

Development and Evaluation of a Hypertension Prediction Model for Community-Based Screening of Sleep-Disordered Breathing

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Purpose: Approximately 30% of patients with sleep-disordered breathing (SDB) present with masked hypertension, primarily characterized by elevated nighttime blood pressure. This study aimed to develop a hypertension prediction model tailored for primary care physicians, utilizing simple, readily available predictors derived from type IV sleep monitoring devices.

Patients and Methods: Participants were recruited from communities in Guangdong Province, China, between April and May 2021. Data collection included demographic information, clinical indicators, and results from type IV sleep monitors, which recorded oxygen desaturation index (ODI), average nocturnal oxygen saturation (MeanSpO2), and lowest recorded oxygen saturation (MinSpO2). Hypertension was diagnosed using blood pressure monitoring or self-reported antihypertensive medication use. A nomogram was constructed using multivariate logistic regression after Least Absolute Shrinkage and Selection Operator (LASSO) regression identified six predictors: waist circumference, age, ODI, diabetes status, family history of hypertension, and apnea. Model performance was evaluated using area under the curve (AUC), calibration plots, and decision curve analysis (DCA).

Results: The model, developed in a cohort of 680 participants and validated in 401 participants, achieved an AUC of 0.775 (95% CI: 0.730–0.820) in validation set. Calibration plots demonstrated excellent agreement between predictions and outcomes, while DCA confirmed significant clinical utility.

Conclusion: This hypertension prediction model leverages easily accessible indicators, including oximetry data from type IV sleep monitors, enabling effective screening during community-based SDB assessments. It provides a cost-effective and practical tool for prioritizing early intervention and management strategies in both primary care and clinical settings.

Keywords: sleep-disordered breathing, prediction model, hypertension, risk predictors

Introduction

Partial or complete blockage of the upper airway during sleep, known as sleep-disordered breathing (SDB), results in breathing difficulties such as apnea or hypopnea. SDB is a pressing public health issue that significantly impacts a large portion of the adult population. In fact, it affects up to 50% of adult males and 23% of adult females.¹ If left untreated for an extended period of time, SDB significantly raises the likelihood of developing cardiovascular diseases (CVD) such as hypertension, heart failure, coronary heart disease, arrhythmias, and stroke, ultimately leading to a higher risk of mortality.^{2,3} 50% of patients with SDB had hypertension,⁴ and 70% of patients with refractory hypertension had SDB combined.⁵ Despite the clear connection between SDB and hypertension, it is estimated that a staggering 80% of middle-aged men and women with SDB remain undiagnosed,⁶ which can be attributed in part to inadequate screening methods and the inconvenience associated with polysomnography (PSG).

Individuals with SDB often experience a noticeable decrease in their oxygen saturation levels overnight. This decline in oxygen saturation while sleeping is a distinguishing feature of this condition. The recurring episodes of nocturnal hypoxemia associated with SDB lead to an increase in sympathetic nervous activity. This heightened activity of the sympathetic nervous

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system greatly contributes to the development and progression of hypertension, which can further lead to various health issues and associated morbidity.⁷ The measurement and evaluation of nocturnal hypoxemia can be effortlessly obtained from a type IV sleep monitor or consumer-grade sleep monitoring devices. These devices are particularly useful for screening SDB in the general population residing in the community.⁸ Moreover, they have the potential to serve as predictors for assessing the prevalent hypertension.⁹

In patients with SDB, 30% have been found to have masked hypertension, primarily characterized by elevated nighttime blood pressure.¹⁰ This subset of patients presents with hypertension that is challenging to detect. Timely screening for SDB and accurately identifying hypertension at an early stage are of utmost importance in reducing the negative health consequences associated with it. Recently, studies have explored risk prediction and management strategies for hypertension and related diseases, providing powerful tools and data support for early intervention and personalized management of high-risk populations.^{11–13} Current predictive tools for SDB-associated hypertension have limitations, primarily due to their development based on patients referred to sleep clinics.^{14,15} Previous research has predominantly focused on individuals with moderate to severe SDB or those exhibiting specific SDB-related symptoms. In contrast, our study draws from a broader population, including mostly asymptomatic individuals or those with undiagnosed SDB symptoms, without stratification by SDB severity. Consequently, our findings are more applicable to the general community. Models like Zeng's, which rely on costly and complex PSG data,¹⁵ and Shi's, which involve 18 variables, present challenges in terms of practicality and feasibility for routine use.¹⁴ Moreover, previous studies have lacked external validation, which is essential for accurately assessing the precision of predictive models.

