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Development and validation of a clinical prognosis prediction model for malignant intestinal obstruction: A retrospective cohort study

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Malignant bowel obstruction (MBO) is a common and complex condition in clinical practice, which seriously affects the quality of life and prognosis of patients. However, the current lack of effective prognostic models for MBO has greatly limited clinical precision treatment and patient management. Focusing on this issue, this study aims to construct and validate a prognostic model for the overall survival (OS) of MBO patients, providing crucial support for clinical decision - making and improving the prognosis of patients. In this study, 41 items of real - world data from 192 patients in the Affiliated Hospital of Nantong University from January 2022 to January 2024 were collected, including 39 independent variables, survival time, and survival status. Subsequently, the patients were randomly divided into groups at a ratio of 7:3. Predictor variables were screened using the Least Absolute Shrinkage and Selection Operator (LASSO) and multivariate Cox regression, and then a Cox model was constructed. The model was validated using the Concordance index (C - index), time - dependent Receiver Operating Characteristic (ROC) curve, and Decision Curve Analysis (DCA). Finally, a nomogram of the model was created. The study found that significant risk factors affecting patient mortality included chemoradiotherapy (β = − 1.24; HR = 0.29;95%CI, 0.14–0.59), conservative treatment (β = 1.34; HR = 3.81; 95%CI, 1.69–8.55), new cases (β = − 0.96; HR = 0.38; 95%CI, 0.19–0.77), AJCC T stage 4 (β = 2.16; HR = 8.64; 95%CI, 1.47–50.76), red blood cell count (RBC, β = − 0.63; HR = 0.53; ; 95%CI, 0.38–0.80), prothrombin time (PT, β = 0.37; HR = 1.45; ; 95%CI, 1.07–1.97), aspartate aminotransferase (AST, β = 0.01; HR = 1.01; 95%CI, 1.00–1.02), and intestinal necrosis (β = 1.73; HR = 5.62; 95%CI, 1.11–28.27). In the development set, the AUC and C - index values of the prognostic models for 30 - day, 90 - day, and 180 - day are 0.87, 0.94, and 0.92 respectively. In the validation set, the corresponding values are 0.83, 0.96, and 0.89. The results of DCA analysis indicated that the model was reliable and could effectively predict the 30 - day, 90 - day, and 180 - day survival periods of MBO patients. This study successfully constructed and validated a prognostic model for the overall survival of MBO patients. This model identified multiple key prognostic factors and exhibited good predictive performance. It provides important reference for clinicians to predict the survival period of MBO patients and develop personalized treatment plans, and is expected to improve the clinical outcomes of MBO patients.

Keywords Malignant bowel obstruction, Malignant tumor, Prognosis, Prediction model, Lasso regression, Nomogram

Intestinal obstruction is one of the common surgical acute abdomen conditions. Among them, malignant bowel obstruction (MBO) has drawn extensive attention due to its special causes and complex conditions[1–3]. MBO is one of the common and serious complications in patients with advanced malignant tumors, especially those with abdominopelvic malignancies. Approximately 25–60% of patients with gynecological cancers and 10–28% of patients with colorectal cancers will eventually develop into MBO[4–7]. It brings great pain to patients and seriously affects their quality of life and survival time.

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For conventional patients with malignant tumors, we can predict the prognosis of patients through the TNM staging of the American Joint Committee on Cancer (AJCC)[8]. However, many MBO patients are already in a state of distant organ metastasis and diffusion, which makes it difficult for us to further evaluate the prognosis of patients[9–11]. Therefore, accurately assessing the prognosis of patients with malignant bowel obstruction is crucial for formulating reasonable treatment plans, improving the quality of life of patients, and prolonging their survival time. We need to conduct a more detailed analysis of other clinical risk factors to obtain this effective assessment tool[9,12,13].

Currently, the prognosis assessment of malignant bowel obstruction mostly depends on a single indicator, and the obtained prognosis information is mostly short-term prognosis, lacking comprehensiveness and accuracy[14]. Different patients have differences in tumor types, metastasis situations, physical conditions, etc., which makes predicting their prognosis a highly challenging task. Therefore, constructing a reliable clinical prognosis prediction model has become an urgent need. This model will integrate multiple relevant factors to provide clinicians with a more accurate prediction tool, thereby better guiding treatment decisions and patient management[1,15–18].

In this study, we collected a large amount of clinical data of MBO from the database of our hospital. Through the retrospective analysis of these data, we constructed prediction models for the survival time of 30 days, 90 days, and 180 days. It will provide new ideas and assistance for the individualized treatment and management of MBO.

Materials and methods

Patients

The data used in this paper were the real data of 192 patients from the Gastrointestinal Surgery Department of our hospital during the period from January 2021 to January 2024. All methods were carried out in accordance with the ethical standards outlined in the World Medical Association Declaration of Helsinki. This study is an observational study and does not involve the selection of medications and treatment regimens. It has been approved by the Ethics Committee of the Affiliated Hospital of Nantong University, and patient informed consent was waived during the research process (82173270).We randomly sampled the data set at a ratio of 7:3 to divide the original data set into a development set and a internal validation set. Among them, the development set contained 134 samples, and the internal validation set contained 58 samples. The inclusion criteria included a definite diagnosis of malignant tumor, the appearance of intestinal obstruction symptoms and confirmation by imaging examinations. The exclusion criteria were patients with other serious diseases that might affect the prognosis judgment and those with incomplete data. The current living time and survival status of the patients were obtained through multiple telephone follow-ups.The flowchart of the patients screening is shown in Fig. 1.

