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ORIGINAL RESEARCH

Development and Validation of a Coronary Heart Disease Risk Prediction Model in Snorers with Hypertension: A Retrospective Observed Study

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Purpose: To develop and validate a risk prediction model for coronary heart disease (CHD) in snorers with hypertension, including traditional and new risk factors.

Patients and Methods: Twenty factors were evaluated in the records of 2810 snorers with hypertension. Training (70%) and validation (30%) sets were created by random allocation of data, and a new nomogram model was developed. The model's discrimination and calibration were measured by calculating the area under the receiver operating curve (AUC) and creating calibration charts. The performance of the nomogram model was compared with that of the Prediction for ASCVD Risk in China (China-PAR) and Framingham models by decision curve analysis. An optimal cutoff point for the risk score in the training set was computed to stratify patients.

Results: In the nomogram model, the AUCs for predicting CHD at 5, 7 and 9 years in the training set were 0.706 (95% confidence interval [CI] 0.649–0.763), 0.703 (95% CI 0.655–0.751) and 0.669 (95% CI 0.593–0.744), respectively. The respective AUCs were 0.682 (95% CI 0.607–0.758), 0.689 (95% CI 0.618–0.760) and 0.664 (95% CI 0.539–0.789) in the validation set. The calibration chart showed that the predicted events from the nomogram score were close to the observed events. Decision curve analysis indicated that the nomogram score was slightly better than the Prediction for ASCVD Risk in China (China-PAR) and Framingham models for predicting the risk of CHD in snorers with hypertension. A cutoff point was identified for being CHD-free (a nomogram score of ≤121), which could be helpful for the early identification of individuals at high-risk of CHD.

Conclusion: The nomogram score predicts the risk probability of CHD in snorers with hypertension at 5, 7 and 9 years, and shows good capability in terms of discrimination and calibration. It may be a useful tool for identifying individuals at high risk of CHD.

Keywords: snorer, hypertension, coronary heart disease, prediction model

Introduction

Snoring is a common disorder with an overall prevalence of 20–40%[1–3] and may be a predictor of obstructive sleep apnea (OSA).[4,5] Several studies have reported the correlation between OSA signs and coronary heart disease (CHD).[6] Current research shows that snoring can increase the intima–media thickness of the carotid arteries,[7] and the risk of carotid stenosis,[8] cardiovascular disease (CVD)[9] and CHD.[10] A large Chinese population-based cohort study estimated an 18% increased risk of ischemic heart disease among habitual snorers aged younger than 50 years.[11] A meta-analysis of prospective studies found that snoring was associated with CVD (hazard ratio [HR] 1.26; 95% confidence interval [CI] 0.98–1.62) and CHD (HR 1.15; 95%

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CI 1.05–1.27).[12] The mechanism involved might include vibratory stimuli, an inflammatory cascade, OSA and atherosclerosis.

A positive relationship between snoring and hypertension has been shown in several studies,[13,14] especially in men,[15,16] which may elevate the risk of CVD, with CHD as one of its manifestations. The association may result from intermittent hypoxia-induced sympathetic activation, oxidative stress and endothelial dysfunction.[17] Hypertension is a recognized risk factor for CHD and CVD,[18,19] and is a serious clinical and public health problem. The most important cornerstone of CHD prevention is to identify high-risk individuals and intervene as early as possible.

Various countries have population-based screening models for CHD or CVD.[20–24] Framingham is a classic model for predicting the incidence of CHD; it can effectively predict individuals at high risk and has been widely used and validated in clinical practice.[25] However, pre-existing models developed for the general population might not be suitable for snorers with hypertension, since they do not account for specific characteristics, such as suffocation, sleep apnea, hypopnea.

Accordingly, we aimed to develop and internally validate a new risk prediction model for CHD in snorers with hypertension, which included clinical data and polysomnography results. We also aimed to create a nomogram score to identify snorers with hypertension at high risk of CHD.

Materials and Methods

Study Design and Participants

We conducted a retrospective cohort study from January 2011 to December 2013 using a database of patients with suspected OSA and hypertension. Inclusion criteria for participants were as follows: no CHD at baseline; self-reported snoring or family members' complaints of snoring; and availability of specific polysomnography monitoring data (including apnea-hypopnea index [AHI] and minimum oxygen saturation [minimum SaO_2]). The follow-up time was from enrollment (January 2011) to the date of the following events: the diagnosis of the endpoint event (CHD) confirmed by medical documentation or the end date of the study (December 2020). The health status or clinical outcomes of registered patients were confirmed by outpatient visits, inpatient medical records, or telephone calls with patients.

