Original Article

A nomogram for predicting nutritional risk before gastric cancer surgery

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Background and Objectives: Gastric cancer (GC) is the fourth leading cause of cancer death worldwide. Patients with GC have higher nutritional risk. This study aimed to construct a nomogram model for predicting preoperative nutritional risk in patients with GC in order to assess preoperative nutritional risk in patients more precisely. **Methods and Study Design:** Patients diagnosed with GC and undergoing surgical treatment were included in this study. Data was collected through clinical information, laboratory testing, and radiomics-derived characteristics. Least absolute shrinkage selection operator (LASSO) regression analysis and multi-variable logistic regression were employed to construct a clinical prediction model, which takes the form of a logistic nomogram. The effectiveness of the nomogram model was evaluated using receiver operating characteristic (ROC) curve, calibration curve, and decision curve analysis (DCA). **Results:** A total of three predictors, namely body mass index (BMI), hemoglobin (Hb) and radiomics characteristic score (Radscore) were identified by LASSO regression analysis from a total of 21 variables studied. The model constructed using these three predictors displayed medium prediction ability. The area under the ROC curve was 0.895 (95% CI 0.844-0.945) in the training set, with a cutoff value of 0.651, precision of 0.957, and sensitivity of 0.718. In the validation set, it was 0.880 (95% CI 0.806-0.954), with a cutoff value of 0.655, precision of 0.930, and sensitivity of 0.698. DCA also confirmed the clinical benefit of the combined model. **Conclusions:** This simple and dependable nomogram model for clinical prediction can assist physicians in assessing preoperative nutritional risk in GC patients in a time-efficient and accurate manner to facilitate early identification and diagnosis.

Key Words: nutritional risk, nomogram, radiomics, prediction, gastric cancer

INTRODUCTION

Gastric cancer (GC) is a highly prevalent malignancy globally, ranking fifth position in terms of incidence and fourth in terms of mortality. According to the American Cancer Society (2020), it is projected that approximately 769,000 individuals will succumb to this illness.[1] Surgical resection remains the primary therapeutic approach for advanced GC, with minimally invasive techniques and surgical robotics significantly reducing patient trauma. Nevertheless, the long-term prognosis of GC is impacted by perioperative complications induced by nutritional risk.[2-4] GC patients inevitably face challenges such as nutrient deficiency, nutrient absorption disorder, cachexia, and other complications caused by tumor consumption. They are prevalent perioperative complications that will negatively affect the prognosis of patients with GC.[5-7] Individualized nutrition therapy for patients with GC is receiving increasing attention from clinicians, and effective nutrition therapy can improve clinical outcomes.[8] Detecting the nutritional risk in patients with GC in a timely and accurate manner is an urgently needed clinical solution.

Nutritional Risk Assessment 2002 (NRS2002) is a nutritional risk screening tool widely used clinically. It aims to identify individuals at nutritional risk among hospitalized patients so that intervention measures can be taken at an early stage. Assessing cancer patients' nutritional risks and treating their malnutrition aggressively may increase their quality of life.[9] There is a close relationship between

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skeletal muscle mass and nutritional status. Due to malnutrition and protein absorption disorders in patients with GC, the incidence of skeletal muscle mass loss is high, which will have a negative impact on the prognosis of patients.[10,11] Radiomics has the potential to study skeletal muscle mass, and some studies have established the reliability of using psoas characteristics of the third lumbar vertebra (L3) as an indicator of skeletal muscle mass loss.[12-14] Our previous study demonstrated a correlation between the area of the L3 psoas major muscle and the nutritional risk,[12] deep learning for radiomics image processing and quantification could enhance the comprehensive evaluation of preoperative nutritional status in cancer patients.

Subjective misunderstandings among participants and the limited scope of one-way communication in the questionnaire may compromise the reliability of the rating results. Therefore, we performed a study at a single medical facility to analyse clinical data from individuals diagnosed with advanced GC. The objective of this study is to identify and validate factors that influence the preoperative nutritional risk of individuals diagnosed with GC. Additionally, the study aims to develop a reliable risk model capable of accurately predicting preoperative nutritional risk in patients with advanced GC. The ultimate goal is to improve the detection rate of nutritional risk in GC patients and establish a robust nutritional prerehabilitation program that includes comprehensive evaluation and effective management of perioperative nutritional status.

METHODS

Patients

A retroactive study was conducted on a cohort of 343 patients who were diagnosed with GC and had surgical treatment at the Department of Gastrointestinal Surgery at the First Affiliated Hospital of Guangxi Medical University during the period from January 2016 to December 2019. Patients must meet the following inclusion criteria in this study: (1) a histological confirmation of primary GC, (2) comprehensive clinical data including laboratory test results obtained within two weeks period prior to surgery, and (3) the absence of any significant organ malfunction. The exclusion criteria encompassed three factors: (1) inadequate data, (2) coexistence of other malignant tumors, and (3) substandard picture quality or discernible distortions surrounding the L3 psoas muscle.

This study was performed in accordance with the guidelines outlined in the Declaration of Helsinki and was approved by the Ethics Committee of the First Affiliated Hospital of Guangxi Medical University. Since this study was retrospective, many of the subjects have either passed away or are no longer reachable. Also, all data were anonymized, leading the Ethics Committee of the First Affiliated Hospital of Guangxi Medical University to waive the requirement for informed consent.

Nutritional assessment

The nutritional risk in GC patients undergoing surgery was evaluated using the Chinese version of NRS2002 by a trained nutritional support team in the hospital ward. NRS2002 assessment tool has two distinct components. The first section of the analysis assessed the nutritional condition of the patient and addressed any recent challenges encountered in food consumption. The subsequent section presents data about the influence of illness severity on the individual's nutritional status. Each section was scored on a scale of 0-3, with additional points given to patients aged ≥ 70 years. The NRS2002 total score ranged from 0-7. An NRS2002 score of ≥ 3 indicated a nutritional risk, while a score of < 3 indicated no immediate nutritional risk.