Development and validation of the model

This study was a retrospective cohort study. Numbers and percentages (N, %) were used to describe categorical data, and the chi-square test was used to compare the differences between the development set and the validation set. Based on previous related studies and clinical experience, there were 39 independent variables as well as the survival time and current survival status of the patients, totaling 41 variables. Among them, the predictor "tumor type" was determined according to the location of the tumor obstruction. The Least Absolute Shrinkage and Selection Operator (LASSO) regression analysis was adopted to screen out appropriate prognostic predictors from these 39 clinical variables. Multivariate Cox regression analysis was used to determine whether the selected variables were significantly related to the disease prognosis, and then the predictors with $P < 0.05$ were input into the Cox proportional hazards model to construct a prediction model for MBO patients, which was represented by a nomogram. The prediction results were the survival probabilities of 30 days, 60 days, and 180 days.The time-dependent Receiver Operating Characteristic (ROC) curve and the Concordance index (C-index) were used to evaluate the predictability of the model. The area under the ROC curve (AUC) and the C-index ranged from 0.5 to 1, and values greater than 0.7 indicated good predictability. Decision Curve Analysis (DCA) was performed to assess the clinical benefits and utilities of the constructed prediction model.All the statistical analysis was in R software (version 4.2.1; https://www.r-project.org/).

Results

Baseline characteristics

The data used in this paper were the real data of 192 patients from our hospital, including 39 independent variables, as well as the survival time and current status of the patients, totaling 41 variables. The specific distribution of each variable is shown in Table 1. In addition, a chi-square test was also performed on the data. The results are shown in Table 1: From the chi-square test results, it can be seen that the p-values of AJCC M stage, Hb content in the blood, FDP, and A/G were all greater than 0.05, indicating that they were secondary factors and might have little impact on the results of subsequent regression analysis. To further explore the roles of these secondary variables, this paper further screened the variables using Lasso regression in the subsequent steps.

Lasso regression

Since there are 39 independent variables in the data set of this paper, directly incorporating them into the modeling process might lead to an overly complex model and potential collinearity issues among variables. Therefore, it is necessary to screen the variables using Lasso regression before modeling. Hence, this paper established a Lasso regression for the data set of 134 patients in the development set. The results are shown in Figs. 2 and 3.

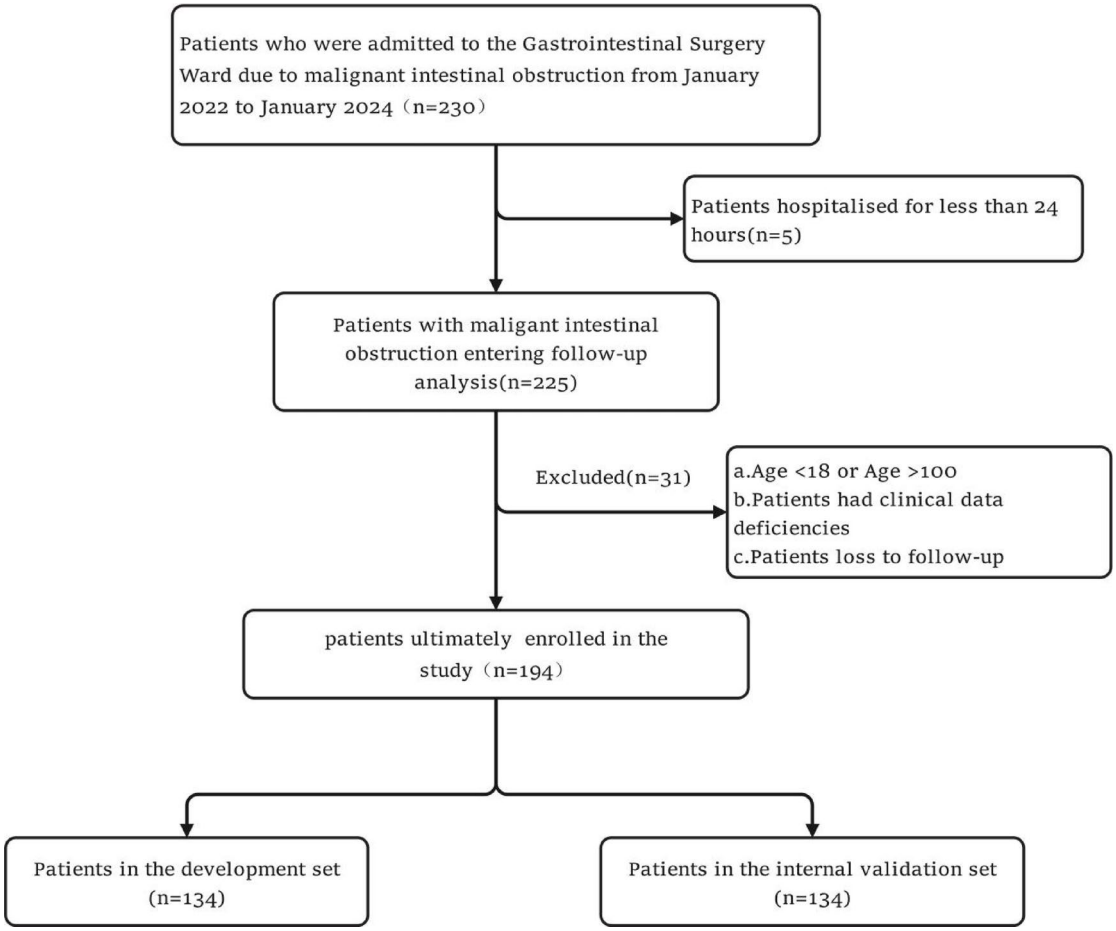

Fig. 1. Flowchart of the patient screening.

Figure 2 is the coefficient path plot of the Lasso regression, which shows how the regression coefficients of each variable change under different penalty parameter lambda values. In the figure, the curves indicate that as the lambda value gradually increases, the coefficients of each variable gradually decrease to 0. The slower the coefficient decreases to 0, the greater the contribution of the variable to the model. Figure 3 shows the impact of different regularization parameter lambda values on the model deviation in the Lasso regression. It is usually used to determine the number of selected variables. Judging from the two vertical curves in the figure, the number of variables selected for the subsequent survival regression should be 15 to 17. In this paper, 17 variables are selected as the independent variables for the subsequent Cox survival regression.