Ethical Approval

The research was authorized by the Medical Ethics Committee of the People's Hospital of Xinjiang Uygur Autonomous Region (No. 2019030662) and was conducted in strict compliance with the ethical standards set forth in the Declaration of Helsinki and its subsequent amendments. Written informed consent was submitted by all patients or their legal relatives participating in this study.[26]

Outcomes

The outcome was CHD that occurred during follow-up, including hospitalized angina, myocardial infarction, coronary revascularization and coronary death.[27]

Data Collection

We screened data for the following conventional risk factors for CVD: sex, age, smoking status, diabetes, body mass index (BMI), systolic blood pressure(SBP), diastolic blood pressure(DBP), serum creatinine (Scr), total cholesterol (TC), triglycerides, high-density lipoprotein (HDL), low-density lipoprotein (LDL), high-sensitivity C-reactive protein (hsCRP), and fasting plasma glucose (FPG). We also incorporated other widely available variables, such as neck circumference (NC), waist circumference (WC), AHI, minimum SaO_2 and kinds of antihypertensive drugs at discharge.

Smoking status was divided into non-smokers (including individuals who had not smoked for at least 1 year) and smokers. BMI was calculated by dividing body weight (kg) by the square of height (m). Glomerular filtration rate (GFR; mL/min/1.73 m^2) was estimated by the MDRD study equation, $eGFR = 186 \times (Scr/88.4)^{-1.154} \times age^{-0.203} \times (0.742\ female)$. AHI indicates the number of apneas plus the number of hypopneas per hour.

Development and Validation Study

The training and validation sets were created by randomly splitting the total data (70:30). Model development was accomplished in the training set and model validation was realized in the validation set.

Statistical Analyses

Descriptive statistics were performed on all variables, with continuous variables expressed as median (interquartile range), and categorical variables expressed as relative frequencies and percentages. Non-parametric tests were computed for continuous variables and chi-square tests for categorical variables. Univariate and multivariate Cox regression analysis was used to identify the HRs of the candidate factors associated with the incidence of CHD.

We performed multiple imputation to replace missing values using information from the other candidate factors and created five datasets. We converted negative values to the smallest extreme value.

LASSO (least absolute shrinkage and selector operator) regression was used to extract for potential predictors of CHD in the training set. LASSO regression involves variable selection and regularization to improve the predictive accuracy and interpretability of the statistical model it generates. It can also reduce model complexity and avoid overfitting of the prediction model.[28] In the training set, we used multivariate Cox regression to develop a new prognostic model of CHD for snorers with hypertension, displayed using a nomogram score.

The discrimination of the model was evaluated by the area under the receiver operating curve (AUC) with 95% CI at 5, 7 and 9 years in the training and validation sets. A value of AUC less than 0.5 indicates no prediction capability, 0.6–0.75 suggests that the prediction model can help distinguish CHD from non-CHD and an AUC ≥0.75 suggests a good degree of discrimination.[29] The nomogram score was evaluated by resampling it 1000 times using the regression coefficients of the selected independent variables. The calibration of the model was assessed by the consistency at 5, 7 and 9 years between the observed CHD-free and nomogram score predicted CHD-free probabilities. A well-calibrated model shows predictions lying on or around the 45-degree line of the calibration plot.

We used decision curve analysis to compare the CHD predictive value of the nomogram score, China-PAR and Framingham models in snorers with hypertension at median follow-up time. We also calculated the AUC, sensitivity, specificity, integrated discrimination improvement index (IDI) and net reclassification improvement index (NRI). IDI and NRI are measures of the predictive capability of the new model versus the old model.[30]

Risk Groups

The nomogram score was used to obtain individual total risk scores. An optimal cutoff point for the risk score in the training set, which was derived using the Youden index, was computed to stratify patients into low-risk or high-risk groups. Tests were two-sided and $p<0.05$ was considered statistically significant. Statistical analyses were performed using IBM SPSS version 22.0 (IBM Corp., Armonk, NY, USA) or R version 4.0.5 (The R Project for Statistical Computing, Vienna, Austria). This article was prepared in accordance with the TRIPOD reporting checklist and the methods were assessed with PROBAST.[31,32]

Results

Baseline Characteristics of Participants

A total of 2810 snorers with hypertension aged ≥18 years without CHD were finally included in our study. We randomly assigned 1967 individuals (70%) to the training set and the remaining 843 (30%) to the validation set. Information was missing in the research cohort about NC (8.3%), WC (0.2%), Scr (1.1%), TC (2.3%), triglycerides (2.3%), HDL (2.3%), LDL (2.3%), hsCRP (3.2%) and FPG (3.4%). We used multiple imputation to replace missing values. There was no significant difference in baseline characteristics between the training and validation sets (Table 1). The median follow-up time of the two groups was 7 years (6.82 ± 0.04 years). During the follow-up period, 227 patients had CHD, including 152 in the training set and 75 in the validation set. Table 1 shows the baseline characteristics between the subgroups with and without CHD in the training and validation sets.