In this study, our main objective was to develop a predictive model utilizing multivariate logistic regression. This model would rely on a combination of oximetry-derived features and demographic information, enabling the distinction of hypertension risk. To ensure its practicality, efficiency, and cost-effectiveness in clinical settings, this model will exclude biological and sleep stage features. Primary care physicians can utilize simple and readily available predictors when employing type IV sleep monitoring devices to screen for SDB, thus assessing patients' prevalent hypertension.

Materials and Methods

Patients and Study Design

Participants for this study were recruited from the "Guangdong Cohort", a subpopulation of the national "Chinese Academy of Medical Sciences Lifespan Cohort Study and Informatization Initiative", conducted from April 9 to May 18, 2021. This cohort was established using a multi-stage, stratified cluster sampling design to select a representative population. In the first stage, Guangdong Province was selected, with Shantou City (Chenghai District, Jinping District, and Nan'ao County) and Meizhou City (Meijiang District and Jiaoling County) chosen as sampling regions. In the second stage, districts within cities and villages within counties were selected. Lastly, with the support of local governments, residents of the selected villages and communities were invited to participate in the study.

Physical assessments were conducted at local community service centers or hospitals in the selected regions, specifically at the following locations:

Chenghai District, Shantou City: Chenghai Party School

Jinping District, Shantou City: Jinhua Street Community Service Center

Nan'ao County, Shantou City: Houzhai Chengxi Village Health Station

Meijiang District, Meizhou City: Jiangnan Community Health Service Center

Jiaoling County, Meizhou City: Jiaoling County Traditional Chinese Medicine Hospital

The research was based on the framework of the China National Health Survey.¹⁶

To be eligible for inclusion in the study, participants needed to meet specific criteria. Firstly, they had to be at least 18 years old. Secondly, participants were required to have an oxygen desaturation index (ODI) of seven or more times per hour, indicating potential SDB. Lastly, individuals who had not received any treatment related to SDB in the past were also included. Exclusion criteria consisted of incomplete baseline data, patients with common causes of secondary hypertension other than SDB such as nephritis, renal failure, and hyperthyroidism, and individuals who regularly used sedative hypnotic drugs. The process of participant recruitment and enrollment in the study is depicted in Figure 1 of the research report.



 $\label{eq:Figure I} \mbox{Figure I} \mbox{ Flowchart of participant selection}.$

Hypertension was diagnosed based on systolic blood pressure \geq 140 mmHg, diastolic blood pressure \geq 90 mmHg or self-reported use of antihypertensive medication.

In this study, a reliable type IV wearable sleep-monitoring device (Figure S1 and S2), developed by Chengdu Cloud Care Healthcare Co. Ltd. in Chengdu, China, was employed to monitor the sleep patterns of participants.

Various parameters were recorded during the monitoring process, including 3% ODI, MeanSpO2, MinSpO2, and T90.

The device was evaluated and validated against PSG at the Sleep Center of Guangdong Provincial People's Hospital.¹⁷ A total of 196 participants underwent overnight PSG and WISM monitoring to assess the sensitivity and specificity of WISM in detecting OSA. Using an apnea-hypopnea index (AHI) threshold of \geq 5 for diagnosing SDB, the type IV WISM demonstrated a sensitivity of 93%, a specificity of 77%, and an area under the curve (AUC) of 0.95. When the AHI threshold was increased to \geq 15, the sensitivity was 92%, the specificity was 89%, and the AUC remained 0.95.

Additionally, 305 participants from Chenghai and Jinping Districts of Shantou City, who were screened with the type IV device, were selected for further monitoring with a type III home sleep apnea test (HSAT) device.¹⁸ The comparison of SDB prevalence and diagnostic consistency between the type IV device and the HSAT confirmed the effectiveness of the type IV device for SDB screening in a healthy community population. In this cohort of 305 participants, the ODI measured by the type IV device strongly correlated with the AHI measured by HSAT ($R^2=0.504$, P<0.001). A Bland-Altman analysis revealed that approximately 93% (284/305) of the data points fell within the 95% limits of agreement between the ODI measured by the type IV device and the AHI measured by HSAT.

When the ODI reached 7.0 times/hour, the sensitivity, specificity, and accuracy of OSA with an AHI \geq 5 times/hour were 86%, 91%, and 95%, respectively. Therefore, the ODI value of \geq 7.0 events/h was considered significant (Figure S1). The specific information of this device can be found in the supplementary materials.

The sample size estimation was based on the prevalence of hypertension in the Chinese SDB population and the principle of 10 outcome events per variable.¹⁹ With a hypertension prevalence of 40% in the study population and 20 predictors, the required sample size was calculated to be 500 participants.

