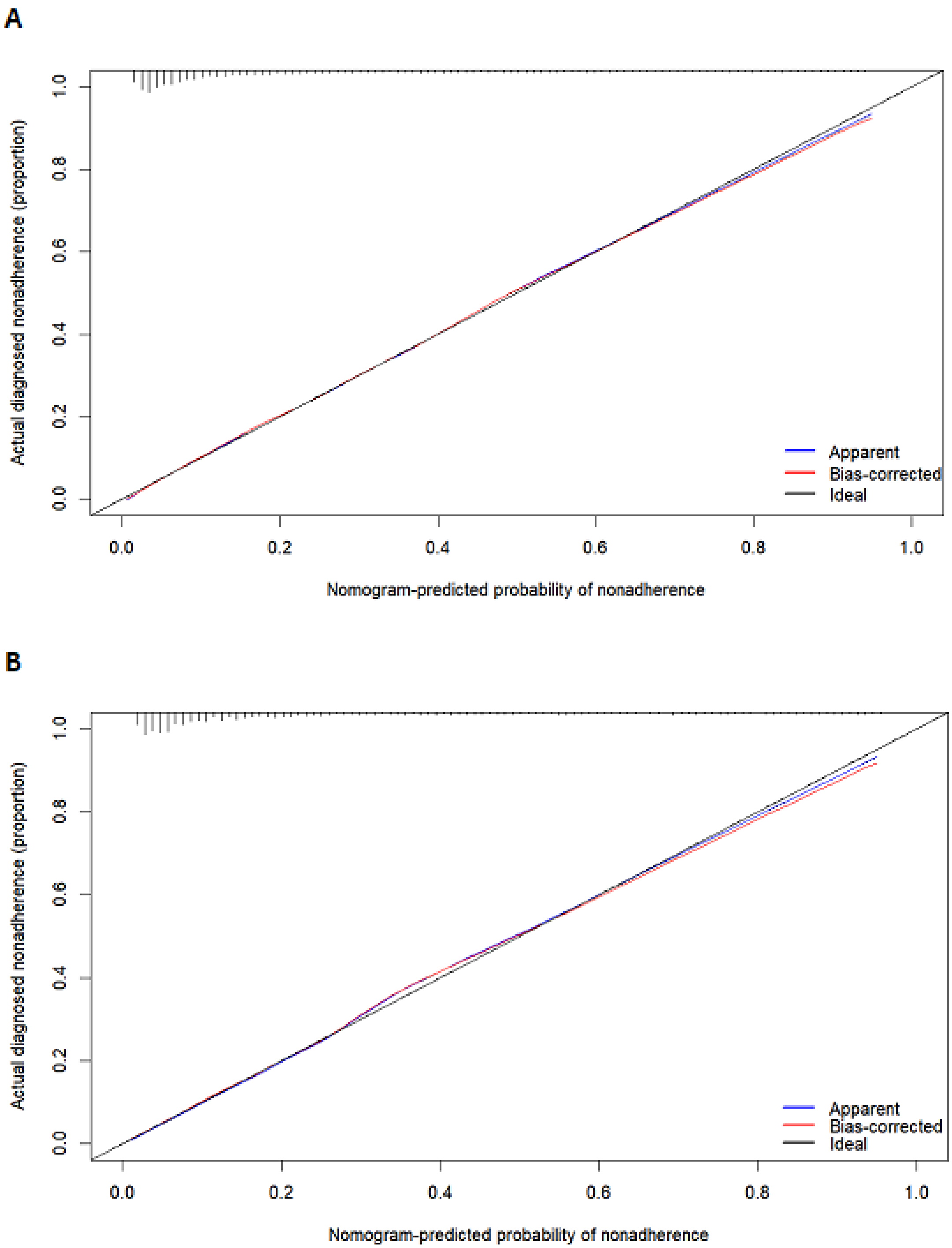

Figure 4

A Calibration plot for the training dataset. B Calibration plot for the validation dataset