Table 1 Characteristics of Snorers with Hypertension in the Training and Validation Set

Variables	Training Set				Validation Set				
	Overall (n=1967)	With CHD (152)	Without CHD (1815)	*P* value*	Overall (n=843)	With CHD (n=75)	Without CHD (768)	*P* value*	*P* value
Gender				0.005				0.416	0.761
Female n (%)	672(34.2)	36(23.7)	636(35.0)		283(33.6)	22(29.3)	261(34.0)		
Male n (%)	1295(65.8)	116(76.3)	1179(65.0)		560(66.4)	53(70.7)	507(66.0)		
Age (years)	47(41–53)	48(43–58)	47(40–53)	0.001	46(40–54)	51(42–58)	46(40–52)	0.001	0.278
Urban n (%)	1618(82.3)	120(78.9)	1498(82.5)	0.269	673(79.8)	60(80.0)	613(79.8)	1.000	0.137
Family history of ASCVD n (%)	121(6.2)	7(4.6)	114(6.3)	0.486	46(5.5)	7(9.3)	39(5.1)	0.175	0.542
Duration of Hypertension (years)	3(1–7)	4(1–8)	3(1–7)	0.071	3(1–7)	4(1–10)	3(1–7)	0.188	0.412
Smoking n (%)	622(31.6)	68(44.7)	554(30.5)	0.000	246(29.2)	23(30.7)	223(29.0)	0.767	0.199
Body mass index (kg/m²)	27.55(25.34–30.12)	28.56(26.30–31.02)	27.47(25.26–30.11)	0.002	27.47(25.47–29.74)	28.30(26.45–31.62)	27.44(25.39–29.69)	0.010	0.468
Neck circumference(cm)	40(37–43)	41(39–43)	40(37–43)	0.000	40(37–42)	41(39–43)	40(37–42)	0.004	0.543
Waist circumference(cm)	99(92–106)	104(97–109)	98(92–105)	0.000	99(93–105)	103(97–109)	98(92–105)	0.000	0.631
SBP(mmHg)	140(130–150)	140(130–158)	140(130–150)	0.015	140(130–150)	140(130–150)	140(130–150)	0.918	0.834
DBP(mmHg)	90(80–100)	90(80–100)	90(80–100)	0.837	90(80–100)	90(80–97.5)	90(80–100)	0.175	0.494
Diabetes n (%)	281(14.3)	41(27.0)	240(13.2)	0.000	114(13.5)	10(13.3)	104(13.5)	0.960	0.594
Laboratory examinations									
eGFR(mL/min/1.73 m2)	96.35(83.84–110.63)	97.20(81.16–115.13)	96.27(83.95–110.55)	0.980	95.01(84.31–109.27)	87.64(73.53–97.47)	95.84(84.82–109.93)	0.000	0.266
TC(mmol/L)	4.44(3.85–5.06)	4.56(4.00–5.31)	4.44(3.84–5.04)	0.057	4.49(3.89–5.06)	4.50(3.76–5.14)	4.49(3.92–5.05)	0.883	0.310
TG(mmol/L)	1.68(1.20–2.39)	1.87(1.31–2.57)	1.66(1.19–2.37)	0.054	1.69(1.22–2.45)	1.81(1.22–2.63)	1.69(1.22–2.43)	0.698	0.475
HDL(mmol/L)	1.07(0.91–1.28)	1.03(0.89–1.21)	1.07(0.92–1.28)	0.053	1.07(0.92–1.27)	1.05(0.86–1.26)	1.08(0.93–1.28)	0.238	0.805
LDL(mmol/L)	2.58(2.08–3.11)	2.76(2.28–3.26)	2.55(2.08–3.10)	0.004	2.61(2.14–3.09)	2.68(2.14–3.11)	2.61(2.14–3.09)	0.878	0.421
hsCRP(mg/L)	2.03(0.88–3.77)	2.68(1.00–4.67)	1.99(0.88–3.74)	0.047	2.00(0.84–3.82)	1.71(0.75–3.82)	2.05(0.85–3.81)	0.348	0.599
FPG(mmol/L)	4.39(3.97–5.05)	4.62(4.04–5.52)	4.38(3.97–5.03)	0.007	4.37(3.92–4.99)	4.37(3.97–5.01)	4.37(3.92–4.99)	0.815	0.265
Polysomnography examinations									
AHI	12.7(5.3–27.9)	18.8(8.0–32.2)	12.4(5.1–27.0)	0.000	12.3(4.9–26.3)	15.2(5.90–30.8)	11.8(4.6–26.2)	0.118	0.385
Minimum SaO2 (%)	82(77–86)	80(74–85)	82(77–87)	0.000	83(77–87)	81(75–86)	83(77–87)	0.099	0.659
Treatment									
Type of antihypertensive drugs	2(1–2)	2(1–2)	2(1–2)	0.001	2(1–2)	2(1–2)	2(1–2)	0.039	0.083
Follow-up time	7(6–8)	5(3–6)	7(6–8)	0.000	7(6–8)	6(3–7)	7(6–8)	0.000	0.909