The training set comprised 680 participants surveyed in Shantou, and its main objective was to develop a nomogram that could effectively distinguish hypertension in patients with SDB. On the other hand, the external validation set consisted of 401 participants surveyed in Meizhou, and its purpose was to assess and validate the diagnostic performance of the developed nomogram.

The study received ethical approval from the Ethics Committee of Guangdong Provincial People's Hospital (GDREC2020221H), ensuring compliance with ethical standards. Additionally, informed consent was sought and obtained from all individuals participating in the study, guaranteeing their voluntary agreement to take part in the research.

Data Collection

Based on literature support, research objectives, and data availability, 20 variables were selected for the study, including (1) demographic characteristics such as age, gender, body mass index(BMI), neck circumference, and waist circumference (WC); (2) lifestyle behaviors, namely drinking, smoking, and adherence to a high-salt diet; and (3) history and indicators associated with SDB, including family history of hypertension, heart disease, diabetes, Epworth Sleepiness Scale results, snoring occurrence, apnea episodes, dryness in the mouth upon waking, morning headaches, ODI, average nocturnal oxygen saturation (MeanSpO2), lowest recorded oxygen saturation during sleep (MinSpO2), and the duration of time spent with oxygen saturation below 90% (T90). The detailed information of the questionnaire and physical examination can be found in the supplementary materials.

Statistical Analysis

For the purpose of constructing and validating the nomogram, the subjects were split into a training set and a validation set by region. To address missing data in the study, we used the k-nearest neighbor (kNN) imputation method. This approach estimates missing values based on the observed values of the k nearest neighbors in the dataset, as determined by a distance metric (eg, Euclidean distance) calculated across all relevant variables. The kNN method was chosen because it preserves the underlying relationships between variables and avoids bias that could arise from simpler imputation methods, such as mean substitution. The number of neighbors (k) was set to 5, as determined through cross-validation to balance imputation accuracy and computational efficiency. This method was applied only to variables with

missing data, ensuring that the imputed values were consistent with the observed distribution of the data. The comparability of these two sets was evaluated subsequently. The Wilcoxon rank-sum test was used to analyze continuous variables, which were described as median (25th percentile, 75th percentile). Categorical data, on the other hand, were presented as numbers (percentage) and analyzed using the chi-square test for comparisons.

To prevent collinearity issues with the inclusion covariates, the LASSO method was employed in the training set to select the most optimal predictive features. LASSO regression was employed to identify the most significant predictors of hypertension among patients with SDB. This technique applies a penalty to the regression coefficients, shrinking less relevant variables to zero and thus selecting only those with the strongest predictive power. Following this, multivariate logistic regression analysis was conducted to develop the nomograms. The receiver operating characteristic (ROC) curve was plotted, and the AUC and calibration curve were used to assess the model's discrimination and calibration. Internal validation was performed using the 1000 bootstrap resamples method.²⁰ External validation was performed using data from an independent cohort (the validation group) recruited from Meizhou City. Decision curve analysis (DCA) was employed to evaluate the clinical utility of the model.²¹ A comparison of AUC values was carried out using the DeLong test.²² All statistical analyses were performed using R software version 4.2. A p-value less than 0.05, considering it as statistically significant, was used as the threshold in all analyses.

Results

Characteristics of Subjects

Among the individuals involved in the study, the overall prevalence of hypertension was recorded at 40.4%, with a total of 437 out of 1081 participants affected. Further analysis of the data indicated that in the training set, 272 out of 680 participants (40%) had hypertension, while in the validation set, 165 out of 401 participants (41%) exhibited the condition. A comprehensive overview of the participants' demographic and clinical characteristics can be found in Table 1. Notably, no significant disparities were observed among the participants in terms of heart disease, smoking, drinking habits, high-salt diet, apnea, headache/dizziness, dry mouth, hypertension, MeanSpO2, age, WC, neck circumference, BMI, MinSpO2, T90, or the prevalence of hypertension. Most of the research factors related to the training set and validation set are comparable.