Data collection

The computerized case system utilized by the First Affiliated Hospital of Guangxi Medical University was responsible for the collection of demographic and clinical information. This included data pertaining to age, gender, height, weight, smoking history, family history and tumor TNM staging. Blood samples were collected in order to assess a range of laboratory parameters, which encompassed Hb, white blood cell count (WBC), neutrophil count (NEUT), total lymphocyte count (TLC), albumin (ALB), prealbumin (PAB), total cholesterol (TC), carcinoembryonic antigen (CEA), alpha-fetoprotein (AFP), tumor marker CA199, tumor marker CA125, and tumor marker CA153. The laboratory measurements of peripheral venous blood were performed within two weeks preceding the surgical procedure. BMI was determined by dividing the respondent's kilogram weight by their square meter height.

Texture feature extraction and selection

Participants in this study had computed tomography (CT) scans of their abdomens before receiving surgical procedure. The picture segmentation process involved utilizing the 3D-Slicer software, specifically version 4.10.2, which is considered stable. The objective was to outline the left and right L3 psoas muscles as the designated volume of interest (Supplementary Figure 2). Pixels exhibiting attenuation values below -50 HU or above 100 HU were eliminated from the analysis to mitigate any interference from neighboring fat, bone, and surrounding organs. The intra-observer ICC, as determined by two reader one extractions, varied between 0.853 and 0.928. Between two readers (L.Q. and P.C.), the inter-observer agreement ranged from 0.846 to 0.907. The results showed good intra- and inter-observer feature extraction agreements.

The Pyradiomics (v3.6.2) software package was utilized to extract radiomics features. First-order statistical features (IH, intensity histogram), shape-based histogram features, and texture features were extracted from the volume of interest (VOI). The image underwent preprocessing using wavelet filtering, followed by the extraction of texture features from the pre-processed image. Using Haar wavelet as filter, three-layer wavelet decomposition is set up to effectively remove noise while preserving image details. In threshold processing, the soft threshold method is selected, which is automatically adjusted according to the coefficient distribution after each layer decomposition to achieve the best noise reduction effect. The Z-Score method normalizes image by subtracting (μmuscle), corresponding to the mean intensity value of the considered ROI (here, the muscle) in training set,

from each voxel intensity I(x) and dividing the result by the standard deviation of the ROI (σmuscle).[15] The same mean and standard deviation were applied to normalize the validation set data:

Iz-score (x) = [I(x) - μmuscle] / σmuscle

Data were further processed to reduce dimension, Spearman's correlation coefficient was first used to remove features with a correlation coefficient greater than 0.9. Then, using the R glmnet software package, the minimum absolute contraction and selection operator was run to reduce the dimensionality of the features again, and the radiomic features related to nutritional risk diagnosis were screened. The calculation of a radiomics signature score was performed for each patient by applying coefficients that were weighted using the LASSO logistic regression model in the training set.

For each VOI, a comprehensive set of 102 raw characteristics and 558 wavelet features were gathered (shown in Supplementary Table 1). The dataset comprised a total of 102 distinct features. There were 18 first-order statistical features, 9 histogram features based on shape, 24 Gray Level Co-occurrence Matrix (GLCM) features, 14 Gray Level Dependence Matrix (GLDM) features, 16 Gray Level Run Length Matrix (GLRLM) features, 16 Gray Level Size Zone Matrix (GLSZM) features, and 5 Neighboring Gray Tone Difference Matrix (NGTDM) features. The radiomic features mentioned in this context have been previously defined in mathematical terms.[16] These definitions can be accessed at the following URL: https://pyradiomics.readthedocs.io/en/latest/.

Statistical analysis

Statistical analysis was performed using R, version 4.2.0, developed by the R Foundation for Statistical Computing in Vienna, Austria. Using the R caret package, the GC patients were randomly split into a training set and a validation set, following a 7:3 ratio. Descriptive statistics were used to summarize baseline characteristics. Continuous data were reported in the form of medians and interquartile ranges, while categorical information was presented in the form of percentages. Statistical methods, including Pearson's chi-square test, Fisher's exact test, Mann-Whitney test, and McNemar's test, were used to conduct group comparisons for both categorical and continuous data, as deemed suitable for this study. The selection and adjustment of predictors were performed using LASSO regression analysis.[17]

A prediction model for assessing the nutritional risk was constructed through the utilization of logistic regression analysis. This was achieved by amalgamating specific features within the LASSO regression model. To obtain the subset of predictors, the LASSO regression analysis minimizes prediction error for a quantitative response variable by imposing a constraint on the model parameters that cause the regression coefficients for some variables to shrink toward zero. The glmnet package in R was utilized to perform LASSO regression. The dependent variable included is categorized as NRS2002 score <3 or ≥3. The analysis used type measures of -2 log likelihood and a binomial family. The LASSO regression was conducted with 10-fold cross-validation to standardize and centralize the variables included. The process selected the optimal lambda value. A 1-standard error rule was applied to obtain a model with good performance while minimizing the number of independent variables included. Thus, the LASSO method was used to analyse the data in the training set to select the optimal predictors of the present risk factors. A nomogram was built based on the concept proposed in reference.[18] The qualities that were reported were presented in the form of odds ratios (OR) along with corresponding 95% confidence intervals (CI). In this study, statistical significance was assessed by evaluating two-tailed *p*-values that were below the threshold of 0.05. The Receiver Operating Characteristic software was used to distinguish between genuine positives and false positives in the nutritional risk nomogram.[19] At the same time, the confusion matrix (R caret package) was used to evaluate the model performance. The nutrition risk nomogram's calibration was evaluated using calibration curves, and its clinical appropriateness was assessed using decision curve analysis by analysing the net benefit at different threshold probabilities (Figure 1).