Notes: Continuous data are presented as median (quartile); categorical variables are presented as n (%). *p value for difference between the subgroups with and without CHD. p value for training set versus validation set for overall characteristics.

Abbreviations: SBP, Systolic blood pressure; DBP, Diastolic blood pressure; GFR, Glomerular filtration rate; TC, Total cholesterol; TG, Triglyceride; HDL, High density lipoprotein cholesterol; LDL, Low density lipoprotein cholesterol; hsCRP, High sensitivity C-reactive protein; FPG, Fasting plasma glucose; AHI, Apnea hypopnea index; Minimum SaO2, Minimum oxygen saturation.

Cox Regression and LASSO Regression to Extract Predictors

Twenty variables were filtered by the Cox regression and LASSO regression method (Table 2). In univariate analysis, sex, age, duration of hypertension, smoking, BMI, NC, WC, SBP, diabetes, TC, HDL, LDL, FPG, AHI, minimum SaO_2 and kinds of antihypertensive drugs at discharge were associated with the occurrence of CHD. However, after multivariate analysis, only age, smoking, WC, diabetes, LDL and minimum SaO_2 remained independently associated with the occurrence of CHD. LASSO regression reduced 20 variables to five potential predictors. Next, a coefficient distribution diagram was generated, as shown in Figure 1A. The cross-validation error diagram is shown in Figure 1B, which indicates the path of the coefficients included in the model with varying logarithmic transformation λ values. The model included five independent predictors: age, smoking, WC, diabetes and minimum SaO_2 (Supplementary Table 1). Among them, age was the strongest predictor of CHD ($p<0.0001$), followed by smoking, WC, and diabetes, while minimum SaO_2 was the least predictive.

Development of a CHD Nomogram Score

A nomogram score was generated by assigning a weighted score to each of the final five independent predictors of CHD (age, smoking, WC, diabetes and minimum SaO_2). This presentation format is a graphical presentation of the original mathematical regression formula. For the variable selected in the nomogram score, the value of the variable corresponds to the fraction on the integral line at the top of the nomogram score through the projection of the vertical line. The total

Table 2 Cox Regression and Lasso Regression of Candidate Factors of CHD in Patients in the Training Set (n = 1967)

Variables	Cox Analysis				LASSO Regression Analysis
	Univariable Cox Analysis		Multivariate Cox Analysis		
	HR (95% CI)	*P* value	HR (95% CI)	*P* value	Lambda 0.0194= log-3.9425
Gender					0
Female	Ref	Ref	NS	NS	0
Male	1.626(1.119–2.364)	0.011	NS	NS	0
Age	1.032(1.017–1.048)	0.000	1.032(1.015–1.048)	0.000	0.00603487318401362
Duration of Hypertension	1.028(1.006–1.051)	0.013	NS	NS	0
Smoking					0
No	Ref	Ref	Ref	Ref	−0.0501883199567381
Yes	1.749(1.270–2.408)	0.001	1.867(1.342–2.597)	0.000	0
Body mass index	1.069(1.031–1.108)	0.000	NS	NS	0
Neck circumference	1.065(1.027–1.106)	0.001	NS	NS	0
Waist circumference	1.038(1.024–1.052)	0.000	1.025(1.010–1.040)	0.001	0.0135261261383105
SBP	1.011(1.003–1.019)	0.005	NS	NS	0
DBP	1.003(0.992–1.015)	0.597	NS	NS	0
Diabetes					0
No	Ref	Ref	Ref	Ref	−0.24612049747424
Yes	2.384(1.666–3.411)	0.000	1.827(1.256–2.656)	0.002	4.65902586212501e-16
eGFR	1.001(0.994–1.009)	0.718	NS	NS	0
TC	1.120(1.002–1.252)	0.047	NS	NS	0
TG	1.019(0.932–1.114)	0.685	NS	NS	0
HDL	0.544(0.304–0.975)	0.041	NS	NS	0
LDL	1.359(1.114–1.657)	0.002	1.300(1.069–1.580)	0.009	0
hsCRP	1.021(0.999–1.043)	0.057	NS	NS	0
FPG	1.114(1.028–1.208)	0.009	NS	NS	0
AHI	1.013(1.006–1.020)	0.000	NS	NS	0
Minimum SaO2	0.968(0.954–0.982)	0.000	0.984(0.968–1.000)	0.046	−0.0052061604516431 2
Type of antihypertensive drugs	1.282(1.087–1.512)	0.003	NS	NS	0