Characteristics	Overall (n=1081)	With Hypertension (n=437)	Without Hypertension (n=644)	Training Set (n=680)	Validation Set (n=401)	P-value
Sex						0.817
Female	598 (55%)	232 (53%)	366 (57%)	378 (56%)	220 (55%)	
Male	483 (45%)	205 (47%)	278 (43%)	302 (44%)	181 (45%)	
Hypertension						0.710
No	644 (60%)			408 (60%)	236 (59%)	
Yes	437 (40%)			272 (40%)	165 (41%)	
Diabetes						0.006
No	916 (85%)	326 (75%)	590 (92%)	592 (87%)	324 (81%)	
Yes	165 (15%)	(25%)	54 (8.4%)	88 (13%)	77 (19%)	
Family history of hypertension						0.007
No	741 (69%)	277 (63%)	464 (72%)	486 (71%)	255 (64%)	
Yes	340 (31%)	160 (37%)	180 (28%)	194 (29%)	146 (36%)	
Heart disease						0.391
No	1027 (95%)	423 (97%)	604 (94%)	649 (95%)	378 (94%)	
Yes	54 (5.0%)	14 (3.2%)	40 (6.2%)	31 (4.6%)	23 (5.7%)	
Smoking						0.584
No	823 (76%)	329 (75%)	494 (77%)	514 (76%)	309 (77%)	
Yes	258 (24%)	108 (25%)	150 (23%)	166 (24%)	92 (23%)	

Table I Baseline Characteristics of the Training Set and Validation Set

(Continued)

Table I (Continued).

Characteristics	Overall (n=1081)	With Hypertension (n=437)	Without Hypertension (n=644)	Training Set (n=680)	Validation Set (n=401)	P-value
Drinking						0.705
No	837 (77%)	328 (75%)	509 (79%)	524 (77%)	313 (78%)	
Yes	244 (23%)	109 (25%)	135 (21%)	156 (23%)	88 (22%)	
High-salt diet						0.052
No	833 (77%)	334 (76%)	499 (77%)	537 (79%)	296 (74%)	
Yes	248 (23%)	103 (24%)	145 (23%)	143 (21%)	105 (26%)	
Snore_loudly						0.513
No	663 (61%)	254 (58%)	409 (64%)	412 (61%)	251 (63%)	
Yes	418 (39%)	183 (42%)	235 (36%)	268 (39%)	150 (37%)	
Apnea						0.210
No	956 (88%)	369 (84%)	587 (91%)	595 (88%)	361 (90%)	
Yes	125 (12%)	68 (16%)	57 (8.9%)	85 (13%)	40 (10.0%)	
Headache_Dizziness						0.646
No	441 (41%)	178 (41%)	263 (41%)	281 (41%)	160 (40%)	
Yes	640 (59%)	259 (59%)	381 (59%)	399 (59%)	241 (60%)	
Mouth Dry						0.503
No	364 (34%)	141 (32%)	223 (35%)	234 (34%)	130 (32%)	
Yes	717 (66%)	296 (68%)	421 (65%)	446 (66%)	271 (68%)	
ESS						0.159
Median (IQR)	3.0 (1.0, 5.0)	3.0 (1.0, 5.0)	3.0 (1.0, 5.0)	3.0 (1.0, 5.0)	3.0 (1.0, 5.0)	
Age						0.267
Median (IQR)	58 (49, 66)	62 (56, 68)	55 (44, 63)	58 (48, 66)	58 (50, 67)	
WC						0.293
Median (IQR)	86 (80, 93)	90 (84, 96)	84 (78, 91)	86 (80, 93)	87 (80, 93)	
NC						0.673
Median (IQR)	35.5 (32.8, 38.0)	35.5 (33.0, 38.0)	35.5 (32.5, 38.0)	35.5 (32.5, 38.0)	35.1 (33.0, 38.0)	
BMI						0.793
Median (IQR)	24.6 (22.5, 26.8)	24.6 (22.6, 26.9)	24.6 (22.4, 26.8)	24.7 (22.5, 26.8)	24.4 (22.4, 27.0)	
MeanSpO2						0.192
Median (IQR)	95.75 (94.66, 96.63)	95.44 (94.40, 96.42)	95.95 (94.88, 96.73)	95.80 (94.80, 96.60)	95.68 (94.33, 96.69)	
MinSpO2						0.350
Median (IQR)	83.0 (79.0, 85.0)	83.0 (79.0, 85.0)	83.0 (80.0, 86.0)	83.0 (80.0, 85.0)	83.0 (79.0, 86.0)	
ODI						0.041
Median (IQR)	(9, 6)	12 (9, 18)	(8, 5)	(9, 5)	12 (9, 18)	
Т90						0.488
Median (IQR)	7 (3, 17)	7 (3, 21)	7 (3, 15)	7 (3, 15)	7 (3, 21)	

Abbreviations: BMI, body mass index; WC, waist circumference; NC, neck circumference; ODI, oxygen desaturation index; MeanSpO2, mean nocturnal oxygen saturation; MinSpO2, lowest recorded oxygen saturation during sleep; T90, the amount of time percentage spent with oxygen saturation below 90%.