RESULTS

Patient baseline data

This study included a cohort of 284 patients diagnosed with GC, with 181 males and 103 females. The GC patients were allocated randomly to either the training set (n=198) or the validation set (n=86). The baseline characteristics of patients are shown in Table 1.

At baseline, age, gender, diabetic, BMI, T stage, N stage, Hb, ALB, PAB, NEUT, TLC, TC, CEA, AFP, CA125, CA153, CA199 and Radscore were assessed. No statistically significant differences were found between the two groups ($p>0.05$), indicating comparability. Intergroup analysis of study variables stratified by NRS2002 status (positive and negative) is shown in the Supplementary Table 3.

Radscore building based on radiomics features

The dimension of the extracted radiomics features was reduced using LASSO logistic regression (Supplementary Figure 1), and the significant features were identified in the training set. A total of six radiomics features were screened out (Supplementary Table 2). The Radscore was calculated as follows: 0.4545577175631209+0.04341*gradient_glcm_Imc2+0.01522*gradient_glrlm_LowGrayLevelRunEmphasis+0.03121*gradient_glszm_SmallAreaLowGrayLevelEmphasis+0.024431*gradient_ngtdm_Coarseness+0.019694*waveletLH_gldm_SmallDependenceLowGrayLevelEmphasis+0.005178*wave-let-LL_glszm_SmallAreaLowGrayLevelEmphasis.

Independent risk factors in the training set

This study included a total of 21 factors pertaining to clinical symptoms, laboratory testing and radiological score. The coefficient distribution plots were created using the log(λ) sequence. By plotting the partial probability deviation (binomial deviation) versus log(lambda), we were able to determine the optimal parameter (lambda) in the LASSO model; then we used the one standard error (1SE) criterion wire to emphasize the vertical line with

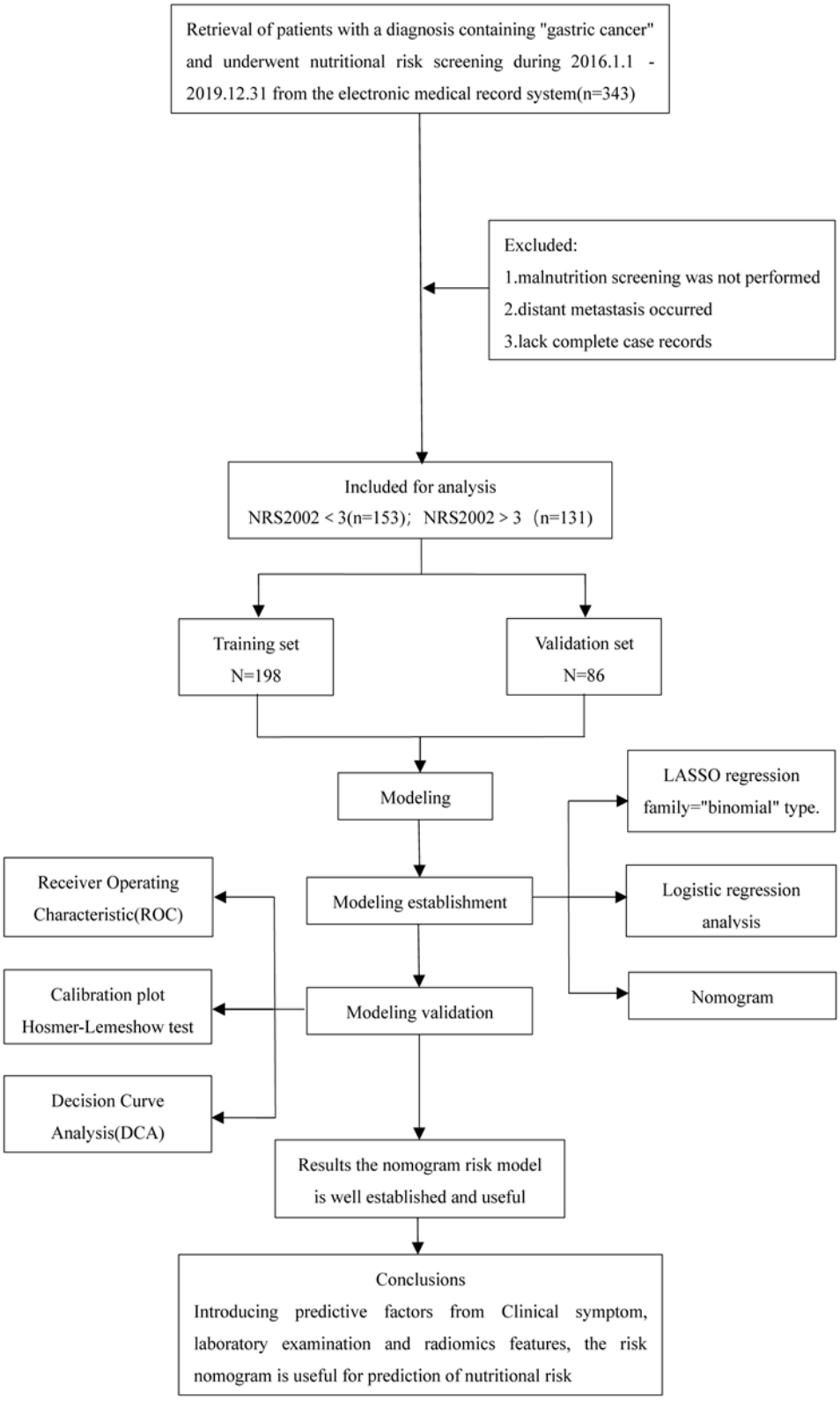

Figure 1. Flow chart of study design. NRS2002, nutritional risk screening 2002; LASSO, least absolute shrinkage and selection operator; ROC, receiver operating characteristic; DCA, decision curve analysis.

dots. By using lambda 1SE, we identified three variables with non-zero coefficients (Figure 2).

