

Development and validation of a nomogram model for mortality prediction in stable chronic obstructive pulmonary disease patients: A prospective observational study in the RealDTC cohort

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Background Chronic obstructive pulmonary disease (COPD) is the third leading cause of death worldwide. There is no nomogram model available for mortality prediction of stable COPD. We intended to develop and validate a nomogram model to predict mortality risk in stable COPD patients for personalised prognostic assessment.

Methods A prospective observational study was made of COPD outpatients registered in the RealDTC study between December 2016 and December 2019. Patients were randomly assigned to the training cohort and validation cohort in a ratio of 7:3. We used Lasso regression to screen predicted variables. Further, we evaluated the prognostic performance using the area under the time-dependent receiver operating characteristic curve (AUC) and calibration curve. We used the AUC, concordance index, and decision curve analysis to evaluate the net benefits and utility of the nomogram compared with three earlier prediction models.

Results Of 2499 patients, the median follow-up was 38 months. The characteristics of the patients between the training cohort ($n = 1743$) and the validation cohort ($n = 756$) were similar. ABEODS nomogram model, combining age, body mass index, educational level, airflow obstruction, dyspnoea, and severe exacerbation in the first year, was constructed to predict mortality in stable COPD patients. In the integrative analysis of training and validation cohorts of the nomogram model, the three-year mortality prediction achieved AUC = 0.84; 95% confidence interval (CI) = 0.81, 0.88 and AUC = 0.80; 95% CI = 0.74, 0.86, respectively. The ABEODS nomogram model preserved excellent calibration in both the training cohort and validation cohort. The time-dependent AUC, concordance index, and net benefit of the nomogram model were higher than those of BODEx, updated ADO, and DOSE, respectively.

Conclusions We developed and validated a prognostic nomogram model that accurately predicts mortality across the COPD severity spectrum. The proposed ABEODS nomogram model performed better than earlier models, including BODEx, updated ADO, and DOSE in Chinese patients with COPD.

Registration ChiCTR-POC-17010431.

Chronic obstructive pulmonary disease (COPD) is a chronic respiratory disease resulting in respiratory symptoms and airway obstruction [1]. COPD is already the third leading cause of death worldwide, causing 3.23 million deaths in 2019 [2,3]. COPD is a rather heterogeneous disease, and stratifying patients by prognosis will improve the likelihood of a precision medicine approach.

Previous studies have reported that increased age is associated with a poor prognosis in COPD, with age over 68 years being one of the predictors of future deterioration risk [4,5]. A review reported that consistently strong predictors were forced expiratory volume in one second percentage predicted (FEV_1 percentage predicted) and age in stable COPD [6]. Low levels of body mass index (BMI), body weight reduction, lower FEV_1 at baseline, and high symptom scores are associated with a higher risk of COPD mortality [7-9]. Previous severe acute exacerbation leads to an increased risk of hospitalisation and mortality in COPD patients [10]. Previous studies found that higher education was related to lower mortality [11,12]. The above-mentioned single predictors or risk factors provide limited predictive value for disease prognosis because several clinical phenotypes exist in COPD patients [1]. Composite models or indexes have the potential to explain many aspects of COPD [13]. Global Strategy for the Diagnosis, Management, and Prevention of Chronic Obstructive Lung Disease (GOLD) recommends using multivariable prediction models to assess the prognostic profile and facilitate follow-up of patients instead of single predictors such as the above predictors [1,14].