Construction of Nomogram

Based on literature support, research objectives, and data availability, 20 variables were selected and included in the LASSO regression model for feature selection (Figure 2). The λ , determined through 10-fold cross-validation, was used as the final model selection criterion, resulting in the identification of six optimal variables (waist circumference, age, ODI, diabetes status, family history of hypertension, and the presence of sleep apnea). A regression equation was then constructed based on the results of the multivariate logistic regression model analysis, and a nomogram was established to predict hypertension risk in the SDB population (Table 2, Figure 3).

Assessment of Nomogram in the Training Set and Validation Set

Internal validation of the training set was performed using the Bootstrap method with 1000 resampling iterations applied to the modeling group. The resulting AUC was 0.763 (95% confidence interval [CI]: 0.728-0.798),



Figure 2 Screening of feature variables using the LASSO regression model. (A) shows the cross-validation curve for the LASSO regression, illustrating the selection process for the optimal penalty coefficient λ . The left dashed line represents the λ with the minimum deviation (λ min), while the right dashed line indicates the λ min plus one standard error, which corresponds to the optimal value for the model. (B) depicts the LASSO coefficient path for the 20 risk factors. Abbreviations: LASSO, least absolute shrinkage and selection operator; SE, standard error.

demonstrating good model discrimination. Similarly, for the validation set, internal validation with 1000 Bootstrap resampling iterations produced an AUC of 0.775 (95% CI: 0.730–0.820), also indicating good model discrimination, as illustrated in Figure 4.

In the training set, the alignment between the predicted model curve and the reference line suggests a high level of calibration accuracy. In the validation set, the close alignment between the predicted model curve and the reference line indicates good calibration, as shown in Figure 5.

Clinical Utility of Nomogram

In the DCA curve, the "All" line assumes that all subjects undergo the intervention for hypertension risk, resulting in a net benefit represented by a negatively sloped diagonal line. The "None" line assumes that no subjects receive the intervention, yielding a net benefit of 0. The use of the screening model demonstrates clinical benefit for subjects within a threshold probability range of 9% to 90%. (Figure 6A). These findings were confirmed in the validation set, where the threshold probability range was 9% to 74% (Figure 6B). Additionally, we employed clinical impact curves based on the results of the DCA to assess the practicality of the nomograms. When the threshold probability exceeds 60%, the prediction model identifies

Predictive factors	Estimate	std.error	Statistic	OR	р			
WC	0.05	0.01	4.846	1.051 [1.030, 1.073]	<0.001			
Age	0.066	0.009	7.595	1.069 [1.051, 1.088]	<0.001			
ODI	0.018	0.013	1.356	1.018 [0.992, 1.044]	0.175			
Diabetes	0.939	0.267	3.521	2.557 [1.527, 4.358]	<0.001			
Family history of hypertension	0.993	0.214	4.633	2.699 [1.781, 4.131]	<0.001			

0.266

3.186

Table 2Multivariable Logistic Regression Analysis Based on the 6 Variables Selected by theLASSO Regression Technique

Abbreviations: WC, waist circumference; ODI, oxygen desaturation index.

0.849

Apnea

0.001

2.337 [1.392, 3.968]



Figure 3 Nomogram prediction model for prediction of hypertension.



Figure 4 ROC curves of the nomogram to predict hypertension (A) training set. (B) the external validation set. The 95% confidence intervals for the AUC values are represented by the dotted vertical lines.

Abbreviations: ROC, Receiver Operating Characteristic; AUC, area under the curve.

individuals at high risk of hypertension with a strong match to those who are actually hypertensive in both the training sets (Figure 7A) and the validation sets (Figure 7B).

Website of Nomogram

Based on the developed model, an interactive dynamic web-based nomogram was created to facilitate user engagement and allow for real-time predictions and assessments. This online tool enables healthcare professionals and researchers to



Figure 5 Calibration plots of the nomogram to predict the hypertension. (A) Training set. (B) External validation set.



Figure 6 DCA of the nomogram. (A) Training set. (B) External validation set. Abbreviation: DCA, Decision curve analysis.

input individual patient data, instantly generating personalized risk assessments and visualizations, thereby enhancing the practical application of the model in clinical settings. The nomogram's accessibility and user-friendly interface make it a valuable resource for both community screenings and clinical decision-making, as depicted in Figure 8.



Figure 7 The clinical impact curves of the nomogram. (A) Training set. (B) External validation set.





Figure 8 An online dynamic nomogram created using R language. (https://fengtong.shinyapps.io/dynnomapp/).