Predictive model construction

The LASSO regression analysis was used to select three predictive variables, which were further analysed using both univariate and multivariate logistic regression analyses (Table 2). Three predictive factors, BMI, Hb and RadScore constructed from radiomics features, were identified with statistically significant differences. A predictive model was developed using multivariate logistic regression, incorporating these variables, to create a preoperative nutritional risk nomogram for GC (Figure 3).

Table 1. Baseline characteristics in training and validation sets

	All patients N=284	Training set N=198	Validation set N=86	*p*-value
Gender, n (%)				0.208
Male	181 (63.7%)	60 (69.8%)	121 (61.1%)	
Female	103 (36.3%)	26 (30.2%)	77 (38.9%)	
Age (years)	56.0 [46.0; 63.3]	55.0 [47.0; 63.8]	57.0 [46.0; 63.0]	0.978
BMI (kg/m^2)	19.5 [17.7; 21.5]	19.3 [17.6; 22.2]	19.5 [17.9; 21.0]	0.738
NRS2002				0.463
<3	153 (53.9%)	110 (55.6%)	43 (50.0%)	
≥3	131 (46.1%)	88 (44.4%)	43 (50.0%)	
Diabetic, n (%)				0.758
No	272 (95.8%)	82 (95.4%)	190 (96.0%)	
Yes	12 (4.20%)	4 (4.60%)	8 (4.00%)	
Smoking, n (%)				0.190
No	186 (65.5%)	51 (59.3%)	135 (68.2%)	
Yes	98 (34.5%)	35 (40.7%)	63 (31.8%)	
Hb (g/L)	116 [99.5; 131]	114 [100; 128]	117 [98.4; 131]	0.492
NEUT (10^9/L)	3.54 [2.70; 4.22]	3.38 [2.75; 4.38]	3.56 [2.65; 4.19]	0.854
TLC (10^9/L)	1.75 [1.38; 2.21]	1.78 [1.31; 2.17]	1.75 [1.41; 2.21]	0.774
ALB (g/L)	39.3 [36.7; 41.2]	39.3 [36.3; 41.1]	39.2 [36.9; 41.3]	0.756
PAB (g/L)	213 [180; 257]	204 [175; 257]	216 [182; 256]	0.152
TC (mmol/L)	4.62 [4.05; 5.14]	4.58 [3.98; 5.01]	4.68 [4.07; 5.18]	0.394
AFP (ng/mL)	7.87 [5.58; 11.6]	7.35 [5.27; 10.9]	8.16 [5.63; 11.8]	0.221
CEA (ng/mL)	2.51 [1.85; 3.52]	2.50 [1.94; 3.46]	2.51 [1.84; 3.53]	0.896
CA125 (U/mL)	10.6 [7.58; 14.6]	11.1 [7.60; 16.0]	10.3 [7.56; 14.2]	0.770
CA153 (U/mL)	7.87 [5.58; 11.6]	7.35 [5.27; 10.9]	8.19 [5.63; 11.8]	0.216
CA199 (U/mL)	7.68 [4.18; 17.3]	7.03 [3.75; 19.6]	7.74 [4.35; 16.9]	0.992
T stage				0.651
T0	2 (0.70%)	0 (0.00%)	2 (1.01%)	
T1	59 (20.8%)	20 (23.3%)	39 (19.7%)	
T2	44 (15.5%)	12 (14.0%)	32 (16.2%)	
T3	43 (15.1%)	16 (18.6%)	27 (13.6%)	
T4	136 (47.9%)	38 (44.2%)	98 (49.5%)	
N stage				0.396
N0	108 (38.0%)	35 (40.7%)	73 (36.9%)	
N1	40 (14.1%)	14 (16.3%)	26 (13.1%)	
N2	53 (18.7%)	11 (12.8%)	42 (21.2%)	
N3	83 (29.2%)	26 (30.2%)	57 (28.8%)	
Radscore	7.73 [5.82; 14.4]	7.86 [5.89; 15.1]	7.73 [5.76; 13.8]	0.853

NRS2002, nutritional risk screening 2002; BMI, body mass index; Hb, hemoglobin; ALB, albumin; PAB, prealbumin; NEUT, neutrophile count; TLC, total lymphocyte count; CEA, carcinoembryonic antigen; AFP, alpha-fetoprotein..