Cox regression

After screening out 17 independent variables through Lasso regression in the previous section, a Cox proportional hazards regression model was established using the development set data. The results are shown in Table 2: From Table 2, it can be seen that the significant factors affecting the death risk include chemoradiotherapy (β = − 1.24; HR = 0.29;95%CI, 0.14–0.59), conservative treatment (β = 1.34; HR = 3.81; 95%CI, 1.69–8.55), new cases (β = − 0.96; HR = 0.38; 95%CI, 0.19–0.77), AJCC T stage 4 (β = 2.16; HR = 8.64; 95%CI, 1.47–50.76), red blood cell count (RBC, β = − 0.63; HR = 0.53; ; 95%CI, 0.38–0.80), prothrombin time (PT, β = 0.37; HR = 1.45; ; 95%CI, 1.07–1.97), aspartate aminotransferase (AST, β = 0.01; HR = 1.01; 95%CI, 1.00–1.02), and intestinal necrosis (β = 1.73; HR = 5.62; 95%CI, 1.11–28.27).

Other variables such as Age also have a certain impact on the death risk, but the significance is weak or not significant.

Nomogram

The model established in this paper was used to draw a nomogram, and the results were presented in Fig. 4. It aims to assist clinicians or researchers in integrating multiple complex predictors into a simple scoring system, thereby enabling risk assessment or prognosis prediction for individual patients.

	Overall patients (*N* = 192)	Development set (*N* = 134)	Validation set (*N* = 58)	χ2	*P* value
Gender				9.188	0.00***
Women	75(39.1%)	46(34.3%)	29(50%)		
Men	117(60.9%)	88(65.7%)	29(50%)		
Age				3	0.08
≤ 73	108(56.3%)	70(52.2%)	98(65.5%)		
> 73	84(43.7%)	64(47.8%)	20(34.5%)		
Chemoradiotherapy				4.083	0.04*
No/unknown	110(57.3%)	77(57.5%)	33(56.9%)		
Yes	82(42.7%)	57(42.5%)	25(43.1%)		
Treatment				6.021	0.01**
Conservative treatment	18(9.3%)	14(10.5%)	4(6.9%)		
Intestinal resection with intestinal anastomosis	79(41.1%)	51(38.1%)	28(48.3%)		
Intestinal resection with intestinal stomy	61(31.9%)	44(32.9%)	17(31%)		
Enterostomy and others(Not intestinal stomy)	34(17.7%)	25(18.5%)	9(15.8%)		
Cancertype				111.021	0.00***
Cancer type-Rectum	23(12%)	16(11.9%)	7(12.1%)		
Cancer type-Colon	148(77.1%)	106(79.1%)	42(72.4%)		
Cancer type-Junction	14(7.1%)	9(6.7%)	5(8.6%)		
Cancer type-Small intestine	7(3.8%)	3(2.3%)	4(6.9%)		
New cases				52.083	0.00***
Yes	146(76%)	103(76.9%)	43(74.1%)		
No	46(24%)	31(23.1%)	15(25.9%)		
AJCC T				98.375	0.00***
T1–T3	132(68.7%)	90(67.2%)	42(72.4%)		
T4	60(31.3%)	44(32.8%)	16(27.6%)		
AJCC M				0.083	0.77
0	98(51%)	63(47%)	35(60.3%)		
1	94(49%)	71(53%)	23(39.7%)		
Tumor grade				90.208	0.00***
I–II	43(22.4%)	32(23.8%)	11(18.9%)		
III–IV	149(77.6%)	102(76.2%)	47(81.1%)		
Liver metastases				46.021	0.00***
Yes	49(25.5%)	36(26.9%)	13(22.4%)		
No	143(74.5%)	98(73.1%)	45(77.6%)		
Multiple abdominal metastases				35.021	0.00***
Yes	55(28.6%)	42(31.3%)	13(22.4%)		
No	137(71.4%)	92(68.7%)	45(77.6%)		
Recurrent obstruction				143.521	0.00***
Yes	13(6.8%)	8(6%)	5(8.6%)		
No	179(93.2%)	126(94%)	53(91.4%)		
Reoperation				154.083	0.00***
Yes	10(5.2%)	8(6%)	2(3.4%)		
No	182(94.8%)	126(94%)	56(96.6%)		
Intestinal necrosis				161.333	0.00***
Yes	8(4.2%)	8(6%)	0		
No	184(95.8%)	126(94%)	58(100%)		
Intestinal perforation				176.333	0.00***
Yes	4(2.1%)	3(2.2%)	1(1.7%)		
No	188(97.9%)	131(97.8%)	57(98.3%)		
ICU				114.083	0.00***
Yes	22(11.5%)	17(12.7%)	5(8.6%)		
No	170(88.5%)	117(87.3%)	53(91.4%)		
Underlying disease				76.625	0.00***
0	83(43.2%)	60(44.8%)	23(39.7%)		
1	71(37%)	44(32.8%)	27(46.6%)		
2	30(15.6%)	23(17.2%)	7(12.1%)		