Model Comparison

The nomogram was observed to display a significantly greater level of precision when it came to predicting hypertension in patients with SDB, as compared to the individual factors that were incorporated in the nomogram (P < 0.01). This can be clearly seen in Figure 9A, Tables 3, and 4. Furthermore, the results of DCA indicated that the nomogram offered greater overall benefits in terms of accurately identifying hypertension, in comparison to relying solely on individual factors (Figure 9B).



Figure 9 Models comparison in the whole study. (A) ROC curve analyses were performed to compare the discriminatory accuracy of the nomogram with that of the individual variables included in the nomogram. (B) DCA analyses were conducted to compare the net benefit of the nomogram with that of the individual variables included in the nomogram.

Abbreviations: ROC, Receiver operator characteristic curves; DCA, Decision curve; AUC, area under the curve.

Discussion

This study developed and validated a convenient and practical nomogram to detect the risk of hypertension in patients with SDB. Compared to traditional nomograms, the online nomogram transforms data into easily understandable and analyzable charts, helping users to better interpret the data. The nomogram in this study includes several simple and easily accessible indicators, which can be used to predict hypertension through an online interactive platform during community SDB screenings. This tool aids in identifying high-risk hypertensive patients and provides strong evidence for clinicians to implement early interventions, thereby improving patient outcomes.

Prior research has indicated that the occurrence of hypertension in individuals with SDB ranges from 36% to 68%, as demonstrated in Table 5.^{23–27} In contrast, our own investigation reveals a prevalence rate of 40% for hypertension in the SDB population. It is worth noting that the aforementioned survey was conducted by various organizations, at different points in time, and across diverse age groups, potentially contributing to incongruities and variations in the findings. Numerous cross-sectional

 Table 3 Models Comparison in the Whole Study, Receiver Operator

 Characteristic Curves of the Models are Presented to Compare Their

 Discriminatory Accuracy for Predicting Hypertension

	AUC (95% CI)	Р
Nomogram	0.763 (95% CI,0.728-0.798)	
WC	0.652 (95% CI,0.611–0.694)	<0.01
Age	0.678 (95% CI,0.639-0.718)	<0.01
ODI	0.558 (95% CI,0.512-0.600)	<0.01
Diabetes	0.578 (95% CI,0.548-0.604)	<0.01
Family history of hypertension	0.535 (95% CI,0.500-0.570)	<0.01
Apnea	0.548 (95% CI 0.519–0.573)	<0.01

Notes: P values show the AUC for the nomogram versus the AUCs for other variables incorporated in the nomogram alone.

Abbreviations: WC, waist circumference; ODI, oxygen desaturation index; AUC, area under the curve; CI, confidence interval.

	NRI(Categorical) [95% CI]	Р	NRI(Continuous) [95% Cl]	Р	IDI [95% CI]:	Р
wc	0.25 [0.181–0.319]	<0.01	0.6936 [0.5495–0.8378]	<0.01	0.141 [0.1139–0.1681]	<0.01
Age	0.114 [0.0536-0.1743]	<0.01	0.6152 [0.469-0.7614]	<0.01	0.1078 [0.0827-0.133]	<0.01
ODI	0.3787 [0.3186-0.4388]	<0.01	0.7181 [0.576-0.8603]	<0.01	0.1987 [0.1681–0.2293]	<0.01
Diabetes	0.3931 [0.3103–0.4774]	<0.01	0.6324 [0.4873–0.7774]	<0.01	0.163 [0.1345–0.1914]	<0.01
Family history of hypertension	0.3956 [0.3151–0.4759]	<0.01	0.6544 [0.5099–0.799]	<0.01	0.2064 [0.1754–0.2374]	<0.01
Apnea	0.3836 [0.3045–0.4614]	<0.01	0.6936 [0.5501–0.8371]	<0.01	0.1936 [0.1635–0.2237]	<0.01

Table 4 Models Comparison in the Whole Study, Net Reclassification Improvement and Integrated Discrimination Improvement of

 the Models are Presented to Compare Their Discriminatory Accuracy for Predicting Hypertension

Abbreviations: WC, waist circumference; ODI, oxygen desaturation index; NRI, net reclassification improvement; IDI, integrated discrimination improvement.