BODE index is a multidimensional index constructed with BMI, airflow obstruction, dyspnoea, and exercise capacity [15]. The previous study exhibited that the BODE index had a similar prognostic capacity to the BODEx index including exercise capacity [16]. Due to the large number of outpatients in China, the feasibility of the exercise capacity experiment, such as the six-minute walking distance, is low. Therefore, we chose to compare BODEx instead of BODE to the nomogram model [16]. Updated ADO index combines age, dyspnoea, and airflow obstruction to predict the risk of mortality across all the COPD severity [17]. DOSE index includes dyspnoea, airflow obstruction, current smoking status, and exacerbation frequency in the past year, which was associated with mortality in COPD patients [18,19]. These indexes are three other major risk assessment systems. A nomogram prognostic model for predicting patient prognosis may contribute to better treatment stratification and clinical outcome assessment [20]. Many prognostic models combining multiple predictors have been developed for outcome prediction in COPD patients, but more than 80% of prognostic models were not calibrated [14]. China is a developing country with lower education levels in the elderly, low cognitive levels, and low awareness of symptoms in COPD patients [21]. Smoking and biomass fuels are the main risk factors for COPD in China [22]. The previous study also showed that the proportion of COPD patients with high acute exacerbation risk and high symptoms is high in China [23]. However, no such nomogram model is available for mortality prediction of stable COPD.

Hence, we intended to identify prognostic factors for COPD patients in China and then develop and validate a new nomogram prognostic model to predict mortality risk in stable COPD patients. We also compared the predictive value of the ABEODS nomogram model with three earlier prediction models (BODEx, the updated ADO, and DOSE).

METHODS

Study participants

This is a prospective observational study named RealDTC study (the analysis of current status in diagnosis and treatment of COPD), which has been reported previously [24]. Participants were included between December 2016 and December 2019 and randomly assigned to the training cohort and validation cohort in a ratio of 7:3. COPD was defined with the FEV_1 divided by the forced vital capacity (FVC) after bronchodilation less than 0.70 according to the GOLD 2017 recommendations [1]. Patients at least 40 years old were included. Patients previously diagnosed with asthma, bronchiectasis, interstitial lung disease, carcinoma, severe heart diseases, chronic liver diseases, or chronic kidney diseases were excluded (based on personal medical records). Patients who had an acute exacerbation (AE) of COPD within one month before the visit to the outpatient clinic were also excluded. This study was approved by the local ethics committee of the Second Xiangya Hospital (number 2016076). Informed consent was obtained from all participants.

Variables and definitions

We collected at baseline age, sex, BMI, smoking status, pulmonary function tests, COPD assessment test (CAT) score, modified medical research council dyspnoea scale (mMRC) score, clinical COPD questionnaire (CCQ) score, number of AE in the past year, the severity of exacerbation (moderate or severe) and inhaled drug

prescription. Smoker was defined as a person with a current or past smoking history of more than 10 packs per year. Patients who had sustained abstinence for more than six months were former smokers [25]. Never-smokers were defined as those who had a lifetime exposure to no more than 100 cigarettes or no more than 10 packs per year [26]. The post-bronchodilator FEV₁ is a percent of the predicted value, classified according to the stages identified by the American Thoracic Society because it can be used to predict health status [27], and the risk of death [8]. This classification (≤ 35 , 36–50, 51–64, ≥ 65) of FEV₁ percentage predicted was applied to the BODE index [15]. We defined moderate exacerbation as requiring a prescription for an oral corticosteroid and/or antibiotic. Severe exacerbation requires hospital management, including emergency visits or admissions [1]. The AE frequency and severity in the past year were obtained retrospectively, but the first year AE frequency and severity were obtained prospectively. We defined ABEODS as a combination of age, BMI, educational level, airflow obstruction, dyspnoea, and severe exacerbation frequency in the first year. BODE index is a multidimensional 10-point scale constructed with BMI, airflow obstruction, dyspnoea, and exercise capacity [15]. BODEx combines BMI, airflow obstruction, dyspnoea, and severe exacerbation frequency in the past year, which has a similar prognostic capacity to the BODE index [16]. The score range for this index is between zero and nine points [16]. The updated ADO index, ranging from zero to 14 points, combines age, dyspnoea, and airflow obstruction to predict mortality risk across all the COPD severity [17]. DOSE index includes four components – dyspnoea, airflow obstruction, current smoking status, and exacerbation frequency in the past year – which was associated with mortality in COPD patients [18,19].