Abbreviations: CI, confidence interval; SBP, Systolic blood pressure; DBP, Diastolic blood pressure; GFR, Glomerular filtration rate; TC, Total cholesterol; TG, Triglyceride; HDL, High density lipoprotein cholesterol; LDL, Low density lipoprotein cholesterol; hsCRP, High sensitivity C-reactive protein; FPG, Fasting plasma glucose; AHI, Apnea hypopnea index; Minimum SaO2, Minimum oxygen saturation; NS, nonsignificant.

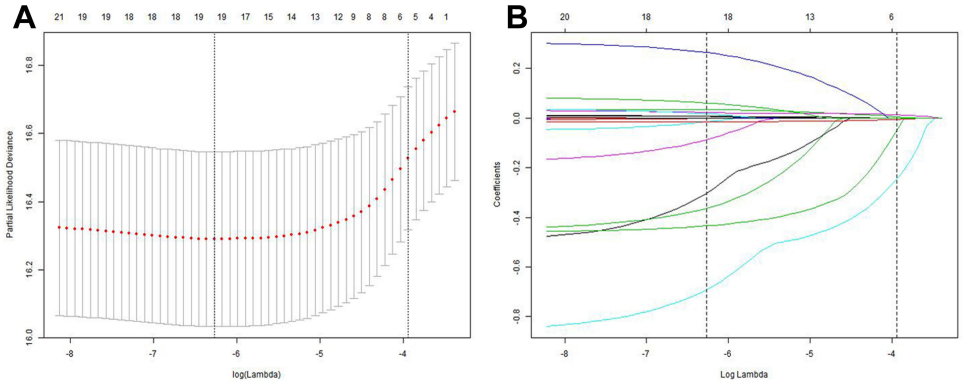

Figure 1 Lasso regression was used to extract predictors. (**A**) Lasso coefficients of 20 factors. (**B**) Optimal penalty coefficient in lasso model(λ) is achieved by 10 times cross validation and minimum criterion. The vertical line on the left represents the minimum error, and the vertical line on the right represents the cross validation error within 1 standard error of the minimum error.

points can be obtained by adding the corresponding scores of each variable. From the total point at the bottom of the nomogram score, the projection of the vertical line corresponds to the probability of an individual being CHD-free at 5, 7 and 9 years. The distribution of risk scores is shown in Figure 2.