Continued

	Overall patients (*N* = 192)	Development set (*N* = 134)	Validation set (*N* = 58)	χ2	*P* value
3	8(4.2%)	7(5.2%)	1(1.7%)		
Personal history of malignant tumors				58.521	0.00***
Yes	43(22.4%)	32(23.9%)	11(19%)		
No	149(77.6%)	102(76.1%)	47(81%)		
History of abdominal surgery				199.292	0.00***
0	126(65.6%)	91(67.9%)	35(60.3%)		
1—2	62(32.3%)	40(29.9%)	22(38%)		
≥ 3	4(2.1%)	3(2.2%)	1(1.7%)		
WBC				81.5	0.00***
Low	20(10.4%)	14(10.4%)	6(10.3%)		
Normal	120(62.5%)	79(59%)	41(70.7%)		
High	52(27.1%)	41(30.6%)	11(19%)		
RBC				15.188	0.00***
Low	69(35.9%)	49(36.6%)	20(34.5%)		
Not low	123(64.1)	85(63.4%)	38(65.5%)		
Hb				0.188	0.67
Low	93(48.4%)	63(47%)	30(51.7%)		
Not low	99(51.6%)	71(53%)	28(48.3%)		
Plt				157.688	0.00***
Low	9(4.7%)	7(5.2%)	2(3.4%)		
Not low	183(95.3%)	127(94.8%)	56(96.6%)		
FDP				2.521	0.11
Negative	85(44.3%)	55(41%)	30(51.7%)		
Positive	107(55.7%)	79(59%)	28(48.3%)		
D-Dimer				72.521	0.00***
Negative	37(19.3%)	26(19.4%)	11(19%)		
Positive	155(80.7%)	108(80.6%)	47(81%)		
PT				108	0.00***
Negative	168(87.5%)	115(85.8%)	53(91.4%)		
Positive	24(12.5%)	19(14.2%)	5(8.6%)		
APTT				85.333	0.00***
Negative	160(83.3%)	111(82.8%)	49(84.5%)		
Positive	32(16.7%)	23(17.2%)	9(15.5)		
ALT				157.688	0.00***
Negative	183(95.3%)	127(94.8%)	56(96.6%)		
Positive	9(4.7%)	7(5.2%)	2(3.4%)		
AST				120.333	0.00***
Negative	172(89.6%)	122(91%)	50(86.2%)		
Positive	20(10.4%)	12(9%)	8(13.8%)		
Cr				123.521	0.00***
Negative	173(90.1%)	118(88.1%)	55(94.8%)		
Positive	19(9.9%)	16(11.9%)	3(5.2%)		
Alb				16.333	0.00***
Low	68(35.4%)	49(36.6%)	19(32.8%)		
Not low	124(64.6%)	85(63.4%)	39(67.2%)		
Glb				168.75	0.00***
Low	6(3.1%)	4(3%)	2(3.4%)		
Not low	186(96.9%)	130(97%)	56(96.6%)		
A/G				0.021	0.89
Low	95(49.5%)	69(51.5%)	26(44.8%)		
Not low	97(50.5%)	65(48.5%)	32(55.2%)		
Na				100.906	0.00***
Low	57(29.7%)	42(31.3%)	15(25.9%)		
Normal	124(64.6%)	84(62.7%)	40(69%)		
High	11(5.7%)	8(6%)	3(5.2%)		
K				168.875	0.00***
Continued					

	Overall patients (*N* = 192)	Development set (*N* = 134)	Validation set (*N* = 58)	χ2	*P* value
Low	42(21.9%)	29(21.6%)	13(22.4%)		
Normal	146(76%)	103(76.9%)	43(74.1%)		
High	4(2.1%)	2(1.5%)	2(3.4%)		
Cl				135.375	0.00***
Low	26(13.5%)	23(17.2%)	3(5.2%)		
Normal	140(73%)	90(67.2%)	50(86.2%)		
High	26(13.5%)	21(15.6%)	5(8.6%)		
Ca				5.469	0.06
Low	59(30.7%)	43(32.1%)	16(27.6%)		
Normal	79(41.1%)	51(38.1%)	28(48.3%)		
High	54(28.2%)	40(29.9%)	14(24.1%)		
P				140.344	0.00***
Low	10(5.2%)	8(6%)	2(3.4%)		
Normal	139(72.4%)	93(69.4%)	46(79.3%)		
High	43(22.4%)	33(24.6%)	10(17.2%)		
Mg				226.219	0.00***
Low	9(4.7%)	6(4.5%)	3(5.2%)		
Normal	162(84.4%)	108(80.6%)	54(93.1%)		
High	21(10.9%)	20(14.9%)	1(1.7%)		
Survival				109.156	0.00***
≤ 30	35(18.2%)	25(18.7%)	10(17.2%)		
30–90	25(13%)	18(13.4%)	7(12.1%)		
> 90	132(68.8%)	91(67.9%)	41(70.7%)		

Table 1. Baseline characteristics of all 192 patients from hospital. *$P < 0.05$, **$P < 0.01$, ***$P < 0.001$, representing the level of statistical significance.

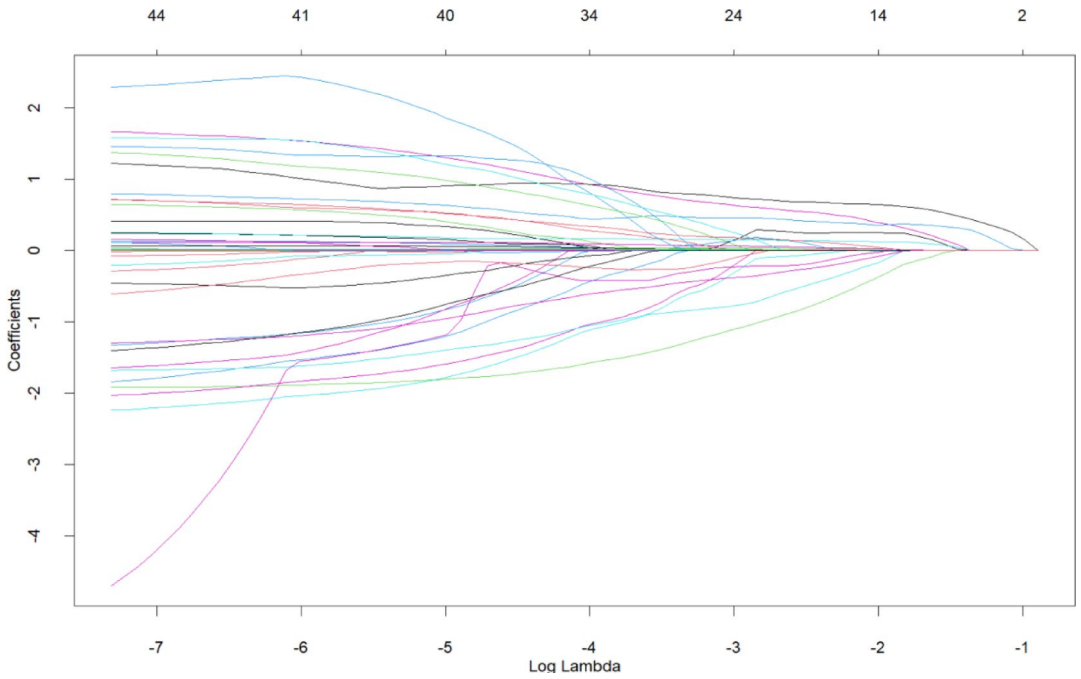

Fig. 2. LASSO Regression Coefficient Path.