We followed up patients every six months after the first visit to the outpatient clinic. The number of exacerbations, the severity of exacerbation (moderate or severe), and survival status were collected per follow-up. We defined all-cause mortality as the outcome. Further, we defined overall survival (OS) as the length of time from the first visit to the outpatient clinic to death or last contact. These were obtained from personal follow-up. The study endpoint was death or the last routine follow-up before 31 October 2022.

Sample size estimation

We calculated the sample size using PASS, version 15.0 (Kaysville, Utah, USA) in the part of Cox Regression. We used the mortality (7.80%), R-squared as 0.074, standard deviation as 0.188 obtained from the pre-experiment, set the interval type as two-sided, and entered the confidence level (1–Alpha) as 0.80 and confidence interval (CI) width (two-sided) as 0.05. Finally, the sample we acquired was 1134.

Statistical analysis

We drew a normal quantile-quantile plot to test whether the distribution of the quantitative data follows the normal distribution. Data meeting the normal distribution were presented as mean and standard deviation (SD), otherwise as median and interquartile range. For normally distributed data, we used a *t* test for comparison between the two groups. Otherwise, we used the Mann-Whitney U-test. Categorical variables were expressed by frequency. We used the χ^2 test to compare the categorical variables of different groups and Lasso regression to screen predicted variables for inclusion in the nomogram. Moreover, we evaluated the OS probabilities by nomogram. We used the concordance index (C-index) and/or area under the time-dependent receiver operating characteristic (ROC) curve (time-dependent AUC) to evaluate discriminative ability. Further, we used calibration curves to evaluate calibrating ability. The cut-off value of variables was based on Youden's index from ROC curve analysis. C-index and/or area under the ROC curve (AUC) more than 0.7 suggest a rational estimation. We used the changes in the net reclassification index and integrated discrimination improvement to compare the accuracy between the nomogram and other prediction models, including BODEx, updated ADO, and DOSE. Time-dependent AUC, C-index, and decision curve analysis were used to evaluate the net benefits and utility of the nomogram model compared with other prediction models. We employed the Kaplan-Meier and multivariable Cox regression analyses for survival analysis. We used a method developed by Hanley and McNeil to compare ROC curves derived from the same subjects [28]. We performed all analyses with the statistical software R, version 4.1.2 (R Core Team, Vienna, Austria), Free Statistics, version 1.7.1 (Freeclinical Ltd, Beijing, China), and MedCalc, version 19.7.2 (MedCalc Software Ltd, Ostend, Belgium). A *P*-value < 0.05 was considered statistically significant.

RESULTS

Subject characteristics

2874 stable COPD patients were included at baseline, and 2499 patients were included for analysis (375 refused to follow up). The median follow-up periods were 38.0 (36.0–46.0) months. The characteristics of

the patients between the training cohort (n = 1743) and the validation cohort (n = 756) were similar (Table S1 in the **Online Supplementary Document**).

Of 1743 patients in the training cohort, 1529 (87.7%) were male patients, with a mean age of 63.1 (SD = 8.0) and a mean FEV₁ percentage predicted of 53.0 (SD = 21.0%). A total of 116 (6.7%) deaths were recorded. There were significant differences in age, BMI, educational level, CAT, mMRC, CCQ, FEV₁/FVC, FEV₁, FEV₁ percentage predicted, COPD severity, GOLD 2017 ABCD group classification, AE/severe AE frequency in the past year, AE/severe AE frequency in first year follow up between survivors and non-survivors (Table S2 in the **Online Supplementary Document**). Besides, the indexes of BODEx, updated ADO, and DOSE were lower among survivors than non-survivors.

Nomogram variable screening, construction, and validation

We included the above baseline differential indicators, sex, and smoking status for Lasso regression screening (Table 1). Furthermore, the comparison of ROC curve analysis demonstrated that the predictive value of AE during the first year for COPD mortality was higher than that for AE (P = 0.02) and severe AE in the

past year (P < 0.01). The predictive value of severe AE in the first year for COPD mortality was higher than for AE in the first year (P < 0.01). (Figure S1 in the **Online Supplementary Document**).