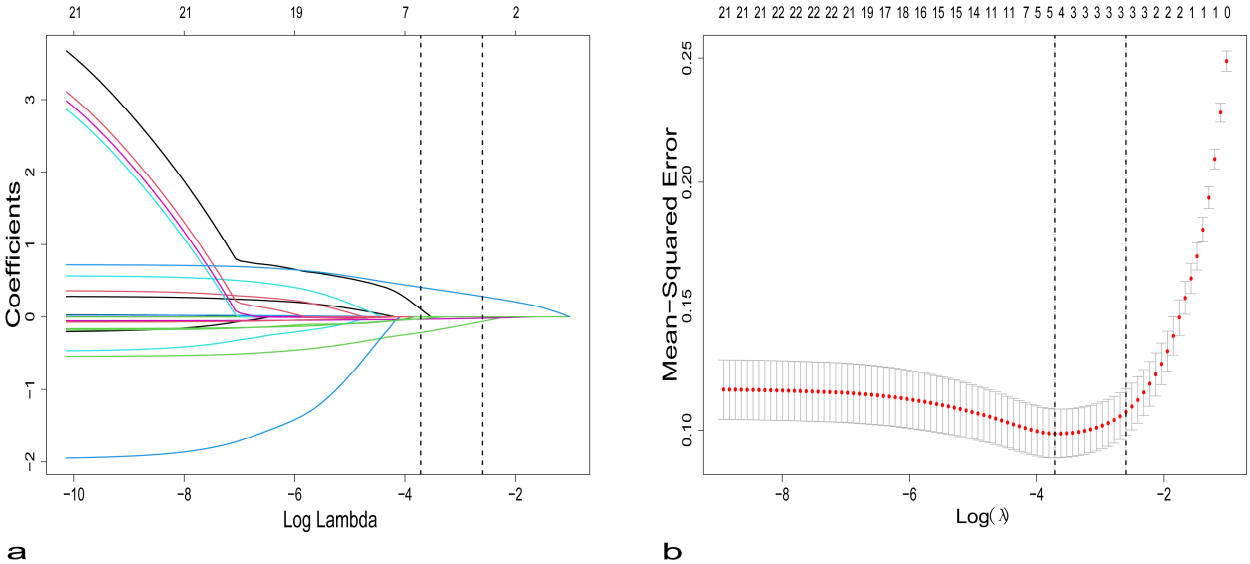

Figure 2. Variable selection using LASSO for binary logistic regression. (a) The optimum lambda selected twenty-one nonzero coefficient variables. Each line represented a parameter with a vertical coefficient at its end. (b) After validating the optimal parameter (lambda) in the LASSO model, the partial likelihood deviance (binomial deviance) curve was plotted against log (lambda) and vertical dashed lines were constructed based on 1 standard error threshold.

Table 2. Univariate and multivariate logistic regression in training set

Characteristics	Uni-B	Uni-SE	Uni-OR	Uni-CI	Uni-Z	Uni-p
BMI	-0.308	0.06691	0.735	0.735 (0.640-0.833)	-4.597	< 0.001
Hb	-0.059	0.00923	0.943	0.943 (0.925-0.959)	-6.368	< 0.001
Radscore	0.546	0.07638	1.727	1.727 (1.509-2.042)	7.152	< 0.001

Characteristics	Multi-B	Multi-SE	Multi-OR	Multi-CI	Multi-Z	Multi-p
BMI	-0.398	0.1264	0.672	0.672 (0.510-0.840)	-3.15	0.002
Hb	-0.053	0.01512	0.948	0.948 (0.918-0.975)	-3.518	< 0.001
Radscore	0.57	0.09055	1.769	1.769 (1.511-2.165)	6.3	< 0.001

Odds ratios, confidence intervals, and *p*-values were shown. $p<0.05$ meant that the difference was statistically significant.

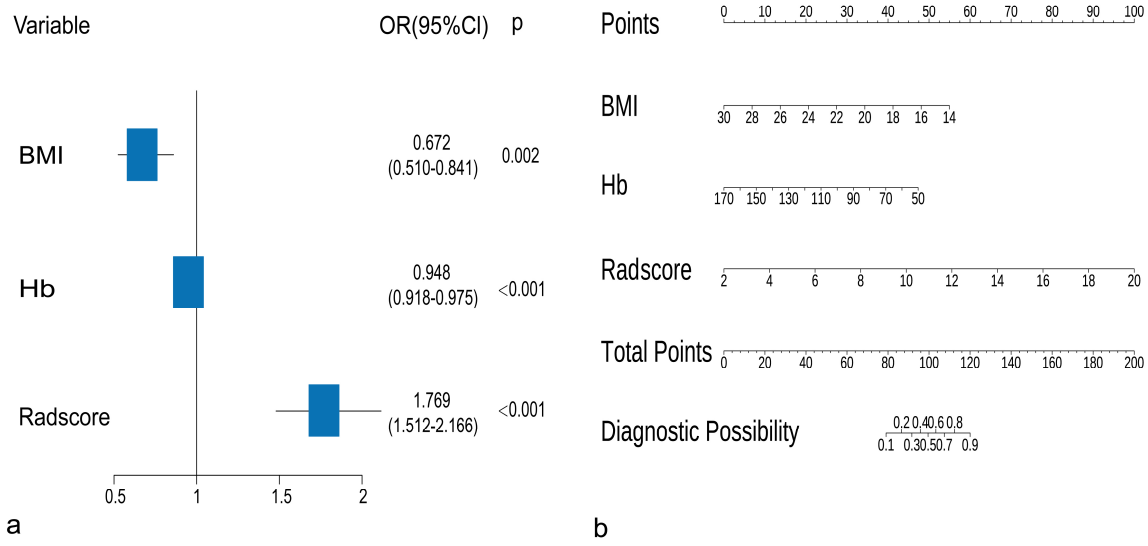

Figure 3. Multivariate logistic regression created the prediction model. (a) Multivariate logistic regression analysis of nutritional risk predictors. (b) Nomogram for nutritional risk prediction in gastric cancer patients. OR, CI, and p values are all shown. $p<0.05$ indicated a statistically significant difference. OR, odds ratio; CI, confidence interval

Predictive model validation

ROC curves and confusion matrix were used to assess the sensitivity and specificity of the prediction models. The performance of the predictive models was assessed using a training set, yielding an AUC value of 0.895 (95% CI 0.844-0.945), a cutoff value of 0.651, a precision of 0.957, and a sensitivity of 0.718. Similarly, the models were tested using a validation set, resulting in an AUC of 0.880 (95% CI 0.806-0.954), a cutoff value of 0.655, a precision of 0.930, and a sensitivity of 0.698. The combined nomograms AUC and confusion matrix demonstrated fair to good performance (Figure 4). We also compared the combined model with the clinical model and the radiomics model (Supplementary Figure 3).