Validation of the prediction model

DCA curves

To evaluate the practical clinical application value of the Cox proportional hazards regression model, this paper respectively used the development set and the validation validation set to draw the Decision Curve Analysis

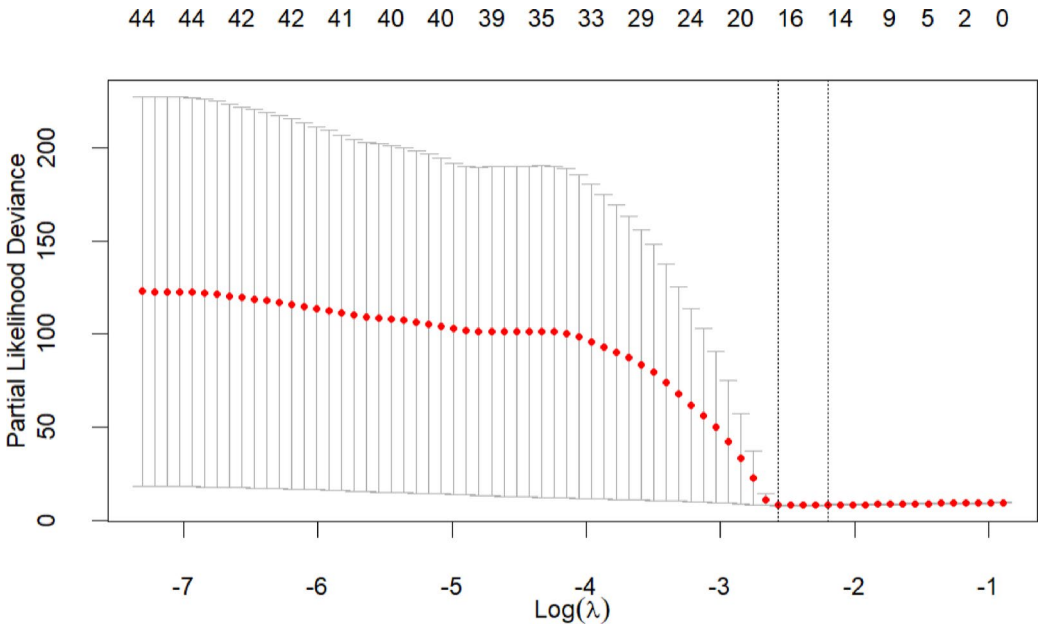

Fig. 3. Lasso Regression Cross-Validation.

Variables	β	HR,95%CI	*P* value
Age	0.02	1.02(0.99,1.05)	0.1
Chemoradiotherapy	− 1.24	0.29(0.14,0.59)	< 0.001
Conservative treatment	1.34	3.81(1.69,8.55)	< 0.001
Intestinal resection with intestinal anastomosis	− 0.19	0.83(0.42,1.63)	0.58
Cancertype. Small intestine	0.67	1.96(0.60,6.34)	0.26
New case	− 0.96	0.38(0.19,0.77)	0.01
AJCC T stage3	1.19	3.29(0.56,19.58)	0.19
AJCC T stage4	2.16	8.64(1.47,50.76)	0.02
AJCC M stage1	0.79	2.19(0.95,5.11)	0.07
Multiple abdominal metastases	0.6	1.82(0.93,3.56)	0.08
RBC	− 0.63	0.53(0.35,0.80)	< 0.001
FDP	0.02	1.02(0.96,1.08)	0.57
PT	0.37	1.45(1.07,1.97)	0.02
APTT	0.05	1.06(0.96,1.16)	0.27
AST	0.01	1.01(1.00,1.02)	< 0.001
Cr	0.01	1.00(0.99,1.01)	0.18
Mg	− 1.38	0.25(0.02,3.36)	0.3
Intestinal necrosis	1.73	5.62(1.11,28.27)	0.04

Table 2. Cox regression.

(DCA) curves for the established Cox model to assess the clinical application value of this model. Figure 5 shows the DCA curve drawn based on the development set, and Fig. 6 shows the DCA curve of the validation set:

Figure 5 presents the DCA curves of the development set, which include the decision curves for three nodes of 30-day survival period, 90-day survival period, and 180-day survival period, corresponding to the left, middle, and right parts of Fig. 5 respectively. From these three nodes, the following can be observed:

For the 30-day survival period, the prediction effect of the model is limited to the high-risk group, and the effect decreases significantly after the threshold exceeds 25%, showing instability.

For the 90-day survival period, the overall performance of the model is the most stable, and it performs well within the 0–50% threshold range, indicating that the model has the best prediction effect for the 90-day survival period and is applicable to a relatively wide range of medium to high-risk patients.

For the 180-day survival period, the model has certain application value at low thresholds, but as time extends, the performance of the model begins to decline, especially the prediction efficiency for the low-risk group is poor.

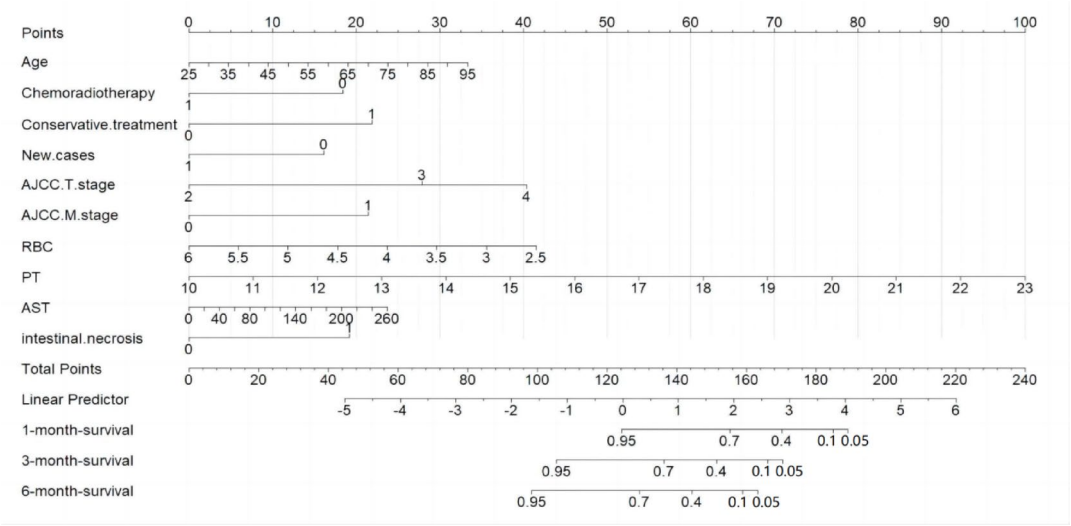

Fig. 4. Nomogram.