Table 1. Screening predicted variables based on Lasso regression in COPD training cohort*

Variable*	HR (95% CI)	P-value
Age in years	1.06 (1.04, 1.09)	<0.01
BMI	0.91 (0.86, 0.96)	0.01
Educational level		
Primary/below	ref	
Middle	0.57 (0.37, 0.90)	0.01
High	0.57 (0.31, 0.99)	0.05
College/upper	0.23 (0.06, 1.01)	0.04
FEV ₁ percentage predicted		
>46.3	ref	
≤46.3	1.65 (0.84, 2.79)	0.02
mMRC	1.45 (1.06, 1.83)	0.01
Severe AE frequency in the first year	1.42 (1.24, 1.88)	<0.01

AE – acute exacerbation, BMI – body mass index, CI – confidence interval, FEV₁ – forced expiratory volume in one second, HR – hazard ratio, mMRC – modified medical research council dyspnoea scale, ref – reference

*COPD severity and group classification were classified using Global Initiative for Chronic Obstructive Lung Disease criteria.

Table 2. Hazard ratios for mortality of variables used in the ABEODS nomogram model in the training cohort

Item	HR (95% CI)	P-value
Age in years	1.06 (1.03, 1.09)	<0.01
BMI		
>20.3	ref	
≤20.3	1.87 (1.29, 2.71)	0.01
Educational level		
Primary/below	ref	
Middle	0.66 (0.43, 1.01)	0.06
High	0.54 (0.30, 0.96)	0.04
College/upper	0.21 (0.05, 0.86)	0.03
FEV ₁ percentage predicted		
>46.3	ref	
≤46.3	1.56 (1.04, 2.36)	0.03
mMRC	1.47 (1.17, 1.83)	0.01
Severe AE frequency in the first year		
0	ref	
≥1	5.52 (3.78, 8.07)	<0.01

AE – acute exacerbation, BMI – body mass index, CI – confidence interval, FEV₁ – forced expiratory volume in one second, HR – hazard ratio, mMRC – modified medical research council, ref – reference

The cut-off value of FEV₁ percentage predicted was 46.3% based on Youden's index from the ROC curve (AUC = 0.62; 95% CI = 0.59, 0.64, P < 0.01). The cut-off value of BMI was 20.3 based on Youden's index from the ROC curve (AUC = 0.64; 95% CI = 0.61, 0.66, P < 0.01). The cut-off value of severe exacerbation frequency was one based on Youden's index from the ROC curve (AUC = 0.71; 95% CI = 0.68, 0.73, P < 0.01). In Cox regression analysis, the hazard ratios (HR) for mortality of variables including age, BMI, educational level, degree of airflow obstruction, dyspnoea, and severe exacerbation are shown in Table 2. The ABEODS nomogram model was constructed to predict the risk of three, four, and five-year mortality in stable COPD according to these independent risk factors (Figure 1). We calculated the total points for individuals' scores by using this nomogram. We obtained the corresponding survival probability by the corresponding points in the nomogram. The formula for calculating the survival probability from the nomogram was:

$$\text{a) three-year survival probability} = 4.74 \times 10^{-7} \times \text{points}^3 + (-0.000377178) \times \text{points}^2 + 0.090241794 \times \text{points} + (-5.889732166);$$

$$\text{b) four and five-year survival probability} = 4.74 \times 10^{-7} \times \text{points}^3 + (0.000368558) \times \text{points}^2 + 0.085719878 \times \text{points} + (-5.356251871).$$

The AUC predicting three, four, and five-year survival likelihood was 0.84 (95% CI = 0.81, 0.88), 0.83 (95% CI = 0.76, 0.90), and 0.86 (95% CI = 0.77, 0.95), respectively in the training cohort. As demonstrated in the validation cohort, the AUC was more than 0.75 for predicting three-year and four-year survival probability. However, the discriminate ability in predicting five-year survival probability was poor (AUC = 0.59). The calibration curves of three, four, and five-year OS probability showed high consistency between predicted survival probability and observed survival probability in these two cohorts (Figure S2–3 in the **Online Supplementary Document**).