 Table 5 Prevalence of Hypertension in Sleep Disordered Breathing Population

	Measurements	Country	Study Population	Number	Age (Range)	Outcome
Hla KM et al 1994 ²³	PSG 24-hour ambulatory blood pressure monitoring	USA	General population	M: 75 F: 72	30–60 y.o	36%
Bixler EO et al 2000 ²⁴	PSG Pneumatic electronic Sphygmomanometer	USA	General population	M: 741 F: 1000	20–100 у.о	Moderate- Severe: M: 59% F: 51% Mild: M: 52% F: 47%
Lavie P et al 2000 ²⁵	PSG Pneumatic electronic Sphygmomanometer	Canada	Hospital-based population	M: 1949 F: 728	20–85 y.o	43% Mild: 37% Moderate: 46% Severe: 54%
J.L. Kiely et al 2000 ²⁶	PSG Standard mercury sphygmomanometer	Britain	Hospital-based population	M: 100 F: 14	51±8.9 y.o	68%
Georgios Natsios et al 2016 ²⁷	PSG History of hypertension or medication use.>	Greece	Hospital-based population	M: 1026 F: 201	50±15.3 y.o	37.6%

Notes: Mild: $5 \le AHI < 15$; Moderate: $15 \le AHI < 30$; Severe: $AHI \ge 30$.

Abbreviations: PSG, Polysomnography; M, Male; F, Female; y.o., Years old; AHI, Apnea hypopnea index.

epidemiological studies have unequivocally revealed a distinct and undeniable link between SDB and hypertension. The Wisconsin Sleep Cohort study conducted a thorough investigation and revealed an intriguing finding. It discovered that even a minuscule elevation in the AHI at the beginning of the study was significantly linked to a tripling in the likelihood of developing hypertension throughout the subsequent four-year monitoring period.²⁸ Involving a substantial sample size of more than 6000 participants, the study found a strong correlation between high AHI and T90 with an elevated risk of developing hypertension. This association followed a dose-response pattern, indicating that the odds of developing hypertension increased proportionally with the severity of AHI and T90.²⁹ Several studies have considered significant confounding factors, including obesity, age, and gender. The association between SDB and hypertension is stronger in younger and less obese participants, as observed in population-based studies.²⁴ A research conducted by Metso uncovered that individuals with refractory hypertension face a significantly higher risk of suffering from SDB compared to those with non-refractory hypertension, even after factoring in age, gender, and comorbidities. The study indicates that the risk of SDB in patients with refractory hypertension is 2.46 times greater (with a 95% confidence interval of 1.03–5.88) than in those with non-refractory hypertension.³⁰ It is plausible to consider that a significant portion of what is commonly classified as essential hypertension could potentially be attributed to hypertension

that is secondary to undiagnosed and untreated SDB. The European Hypertension Guidelines have placed even greater emphasis on the significant impact of SDB as a key factor influencing elevated blood pressure levels.³¹ There is also support from reports that demonstrate improved hypertension management following the correction of SDB.³² Early and timely screening for SDB and accurate identification of hypertension related to SDB are vital in reducing the detrimental health effects associated with it.

In China, several risk prediction models for SDB related hypertension have been established. Zeng, for instance, developed and validated a clinical nomogram using a hospital population to predict hypertension occurrence in SDB patients. This study identified body mass index, REM-AHI, REM-MinSpO2, and T90 as predictors of SDB associated hypertension.¹⁵ The model demonstrated satisfactory discrimination with an AUC of 0.817. However, PSG is both costly and time-consuming. The scarcity of PSG devices can pose limitations, and data collection (eg, REM-AHI, REM-MinSpO2) may not be routinely conducted in community hospitals. Consequently, utilizing this tool for hypertension screening, particularly for primary care physicians, might be inefficient. In hospital settings, it is common to observe patients who experience moderate-to-severe SDB or display at least one symptom associated with SDB. This select population may introduce selection bias, as they seek medical attention from sleep medicine centers for various reasons, such as suspected sleep-disordered breathing by clinicians or diagnostic check-ups. On the other hand, our sample was obtained from the overall population, encompassing individuals who displayed no symptoms or experienced symptoms that went unnoticed. Additionally, the severity of SDB was not specifically categorized in our study. As a result, our findings are more relevant and can be more readily applied to communitybased general populations. In another study, Shi developed a prediction model for SDB-related hypertension using machine learning techniques.¹⁴ However, the model contains 18 variables, which reduces its practicability. Our model was straightforward and uncomplicated to compute. In addition, the common limitation of these two studies is that no external validation was performed. Therefore, this study may be the first nomogram of hypertension prediction in community SDB population in China through a comprehensive assessment and validation process.