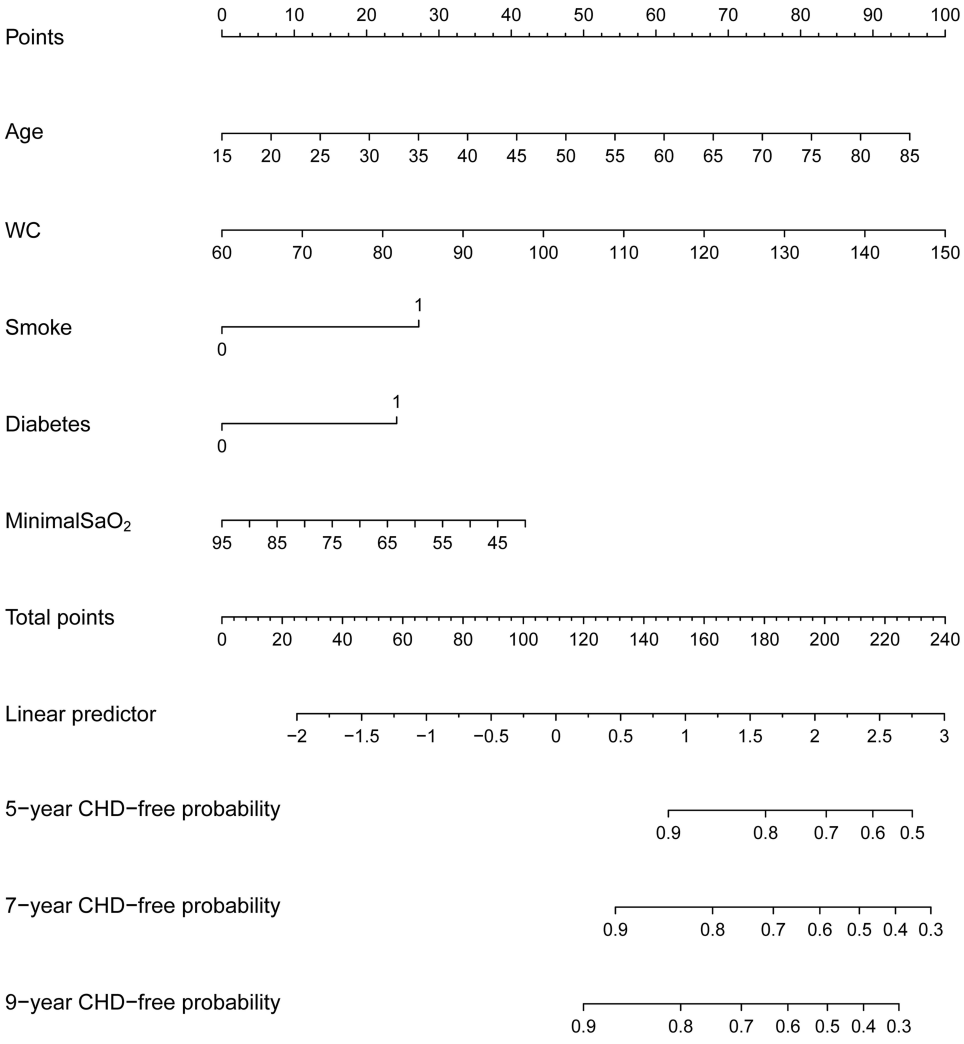

Figure 2 Nomogram score. For the variable selected in the nomogram score, the value of the variable corresponds to the fraction on the integral line at the top of the nomogram score through the projection of the vertical line. The total points can be obtained by adding the corresponding scores of each variable. From the total point at the bottom of the nomogram score, the projection of the vertical line corresponds to the probability of an individual being CHD-free at 5, 7 and 9 years.

Performance of the CHD Nomogram Score

The AUCs of the nomogram score to predict CHD at 5, 7 and 9 years were 0.706 (95% CI 0.649–0.763), 0.703 (95% CI 0.655–0.751) and 0.669 (95% CI 0.593–0.744), respectively, in the training set (Figure 3A). These values represent good performance and were higher than those in the internal validation set at 5, 7 and 9 years, which were 0.682 (95% CI 0.607–0.758), 0.689 (95% CI 0.618–0.760) and 0.664 (95% CI 0.539–0.789), respectively (Figure 3B). With the passage of time, the diagnostic efficiency of the nomogram score decreased gradually. Furthermore, the nomogram score was well calibrated for predicted and actual values related to participants being CHD-free at 5, 7, and 9 years in the training set; however, deviation was observed in the validation set (Figure 3C and D).

Comparison of the Nomogram Score, China-PAR and Framingham Models

In decision curve analysis with a 7-year survival estimation, the nomogram score had a higher overall net benefit compared with the China-PAR and Framingham models (Figure 4). The discriminatory capability of the nomogram score to predict CHD risk (0.699, 95% CI 0.658–0.739) was higher than that of the China-PAR (0.669, 95% CI 0.624–0.713) and Framingham (0.646, 95% CI 0.603–0.689) models. The sensitivity and specificity of the nomogram score to predict CHD were 70% and 55%, respectively. We compared the diagnostic accuracy and differential capability of the nomogram score, China-PAR and Framingham models to predict the risk of CHD by calculating the IDI and NRI. The findings indicated that the nomogram had better predictive and discriminatory capability than the China-PAR (1.9%) or Framingham models (2.0%). The results are shown in Supplementary Table 2.