Clinical value of the nomogram model compared with three earlier prediction models

The changes in the net reclassification index were more than zero between the nomogram model and BODEx. The changes

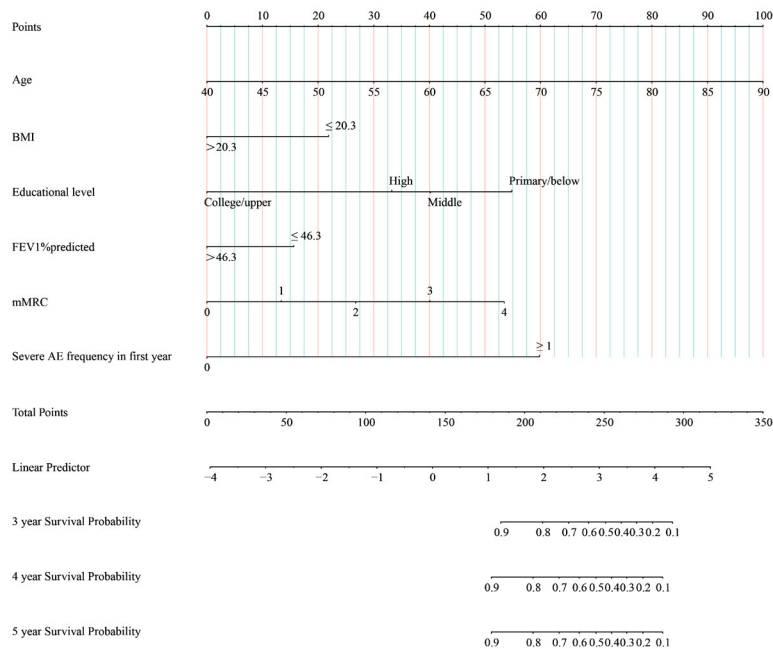


Figure 1. ABEODS nomogram model to predict the risk of mortality in stable COPD. ABEODS – combination of age, BMI, educational level, airflow obstruction, dyspnoea and severe exacerbation in the first year, BMI – body mass index, COPD – chronic obstructive pulmonary disease, FEV₁ – forced expiratory volume in one second, mMRC – modified medical research council dyspnoea scale.

Table 3. Net reclassification index and integrated discrimination improvement analysis between nomogram and three existing models in mortality prediction in the training cohort

	Estimate (95% CI)	P-value
ABEODS nomogram model vs BODEx model		
Integrated discrimination improvement	0.03 (-0.01, 0.06)	0.07
Net reclassification index	0.28 (0.13, 0.39)	<0.01
Median improvement in risk score	0.04 (0.01, 0.06)	<0.01
ABEODS nomogram model vs updated ADO model		
Integrated discrimination improvement	0.02 (0.01, 0.04)	<0.01
Net reclassification index	0.26 (0.08, 0.36)	<0.01
Median improvement in risk score	0.02 (0.01, 0.04)	<0.01
ABEODS nomogram model vs DOSE model		
Integrated discrimination improvement	0.03 (0.01, 0.05)	0.01
Net reclassification index	0.31 (0.15, 0.41)	<0.01
Median improvement in risk score	0.03 (0.01, 0.04)	<0.01