The prediction models were calibrated using calibration curves and the Hosmer-Lemeshow test, the *p*-value of the Hosmer-Lemeshow test for the training set is 0.689, and the *p*-value of the Hosmer-Lemeshow test for the validation set is 0.7346. The calibration curve revealed strong alignment between the projected model and validation set. The Hosmer-Lemeshow study showed remarkable agreement between calculated and observed probabilities (Figure 5). The nomogram DCA also suggested that this model could be valuable in a clinical setting (Figure 6).

DISCUSSION

Malnutrition is a significant clinical issue in patients with GC, which can impact both treatment effectiveness and patients' quality of life. The initial step in preventing and treating malnutrition in these patients is to conduct nutritional risk screening. It is crucial to promptly and accurately identify the nutritional risk, followed by a comprehensive nutritional assessment to diagnose malnutrition. This allows clinicians to take appropriate measures for GC patients. Adequate nutritional interventions and support can improve the patient's treatment response and promote recovery. In this study, we retrospectively analysed relevant data of GC patients before surgical treatment to develop and validate a nomogram model.

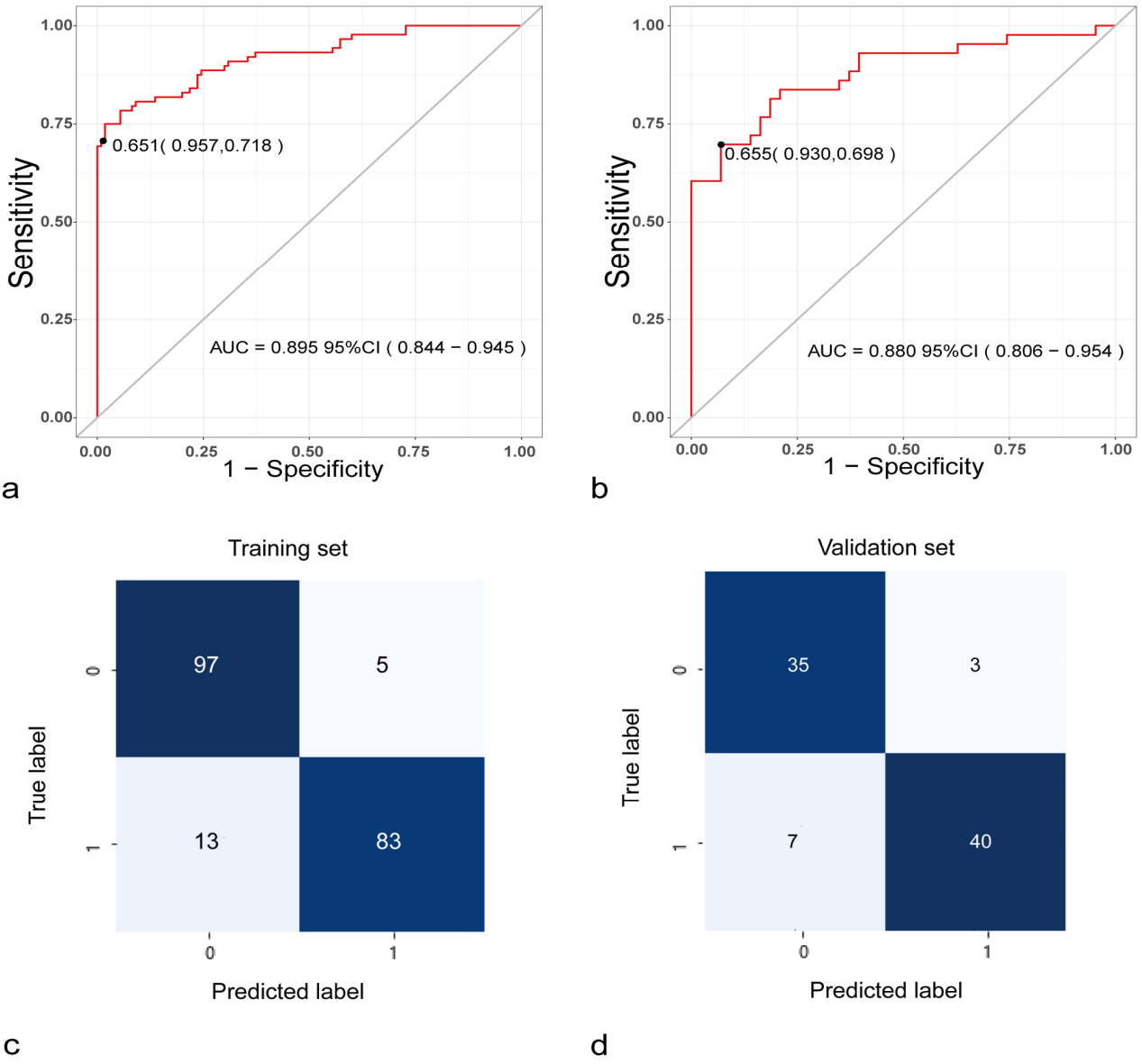

Figure 4. The ROC curve and confusion matrix for training set (a and c) and the validation set (b and d). ROC: receiver operator characteristic curve. AUC: area under the curve.