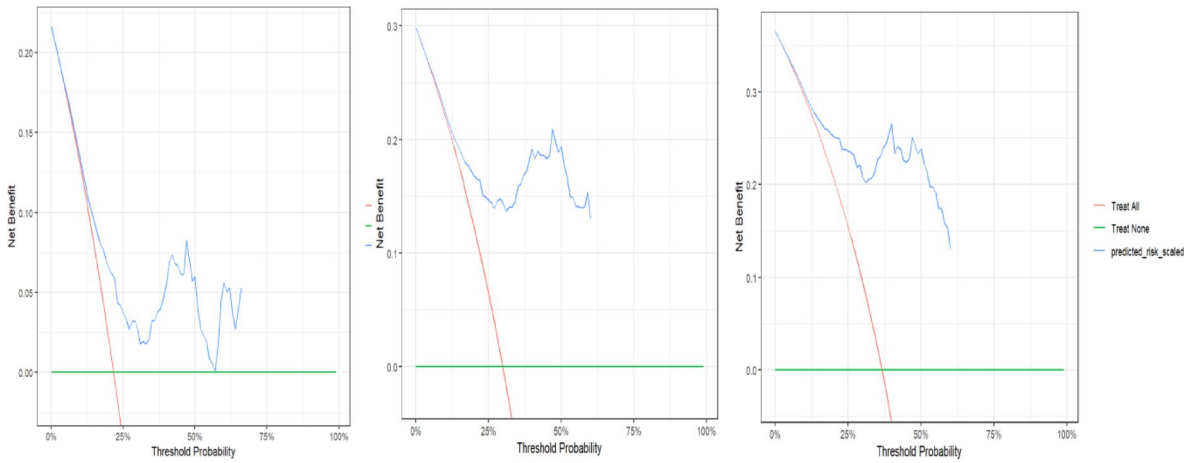

Fig. 5. DCA Curve of the Development Set.

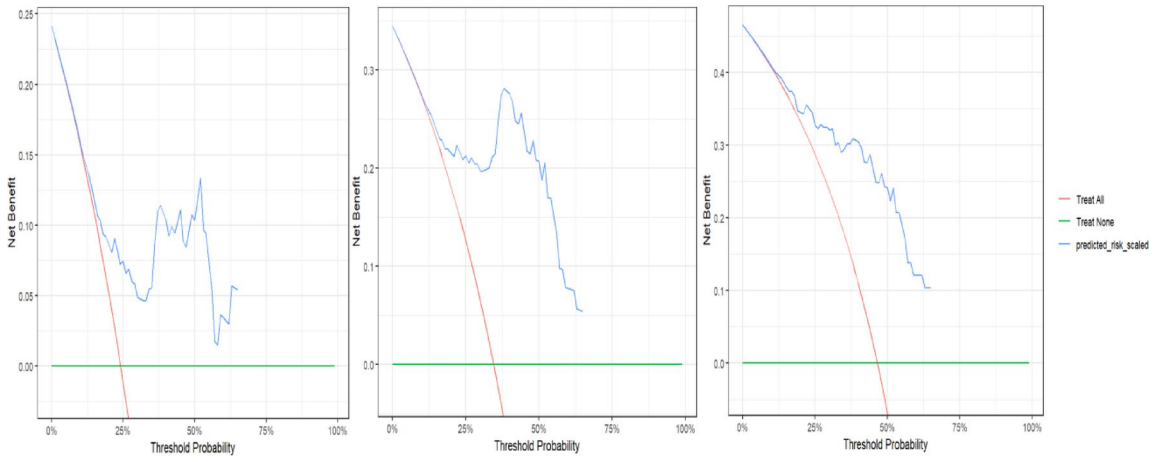

Fig. 6. DCA Curve of the Validation Set.

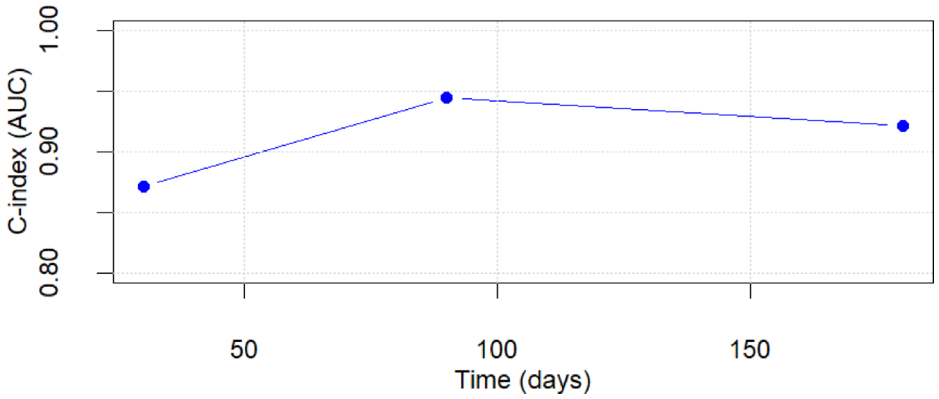

Fig. 7. C-index Curve of the Development Set.

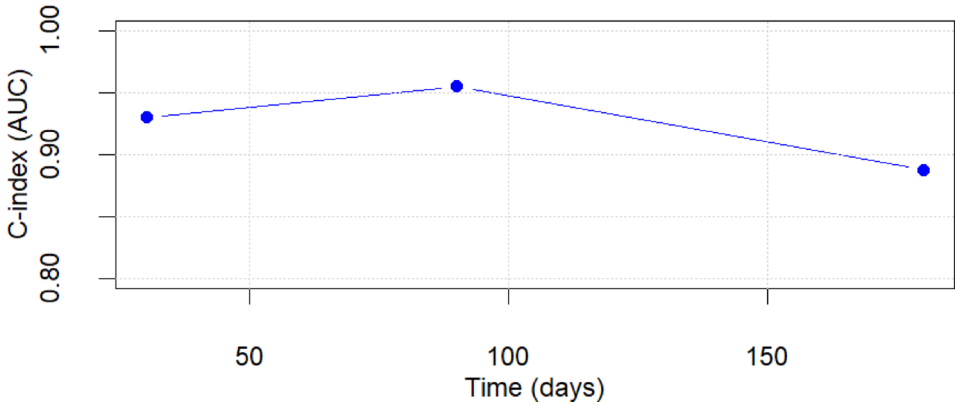

Fig. 8. C-index Curve of the Validation Set.