ABEODS – a combination of age, BMI, educational level, airflow obstruction, dyspnoea, and severe exacerbation in the first year, updated ADO – a combination of age, dyspnoea, obstruction, BMI – body mass index, BODEx – a combination of BMI, airflow obstruction, dyspnoea, and exacerbations, CI – confidence interval, DOSE – a combination of the dyspnoea, obstruction, smoking, exacerbation

adjusted mortality risk increased 9.43 times for patients classified to quartile three when compared with patients classified to quartile one. The adjusted mortality risk increased 38.86 times for patients classified to quartile four when compared with patients classified to quartile one. Finally, we defined patients in quartile one as low risk, patients in quartiles two and three as moderate risk, and patients in quartile four as high risk. (Figure 2). Further survival analysis adjusted for different variables at baseline found that patients classified as moderate risk (HR = 6.00; 95% CI = 3.43, 10.47, $P < 0.01$) and high risk (HR = 36.89; 95% CI = 18.82, 72.33, $P < 0.01$) in ABEODS had a significantly higher mortality risk than patients classified to low risk.

in the net reclassification index and integrated discrimination improvement were more than zero between the nomogram model and the updated ADO model. A similar trend was also found in the comparison of the nomogram model and DOSE (Table 3). The time-dependent AUC and C-index of the nomogram model were higher than those of the BODEx, updated ADO, and DOSE, respectively. Decision curve analysis showed that the nomogram model could better predict the three, four, and five-year survival probability, as it added more net benefits compared with these three earlier prediction models for almost all threshold probabilities (Figure S4–5 in the Online Supplementary Document).

Construction and Cox regression analysis of the ABEODS index

To apply the ABEODS model more conveniently to clinical practice, we scored the metrics of this model quantitatively (Table 4). The cut-off value of age was 62 based on Youden's index from ROC curve analysis (AUC = 0.68; 95% CI = 0.65, 0.70, $P < 0.01$). The value for mMRC was consulted for the categories used in BODE. We estimated these values based on the points in the nomogram including age, BMI, educational level, FEV₁ percentage predicted, mMRC, and severe exacerbation frequency. The score range for this index was between zero and 14 points. The following quartiles were considered: quartile one (0–5 points), quartile two (6–7 points), quartile three (8–9 points), and quartile four (≥ 10 points).

To apply the model to clinical practice, we scored and stratified the indicators in the model. Patients with higher ABEODS scores were at higher risk for death; the HR for death from any cause per one-point increase in the ABEODS score was 1.75. We also compared the strata by using the Kaplan-Meier analysis. The adjusted mortality risk increased 4.82 times for patients classified to quartile two when compared with patients classified to quartile one. The

Table 4. Variables and point values used for the computation of the ABEODS index

Variables	Points on ABEODS index*			
	0	1	2	3
Age in years	40–62			≥63
BMI	≥20.3	<20.3		
Education level	College/upper	High	Middle	Primary/below
FEV ₁ percentage predicted	>46.3	≤46.3		
mMRC	0–1	2	3	4
Severe exacerbation in the first year	0			≥1

ABEODS – a combination of age, BMI, educational level, airflow obstruction, dyspnoea and severe exacerbation in the first year, BMI – body mass index, FEV₁ – forced expiratory volume in one second, mMRC – modified medical research council dyspnoea scale

*The score range for this index is between zero and 14 points. The cut-off values of age, BMI, FEV₁ percentage predicted, and severe exacerbation are based on Youden's index from the receiver operating characteristic curve. The education level categories are based on the Cox regression model. The value for mMRC was consulted for the categories used in BODE.