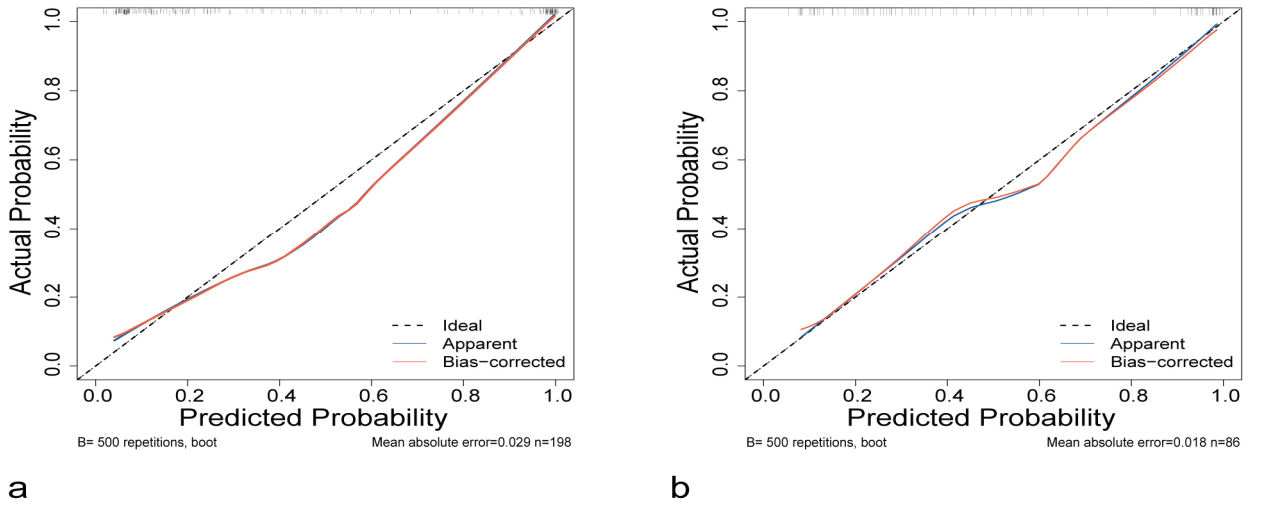

Figure 5. Nutritional risk prediction nomogram calibration curves. NRS2002 ≥ 3 cases are depicted along the y-axis, and expected nutritional risks are displayed along the x-axis. A closer alignment with the diagonal dotted line, which represents an ideal model's flawless prediction, indicates a more precise forecast, as well as the solid line representing the performance of the training set (a) and validation set (b).

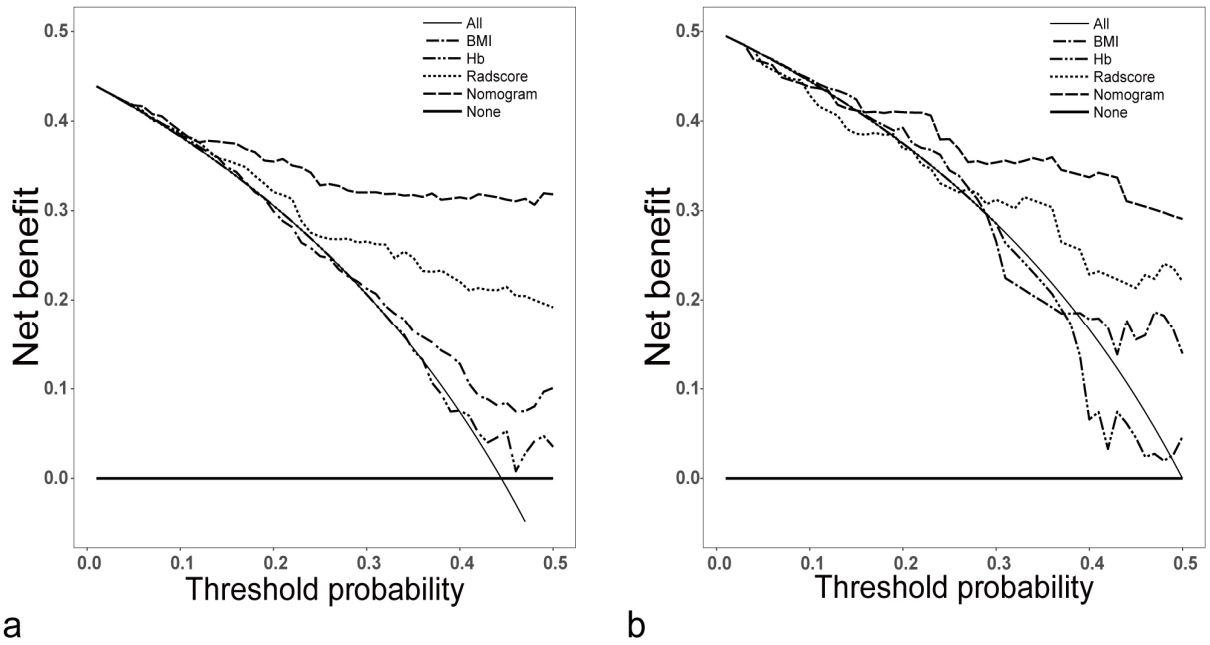

Figure 6. Nutritional risk nomogram decision curve analysis. The y-axis represents the net benefit. The thick solid line signifies the assumption that no patient is at nutritional risk, the thin solid line indicates the assumption that every patient is at risk. Solid lines in other patterns represents the risk nomogram. (a) from the training set. (b) from the validation set.

This model combined clinical data and radiological features to predict nutritional risk in GC patients before surgical treatment. By utilizing this model, clinicians can make informed clinical decisions and implement a comprehensive assessment and diagnosis of nutritional risk in GC patients before surgical treatment.