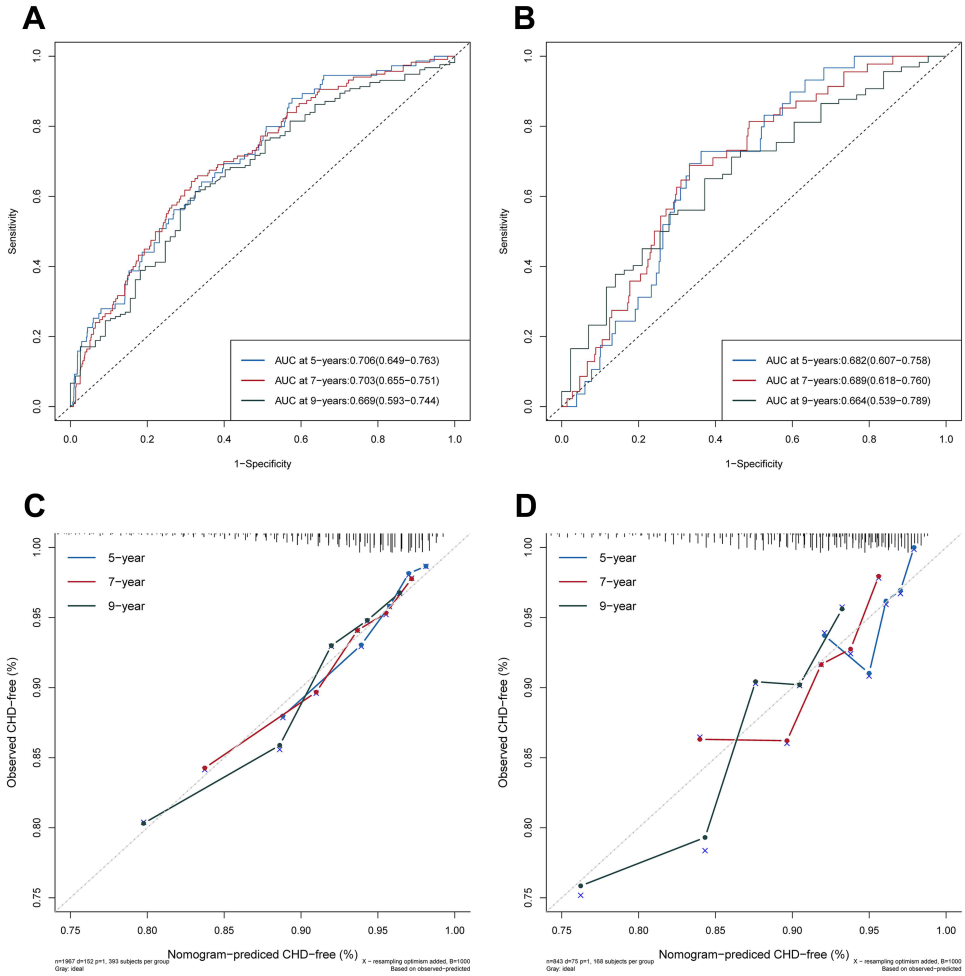

Figure 3 Nomogram score accuracy evaluation. AUC in the training set (**A**) and validation set (**B**). Calibration in the training set (**C**) and validation set (**D**). The CHD-free risk predicted by the nomogram score is plotted on the x-axis and the observed CHD-free risk is plotted on the y-axis.

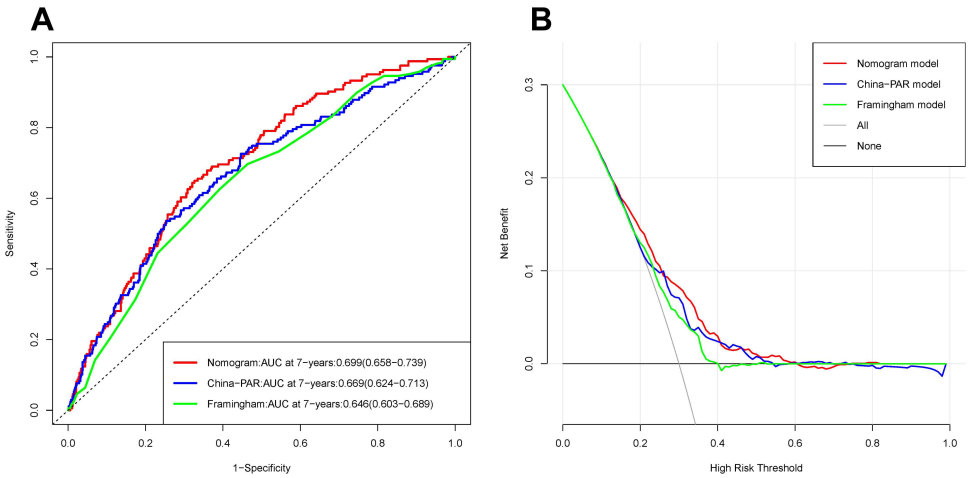

Figure 4 AUC (**A**) and Decision curve analysis (**B**) of Nomogram, China-PAR and Framingham models based on 7-year survival estimation.

Application of the Nomogram Score

Patients were stratified into two risk groups (high risk vs low risk) using the calculated optimal cutoff for the risk scores in the training set (≤121 points for being CHD-free in the nomogram). For the application of the nomogram scores, input the corresponding values of the five predictor variables first, and then the points of every predictors can be obtained in the "update the domain". The total points in the table and CHD probability at 5-, 7-and 9-year "update the domain" in the same way to obtain the total points for risk stratification and the probability of an individual's risk of CHD at 5, 7 and 9 years. As an example, a man who snores and has hypertension who is 30 years of age (20 points), has diabetes (24 points), smokes (27 points), has a WC of 120 cm (67 points) and a minimum SaO_2 of 86 (7 points) has a high risk of CHD (total score 145; more than the ≤121 cutoff). This individual's risk probability of CHD at 5, 7 and 9 years is 9%, 13% and 16%, respectively (Table 3).