Overall, the model for predicting the 90-day survival period has the best clinical application prospects, while the models for 30-day and 180-day survival periods have limited applicability under specific thresholds.

Figure 6 shows the DCA curves of the validation set, which also include the decision curves for the three nodes of 30-day, 90-day, and 180-day survival periods, corresponding to the left, middle, and right parts of Fig. 6 respectively. From these three nodes, it can be seen that:

At the 30-day node, the model is effective for low-risk patients in short-term prediction, but the effect fluctuates greatly for medium and high-risk patients, with limited applicability.

At the 90-day node, the model performs best among low to medium-risk patients, with robust prediction efficiency and the highest clinical application value.

For the 180-day model, the net benefit decreases as time extendtrains, and it is mainly applicable to low-risk patients, with limited prediction efficiency for high-risk patients.

According to the consistent trends of the DCA curves of the ing set and the validation set at the three nodes of 30-day survival period, 90-day survival period, and 180-day survival period, it indicates that the performance of the model has good generalization ability on the development set and the validation set, that is, the prediction effect of the model is consistent on different data sets, further demonstrating that the model established in this paper is reliable and robust.

C-index

To further evaluate the prediction ability of the Cox proportional hazards regression model established in this paper, the C-index curves were drawn for the development set and the validation set respectively. The C-index is used to assess the prediction performance of the model. The value range of the C-index is between 0.5 and 1, and the closer the value is to 1, the higher the prediction accuracy of the model. The results are shown in Figs. 7 and 8.

Figure 7 shows the C - index curves of the training set for 30 - day, 90 - day, and 180 - day survival. The C - index of the model for 90 - day survival is 0.94, indicating a very high predictive ability. This shows that in mid - term risk prediction, the model can effectively distinguish individual risks and is highly suitable for clinical decision - making. Although the C - index for 30 - day survival (0.87) and that for 180 - day survival (0.92) are slightly lower than that for 90 - day survival, the overall C - index of the model is still high, suggesting that the prediction models for 30 - day and 180 - day survival perform well and can still provide a reliable basis for risk prediction.

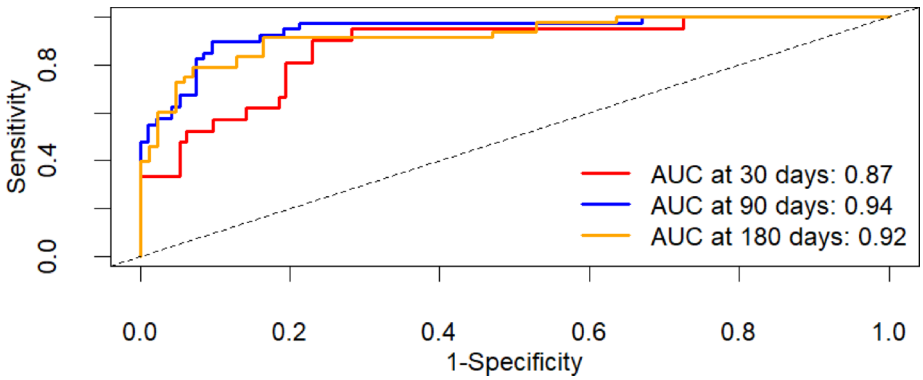

Fig. 9. ROC Curve of the Development Set.

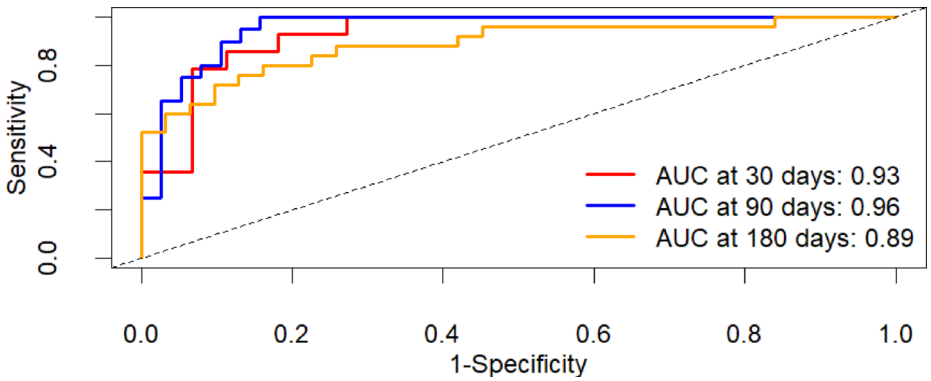

Fig. 10. ROC Curve of the Validation Set.

Figure 8 shows the C - index curves of the validation set for 30 - day, 90 - day, and 180 - day survival. The trend of its C - index is consistent with that of the training set. The C - index reaches the highest value (0.96) at 90 - day survival, and the C - indices for 30 - day and 180 - day survival are 0.93 and 0.89 respectively. This indicates that the Cox proportional - hazards regression model established in this paper has good generalization ability and is robust and reliable.

ROC curves

To evaluate the performance and predictive ability of the Cox regression model established in this paper, ROC curves were drawn for the three time nodes of the 30-day survival period, 90-day survival period, and 180-day survival period. Meanwhile, to verify the generalization ability of the Cox regression model, ROC curves were drawn on both the development set and the validation set, and the AUC values were compared. The closer the AUC value is to 1, the better the performance of the model. The results are shown in Figs. 9 and 10:

Figures 9 and 10 are the ROC curves of the model on the development set and the validation set respectively at three different time nodes, namely the 30-day survival period, the 90-day survival period, and the 180-day survival period. On different data sets, the AUC values of the ROC curves of the Cox regression model established in this paper are the highest for the 90-day survival period and are very close to 1. This indicates that both the performance and the generalization ability of the model are very good. In addition, the model is highly suitable for medium-term risk prediction. However, it is also applicable to long-term risk prediction since the AUC value of the ROC curve for the 180-day survival period is also very close to 1.