The results from the LASSO indicated that WC, age, ODI, history of diabetes, family history of hypertension, and apnea were ere identified as significant independent risk factors for hypertension associated with SDB. These findings are consistent with prior studies. In our previous research within the police force in southern China, we observed that there exists a direct correlation between the age of patients and the prevalence of this condition.³³ Furthermore, Ruzena et al reported that ODI was a superior predictor of hypertension when compared to the AHI.³³ ODI provides a reliable measure of intermittent hypoxemia during sleep. Repeated episodes of intermittent hypoxia in SDB patients during sleep can result in a prolonged activation of the sympathetic nervous system. This activation subsequently triggers the renin-angiotensin-aldosterone system, which ultimately leads to the retention of water and sodium. As a result, hypertension is exacerbated.³⁴ Furthermore, it has been demonstrated that intermittent hypoxia-reoxygenation that is linked to obstructive respiration can cause systemic inflammation and oxidative stress. Consequently, this can result in endothelial dysfunction, inflammation within the vascular wall, and the subsequent development of atherosclerosis.³⁵ Chronic intermittent hypoxemia may further impair the diurnal blood pressure control by affecting the vascular endothelium (Figure 10). Evidence from a rat model has established a clear and causal connection between intermittent hypoxemia during sleep and the development of systemic hypertension.³⁶

To the best of our understanding, this research introduces the inaugural clinical nomogram model designed to forecast the likelihood of hypertension in a community-based population. The model incorporates demographic data and blood oxygen parameters, providing a more accurate and applicable alternative to traditional subjective questionnaires. Importantly, DCA demonstrated that the model had superior predictive accuracy within a threshold probability range of 9–90% for hypertension in SDB patients. This particular model has the potential to assist in the prompt clinical detection of patients with SDB who are at a heightened risk of hypertension. The proposed hypertension prediction model has significant potential for application in both community-based screenings and clinical settings. By utilizing readily available demographic and oximetry-derived data from type IV sleep monitoring devices, the model provides an accessible tool for primary healthcare providers to identify individuals at high risk of hypertension during sleep-disordered breathing (SDB) screenings. This enables early detection and prioritization of interventions, such as advanced diagnostics or treatment strategies like continuous positive airway pressure (CPAP) therapy. Additionally, the model's integration into an online dynamic nomogram (accessible at https://fengtong.shinyapps.io/dynnomapp/) allows for real-time, individualized risk assessment, enhancing its practicality in diverse healthcare environments. This application is particularly valuable in optimizing resource allocation and improving health outcomes in resource-limited settings.



Figure 10 Pathophysiological consequence of sleep-disordered breathing and hypertension.

While the predictive model demonstrated robust performance in both the internal and external validation cohorts, certain limitations must be acknowledged. First, the study population was derived exclusively from communities in Guangdong Province, China, and primarily consisted of individuals of Chinese descent. As a result, the generalizability of the model to populations with different ethnic, geographic, or socioeconomic backgrounds may be limited. Future studies should conduct multicenter external validation in diverse populations to assess the model's broader applicability.

Second, although the model incorporates readily available demographic and oximetry-derived predictors, the potential impact of unmeasured confounders cannot be ruled out. Factors such as physical activity levels, dietary habits, or psychosocial stress, which were not included in this study, may also influence hypertension risk in patients with SDB. The absence of these variables may introduce residual confounding, which could affect the precision of the model's predictions. Addressing these gaps in future research could further enhance the model's robustness and predictive accuracy. Despite these limitations, the model offers a practical and cost-effective approach to hypertension risk stratification in community settings, aligning well with the study's objectives and contributing meaningfully to early detection and intervention efforts.

To further enhance the model's applicability and robustness, future research should focus on conducting multicenter validation studies in diverse populations with varying ethnic, geographic, and socioeconomic backgrounds. Additionally, the incorporation of other potential predictors, such as physical activity levels, dietary patterns, or psychosocial stress, could refine the model and improve its predictive accuracy. These efforts will help to ensure the model's practical value and reliability in real-world settings, ultimately contributing to improved public health outcomes.

Conclusion

This research, utilizing six basic indicators, incorporates the readily available ODI data from a type IV sleep monitor or consumer-grade sleep monitoring devices. It offers a practical approach to identifying hypertensive patients at high risk during community SDB screenings. The nomogram created can be utilized as a valuable resource for both community screenings and clinical settings, assisting in determining treatment priorities.

Data Sharing Statement

Data are available from the authors upon reasonable request. The authors may be contacted at ouqiong2776@hotmail.com.

Ethics Approval and Consent to Participate

This study was approved by the Ethics Committee of Guangdong Provincial People's Hospital (GDREC2020221H). All participants provided informed consent before enrollment. The study was conducted in accordance with the principles outlined in the Declaration of Helsinki.

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Disclosure

The authors declare no conflict of interest.

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