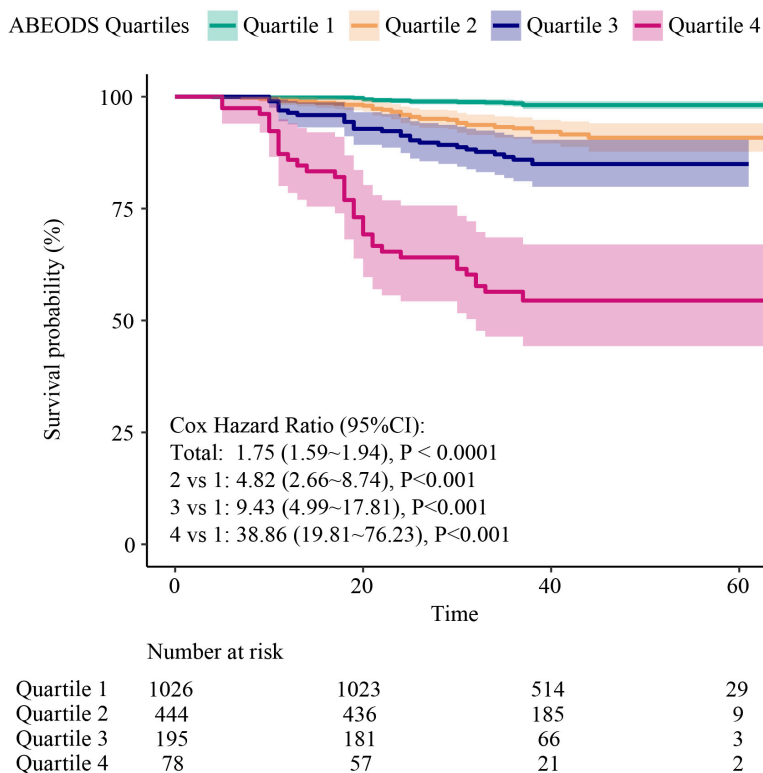


Figure 2. Kaplan-Meier overall survival curves for the four quartiles of the ABEODS index. The score range for this index is between zero and 14 points. The following quartiles were considered: quartile one (0–5 points), quartile two (6–7 points), quartile three (8–9 points), and quartile four (≥10 points). ABEODS – a combination of age, BMI, educational level, airflow obstruction, dyspnoea, and severe exacerbation in the first year, BMI – body mass index, CI – confidence interval.

above. Unlike other common prediction models, our nomogram model incorporates educational levels into the prediction model. Previous studies demonstrated that a higher educational level was associated with the mortality of COPD [11,12]. Educational level is one of the indexes of socioeconomic status [30] which may affect the patient's ability to bear the disease burden. Study showed that socioeconomic status affects the risk of health conditions including multimorbidity, frailty, and disability [30]. Bartosz et. al found that a lower educational level was an independent predictor of poor therapy adherence [31]. Poor medication adherence to inhaled corticosteroids and tiotropium was associated with a higher risk of mortality [32]. These findings further support the association of educational level with COPD mortality.

Patients who deceased had higher CAT, CCQ, and mMRC scores than survivors. ROC analysis presented that higher CAT (AUC = 0.65; 95% CI = 0.62, 0.67), CCQ (AUC = 0.63; 95% CI = 0.61, 0.65), and mMRC (AUC

Comparison among the ABEODS index and three earlier indexes

The AUC of the ABEODS index was higher than the AUC of other composite predictor indexes, such as the BODEx ($P < 0.01$), the updated ADO ($P < 0.01$), and the DOSE ($P < 0.01$) (Figure S6 in the **Online Supplementary Document**).

DISCUSSION

In this study, we aimed to develop and validate a prognostic nomogram model for mortality prediction in stable COPD patients. This nomogram model can be used to predict mortality in COPD individuals, achieving individualised prognostic assessment and providing some value for adjusting treatment assessment.

Predictor variables were screened based on the Lasso regression, and the nomogram model ultimately included severe AE frequency during first-year follow-up rather than AE frequency in the past year. The data on AE frequency in the past year was recalled by the patient, and it may be inaccurate [29], which will reduce the predictive value of mortality. Furthermore, the predictive value of severe AE in the first year for mortality was higher than that for AE in the first year. A 17-year follow-up cohort study exhibited that every new severe exacerbation increases the risk of death, the peak does not rise much more after the third severe exacerbation [10]. Juan et. al found that severe exacerbation during the first year follow-up presented as an independent adverse prognostic factor [16]. These studies further provide an explanation for the better predictive value of severe exacerbation frequency over the number of exacerbations during the first year.