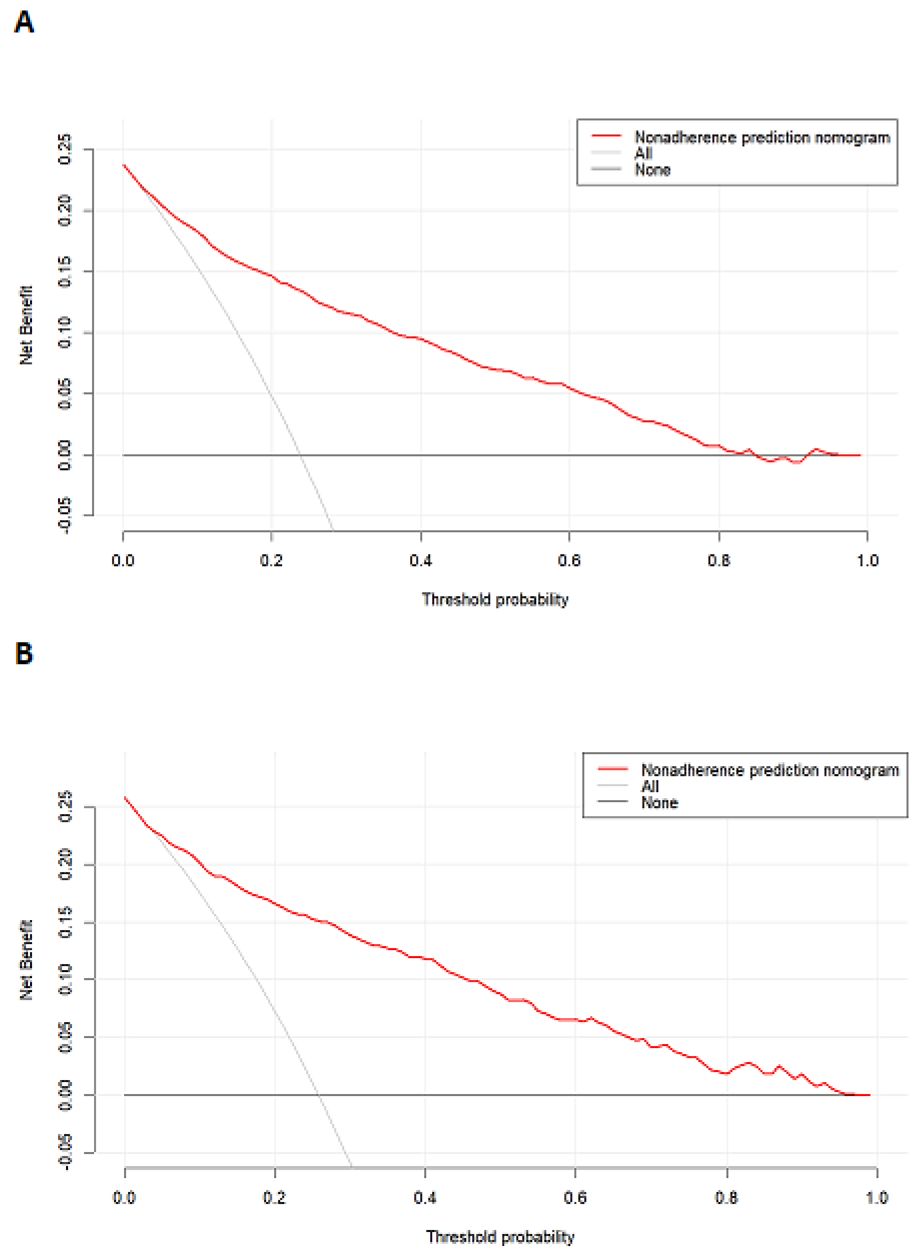

Figure 5

A DCA curves for the training dataset. B DCA curves for the validation dataset

Supplementary Files

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