NRS2002 is a well-known method for detecting individuals at nutritional risk, and it is often used for nutritional screening in cancer patients. According to research by Zang et al., cancer patients at risk of malnutrition had a reduced overall survival rate and an increased likelihood of developing complications after surgery.[20] However, a multicenter study utilized NRS2002 to evaluate the nutritional risk among individuals with gastrointestinal diseases. The findings revealed that the prevalence of malnutrition among individuals diagnosed with gastrointestinal cancer was a mere 17.6%, certain patients diagnosed with GC evaded detection by screening instruments.[21] Furthermore, a comparative analysis of the diagnostic accuracy of various nutrition screening instruments for adult malnutrition was conducted by Cheung et al. NRS2002 demonstrated exceptional diagnostic capability but the rate of missed diagnoses was 27.7%.[22] False negative results of nutritional risk screening may be more detrimental to cancer patients than false positive results. The improvement of cancer nutritional risk assessment is a clinical issue that requires resolution. We were motivated by the study of Xie et al., who coupled systemic inflammatory indicators with GLIM criteria and found that GLIM criteria based on inflammatory markers had greater predictive power in assessing the short-term and long-term prognosis of cancer patients.[23] Therefore, we firmly believe that the multi-dimensional nutritional risk prediction system for patients diagnosed with GC holds practical applicability in clinical settings. Our goal is to develop a predictive model that integrates radiomics features and clinical data. It has been validated that the model possessed decent predictive ability. (AUC > 0.8).

Hb levels may be used to indicate nutritional risk in patients. Hb declines as malnutrition progresses, and investigations have verified this association.[24,25] However, Zhou et al. discovered that only the Hb index was employed to evaluate the nutritional status of hospitalized patients, and the percentage of nutritional risk identification was only 24%.[26] Similarly, BMI is an indicator that is used to analyse the connection between weight and height, giving information on a person's weight status and reflecting some nutritional status features.[27,28] Although the NRS2002 included BMI as an auxiliary indication for nutritional risk screening, assessing nutritional status just by utilizing the scale's BMI cut-off points may be inaccurate. Several tools were employed in a study to evaluate the nutritional health condition of elderly inpatients. The findings revealed that the detection rate of risk screening based on BMI alone was the lowest at 23.7%.[29] Overall, relying on a single indicator to assess patients' nutritional status is insufficient. Our findings showed that BMI and Hb are independent risk factors for preoperative nutritional risk in patients with GC. This prediction model may thoroughly analyse patients' nutritional status using numerous criteria, optimize the importance of risk factors, and increase the accuracy of preoperative nutritional risk screening.

Radiomics is an emerging image analysis method that convert CT, MRI, and PET-CT images into high-throughput radiomics feature data.[30] These features can then be used to establish radiomics by linear or nonlinear machine learning methods, which can be further analyzed.[31] Studies have reported that radiomics features can be used to predict sarcopenia in patients with GC, and that it is associated with the prognosis of these patients. For example, Lan et al. used CT images to extract radiomics features of sarcopenia and combined them with a

clinical prediction model to individually predict postoperative complications in patients with GC, showing good prediction performance (training set AUC is 0.763).[32] Chen et al. used LASSO analysis to identify 14 psoas major muscle radiomics features, which were then incorporated in the radiomics scoring model. The subjectivity of sarcopenia assessment was minimized after quantitative examination, and prediction accuracy was enhanced.[33] The methodologies outlined above are utilized in this study, radiomics data from the psoas major muscle at the L3 level were retrieved from CT images of 284 individuals with GC. Six relevant radiomics features were chosen for the scoring model and then coupled with clinical data to create a nomogram model to predict the preoperative nutritional risk in patients. In these radiomics features, GLCM represented second-order statistics, which described the correlation of neighboring voxels according to different angles. GLRLM represented run length of similar gray-level in the image. GLSZM represented different gray-level zones in the image and their distribution. NGTDM represented the difference between gray-level and the average within certain distances. GLDM represented gray-level dependencies independent from angles.[34,35] In consideration of physical condition and radiomics score, the model was capable of conducting a comprehensive evaluation of patients' nutritional status. The nomogram presented clinically relevant recommendations for comprehensive screening of nutritional risk by displaying the proportion of each influential factor.

This study focused on the integration of clinical data and imaging studies, which are crucial components in the development of a clinical practice prediction system. Our established clinical prediction model is user-friendly and enables accurate and prompt assessment of nutritional risk in GC patients. It has undergone comprehensive and successful verification. However, our clinical prediction model does have certain limitations. Firstly, the sample size of this study is modest, and it is required to increase the sample size in the future in order to enhance the correlation of radiomics scores and to collaborate with other institutions for external verification. Secondly, in future clinical studies, the model can be further improved by incorporating body composition analysis to better cater to the needs of gastrointestinal surgeons. Furthermore, apart from NRS2002, there are several other excellent nutrition assessment tools that are widely used in clinical settings. The integration of multiple screening tools may offer valuable insights into the clinical potential of the nutritional risk nomogram prediction model.

Conclusion

Based on the laboratory examination, pathological data and analysis of clinical data and radiomics features of GC patients conducted at our institution, we found that BMI, Hb and Radscore were independent risk factors for preoperative nutritional risk in GC patients. To assist doctors in assessing the nutritional risk in GC patients before surgical treatment, we have developed a simple and repeatable nomogram clinical prediction model. This model can effectively guide clinicians in identifying and diagnosing GC patients at nutritional risk.

SUPPLEMENTARY MATERIALS

All supplementary tables and figures are available upon request.

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CONFLICT OF INTEREST AND FUNDING DISCLOSURES

The authors declare no conflict of interest.

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