In the Cox prediction regression model, the risk of death among patients with primary or below educational level was more than four times higher than that at college or

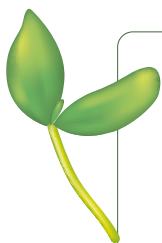
= 0.67; 95% CI = 0.65, 0.69) scores were related to higher mortality. The above results are consistent with those of the previous study [9,33]. Lasso regression selected mMRC as one of the variables of the nomogram prediction model, which is consistent with the composition of other earlier models such as BODE, BODEx, ADO, updated ADO, and DOSE [14–18]. There was no difference between the baseline smoking status of the dead COPD patients and the survivors, and this indicator was ultimately not included in the prediction model. As we know, smoking cessation is an effective intervention in increasing survival and reducing morbidity [34]. In the real world, there is uncertainty about smoking cessation during follow-up, which we believe may be one of the reasons why the baseline smoking status is not included in the prediction model.

According to the time-dependent ROC and DCA analysis, the proposed ABEODS nomogram model performed better than earlier models, including BODEx, updated ADO, and DOSE in COPD patients. In addition to these existing prediction models, a previous study conducted on a machine-learning mortality prediction model outperformed four existing models for predicting all-cause mortality across two COPD cohorts [35]. However, the indicators required by the model are numerous; some indicators, such as six-minute walking distance and oxygen saturation, are difficult to obtain in the outpatient department routine, which may reduce the clinical application value of the model. Other machine-learning models for the prediction of mortality in COPD included imaging parameters [36–38]. Although such prediction models have good prediction ability for COPD patients, patients must finish the chest computed tomography scanning, and imaging professionals to evaluate the relevant impact indicators of emphysema to complete the prediction of mortality. The above factors may lead to the model being less practical and convenient in clinical application than our model. Moreover, the predictive value of the ABEODS index was higher than that of the BODEx index, updated ADO index, and DOSE index which further proved that the ABEODS index has a good predictive value for COPD mortality.

The validation cohort exhibited that the predictive ability was strong for predicting the three-year and four-year survival probability of this nomogram model. The poor discriminate ability in predicting the five-year survival probability may be due to the small number of patients over a five-year follow-up in the validation cohort. The predictive ability of this nomogram model for five-year survival probability needs to be further validated in cohorts with more participants and longer follow-ups. As China is a developing country with a lower education level in the elderly, low cognitive level of COPD in patients, and low awareness of symptoms [21], this may lead to better application of this nomogram model in patients in developing countries like China. We also hope for more research to further validate the effectiveness of this nomogram model in population cohorts of different countries in the future. In addition, there are other limitations in the study. This study was limited to one centre, which may lead to reduced representation. However, our subjects included mild to very severe COPD patients, and the study population was collected in eight provinces and over 30 cities in China, which helped to improve the representation of COPD patients. Lastly, the study did not adjust the Charlson comorbidity index due to the limitations of the real-world study, but we have excluded other chronic pulmonary diseases, cancer, severe heart disease, chronic liver disease, and chronic kidney diseases based on personal medical records at baseline which may reduce the confounding deviation of comorbidities to a certain extent.

CONCLUSIONS

We developed and validated a prognostic nomogram model that accurately predicts mortality across the COPD severity spectrum. The constructed ABEODS nomogram model may have a better prognostic performance than the existing BODEx, updated ADO, and DOSE models in Chinese patients with COPD.



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Ethics statement: All procedures followed were in accordance with the Helsinki Declaration. All participants had signed the informed consent form. This study was approved by the local ethics committee of the Second Xiangya Hospital (number 2016076).

Data availability: The data that support the findings of this study are available upon reasonable request from the first author.

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Disclosure of interest: The authors completed the ICMJE Disclosure of Interest Form (available upon request from the corresponding author) and disclose no relevant interests.

Additional material

Online Supplementary Document.

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