Discussion

CHD is the most common type of CVD and is a major cause of death worldwide.[33,34] In this study, 227 cases of CHD were detected among 2810 snorers with hypertension (8.1% prevalence), which is higher than the prevalence of CHD in the general population in China (6.3%).[35] We constructed a new nomogram score to evaluate the risk probability of CHD for snorers with hypertension at 5, 7 and 9 years.

Our analysis used regression models with LASSO screened predictors. Unlike other statistical modelling methods, LASSO uses shrinkage property, which results in more stable variable selection.[36,37] The new nomogram score, which

Table 3 Nomogram Score for Predicting CHD in Snorers with Hypertension

Predictors	Predictors	Formulas to Calculate Points of Every Predictors
Age	30	20.377010055
Abdominal	120	66.666666653
Smoking	1	27.20751
Diabetes	1	24.15384
MinimalSaO2	86	6.8627679479999
Total points	**145.267794656**	
CHD Probability	Formulas to calculate CHD probability at 5-, 7-and 9-year	
At 5-year	0.0956782571674	
At 7-year	0.1329014328927	
At 9-year	0.1686539764267	

includes age, smoking, WC, diabetes and minimum SaO_2 as predictive factors, helps to determine an individual's risk of CHD at 5, 7 and 9 years. This score could help clinicians to identify high-risk patients early enough to intervene and prevent CHD.

Our nomogram score contains classic CVD risk factors such as age, smoking and diabetes. However, Framingham, QRISK and Reynold risk scores do not include WC, whereas our risk score does. Increasing evidence indicates that WC is a CVD risk marker that is independent of BMI.[38,39] In fact, WC is a highly significant predictor in our nomogram score. Our previous studies have demonstrated that WC is an important risk factor for CHD in snorers with uncontrolled hypertension.[27] We think that this is because WC is a better indicator of abdominal obesity in snorers than BMI. Epidemiological data show that snorers have increased abdominal obesity[1] and WC is positively associated with CHD.[40] WC is a simple and effective anthropometric index, which has low acquisition cost and is easy to implement in clinical practice, and this makes the nomogram score easy to obtain.

New markers for predicting the risk of CHD are emerging. We included polysomnography results, including AHI and minimum SaO_2, as candidate factors in our risk prediction model. Minimum SaO_2 was one of five predictors in the nomogram score. A decrease in minimum SaO_2 increases the risk of CHD. Repeated cycles of hypoxemia and reoxygenation elicited by OSA result in oxidative stress and systemic inflammation, which contribute to coronary atherosclerosis and acute myocardial infarction events.[41] Although minimum SaO_2 is weak in predicting CHD in the nomogram, our findings suggest that common but non-classical CVD risk factors should be evaluated in future studies.

To enable the nomogram score to be used in clinical settings, we integrated our findings into a risk score that can automatically predict patient outcomes. Patients were assigned scores based on their age, smoking, WC, diabetes and minimum SaO_2, and a total score was obtained. The probability of CHD in different years was calculated according to the underlying mathematical formula of the nomogram score. Our nomogram score can also be stratified using high-risk and low-risk groupings by total score. The patient described in a clinical example of how to calculate the nomogram total score (Table 3) developed CHD during the third year of follow-up. The China-PAR model was developed to predict the 10-year risk of atherosclerotic CVD in the Chinese population.[42] However, patients assessed as at intermediate risk of atherosclerotic CVD with the China-PAR model are assessed as low risk with the Framingham model. This inconsistency suggests that the based population model may not be applicable to specific patient groups. Alternatively, it may be because age <40 years is a protective factor in Framingham. The performance of our nomogram score was slightly better than that of the China-PAR and Framingham models in snorers with hypertension, and could help in the early identification and management of these patients. In particular, hypoxia burden should be identified in snorers, as it seems to be clinically important.

Our study has several important limitations. First, this was a retrospective study completed in snorers with hypertension, so the findings may not be applicable for widespread use. Second, we included minimum SaO_2 in our nomogram model. However, sleep monitoring and data analysis might be different in other medical institutions. Lastly, the new nomogram score requires external or prospective validation. In the future, we need to further verify the performance of the nomogram model.

Conclusion

In conclusion, our nomogram score is simple to use and can predict the risk probability of CHD in snorers with hypertension. The nomogram score can be used to identify high-risk patients, who may benefit from early intervention.

Data Sharing Statement

The datasets used and/or analyzed in the current study are available from the corresponding author upon reasonable request.

Ethics Approval and Consent to Participate

This study was conducted according to the Declaration of Helsinki guidelines and was approved by the Ethics Committee of the People's Hospital of Xinjiang Uygur Autonomous Region. All participants agreed to participate in this study and provided informed written consent.

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Disclosure

The authors declare no conflicts of interest in this work.

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