Discussion

Although previous studies have explored the prognostic factors of intestinal obstruction and advanced malignant tumors and constructed corresponding prognostic models, due to factors such as short prognostic observation time and small sample size, there is still a lack of effective prognostic models for malignant intestinal obstruction[1,3,13,14,16,19–22]. Some previously published scoring systems mainly focused on the pathological characteristics of tumors or paid more attention to the basic physiological indicators of patients. These scoring systems often rely on only one or a few factors and are difficult to comprehensively reflect the complex conditions of patients with malignant intestinal obstruction.

To explore the prognosis of patients with malignant intestinal obstruction, this study carried out the identification of prognostic risk factors and the development of a prognostic model, aiming to provide valuable guidance for clinical prognosis judgment and individualized treatment. Based on the real - world clinical data of

192 patients, this study covered 39 independent variables, as well as the survival time and current status of the patients, totaling 41 variables. The samples were randomly divided into a development set and a validation set. The development set initially identified some possible secondary factors through the chi - square test, such as AJCC M stage, Hb content in the blood, FDP, and A/G, all with P - values greater than 0.05. Subsequently, to explore the roles of these variables more comprehensively, Lasso regression was further used for variable screening. This combined approach of multiple methods helped to obtain more valuable variables[23]. Through Cox regression, eight independent prognostic factors significantly related to the survival of patients with malignant intestinal obstruction were determined: chemoradiotherapy, conservative treatment, new cases, AGCC T4, red blood cell count, prothrombin time, AST, and intestinal necrosis.

Compared with previous studies, this study has significant differences in methodology. In the past, few studies combined the chi - square test with Lasso regression for variable screening. However, this study adopted this method, effectively avoiding the problem of overfitting caused by too many variables and making the selected variables more representative. In terms of results, this study found that in the AJCC staging system, the T stage has a greater impact on the prognosis of MBO patients than the distant metastasis of the tumor, which is different from the traditional understanding[24–28].

In the analysis of the Cox regression results, chemoradiotherapy, a higher red blood cell count at admission, and the status of being a new case can reduce the prognostic risk. Chemoradiotherapy improves the prognosis by controlling tumor progression and reducing intestinal invasion. A higher red blood cell count reflects the patient's good physical reserve, which is beneficial for coping with the disease and subsequent treatments. Being a new case means that the disease may be in a relatively early stage. In contrast, conservative treatment, AGCC T4 stage, an increase in prothrombin time and AST, and intestinal necrosis increase the prognostic risk. Conservative treatment is chosen because patients cannot tolerate surgery, and it has limited effects on relieving obstruction and controlling tumor development. Abnormal increases in prothrombin time and AST indicate abnormal coagulation and liver function, affecting the patient's physical condition and treatment tolerance. Intestinal necrosis, as a serious complication of intestinal obstruction, causes severe infections and disorders of the body's functions, greatly increasing the possibility of a poor prognosis[29].

In terms of clinical relevance, the model constructed in this study is of great significance. In clinical practice, patients can be stratified and managed according to these risk factors. For patients with factors that reduce the prognostic risk, the favorable state can be actively maintained and the treatment plan can be optimized. For patients with factors that increase the prognostic risk, close attention should be paid to the changes in the disease condition, complications should be actively prevented, and more targeted comprehensive treatment measures should be taken. For example, for patients in the AJCC T4 stage, doctors should closely monitor the condition and take active treatment. For patients with a low red blood cell count, targeted red blood cell transfusion can be considered to reduce the risk of death. In addition, this study drew a nomogram to integrate multiple complex predictors into a simple scoring system, facilitating clinical doctors or researchers to conduct risk assessment and prognosis prediction for individual patients[30].

According to the model validation results, all C - index and AUC values are greater than or close to 0.9, indicating that the model has excellent predictability and accuracy[31,32]. The DCA analysis shows that the DCA curves of the training set and the test set are consistent at the three nodes of 30 - day, 90 - day, and 180 - day survival, indicating that the model has good generalization ability on both the training set and the validation set[33]. This means that the model can predict the survival of patients relatively stably on different data sets and provide a reliable basis for clinical decision - making.

However, this study also has some limitations. As a retrospective study, there may be selection bias. Collecting data from existing case records makes it difficult to cover all factors that may affect the prognosis, and there may be errors in the measurement of some variables[34,35]. The relatively limited sample size may affect the stability and universality of the model[36,37]. Future research needs to expand the sample size to improve the reliability of the model. At the same time, this model has only been validated in the internal data set and lacks external validation. External validation is crucial for determining the universality of the model. In the future, external validation needs to be carried out in different medical institutions and populations to further evaluate the performance of the model[38,39]. The prognosis of malignant intestinal obstruction is affected by many factors, such as the patient's underlying diseases, treatment compliance, and psychological state. Although this model has considered many clinical factors, it may still not cover all influencing factors[11,40]. Future research can further explore potential influencing factors to improve the stability and predictive accuracy of the model.

Conclusions

This study successfully constructed clinical prognostic prediction models for the 30-day, 90-day, and 180-day survival periods of malignant intestinal obstruction and verified the models through various statistical methods. The model has high accuracy and clinical application value and can provide important references for the clinical management of malignant intestinal obstruction. However, the model also has certain limitations and needs to be further improved and optimized in future studies. In the future, it is necessary to further expand the sample size, carry out prospective studies and external validation to continuously improve the performance and universality of the model. At the same time, other technical means such as machine learning and artificial intelligence can also be combined to further improve the prediction ability and accuracy of the model, providing more scientific and effective tools for the treatment and prognosis evaluation of patients with malignant intestinal obstruction.

Data availability

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

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Conceptualization: J.Q.、H.D.、R.T. Data collection: H.D.、R.T. Data analysis: H.D.、R.T. Writing and editing manuscript: H.D.、R.T. All authors read and approved the final manuscript.

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Declarations

Competing interests

The authors declare no competing interests.

Additional information

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