Radiomics in Addition to Computed Tomography-Based Body Composition Nomogram May Improve the Prediction of Postoperative Complications in Gastric Cancer Patients

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\textbf{Abstract}
\textbf{Objectives:} The study aimed to determine the impact of computed tomography (CT)-based body composition and radiomics nomogram on the prediction of postoperative complications in gastric cancer. \textbf{Methods:} The clinical data of 457 individuals with surgically confirmed gastric cancer, 320 patients in the training cohort (TC) and 137 patients in the validation cohort (VC), were retrospectively analyzed. Body composition data were measured using CT. Postoperative complications were graded using the Clavien-Dindo system. Dedicated radiomics prototype software was used to segment lesions and extract characteristics from preoperative portal venous-phase CT images. Clinical, radiomics, and combined models were developed using logistic regression analysis. Model performance was evaluated using the area under the curve (AUC) of receiver operating characteristic curve, and the prediction ability of the optimal model was evaluated using calibration curves and decision curve analysis (DCA). \textbf{Results:} Nutritional Risk Screening 2002 (NRS2002) score, sarcopenia, and blood loss were independent predictors of postoperative complications in gastric cancer. A radiomics signature was created using 19 conserved radiomics features. The nomogram based on both the clinical model and radiomics signature showed the greatest predictive performance, with AUCs of 0.763 (95\% confidence interval [CI], 0.708–0.817) and 0.748 (95\% CI: 0.667–0.818) in the TC and VC, respectively. The calibration curve and DCA revealed that the nomogram was beneficial in clinical practice for the preoperative prediction of postoperative complications.

\textbf{Conclusions:} The combined model consisting of NRS2002 score, sarcopenia, blood loss, and a radiomics signature holds potential application value for the individualized prediction of postoperative complications in gastric cancer patients.

\textbf{Introduction}
Gastric cancer (GC) is the 5th leading cause of cancer in the world and the 4th leading cause of cancer-related deaths [1]. Gastrectomy with adequate lymph node dis-
Postoperative complications can prolong hospital stay and adversely affect the recurrence-free and overall survival of patients. Therefore, reliable preoperative assessment tests are crucial for the prediction of postoperative complications in GC patients.

The literature remains mixed on the risk factors for the development of postoperative complications in GC patients. Tumor heterogeneity influences the growth and malignant progression of GC, and is considered an important factor affecting the failure of cancer treatment and inaccurate prognostication [4]. In addition, the progression of GC is correlated with a drastic decline in nutrition and function of the human body, which also leads to poor treatment response and worse prognosis [5]. Malnourishment is a widespread and serious issue among GC patients. Numerous studies have shown that malnutrition is a risk factor for postoperative complications in GC patients [6, 7]. Hence, tumor heterogeneity and nutritional status in GC patients warrant closer examination.

Nutrition Risk Screening 2002 (NRS2002), Patient-Generated Subjective Global Assessment, and Mini Nutritional Assessment, among others, are commonly used nutritional screening and assessment tools. However, all these tools are limited by their subjective assessment [8, 9]. Currently, body composition is becoming an increasingly popular topic of nutritional research. Fat tissue and skeletal muscle can reflect the nutritional status of patients [7, 10]. The current gold standard for assessing body composition is computed tomography (CT) [11]. Moreover, CT plays an important role in the diagnostic and therapeutic evaluation of GC patients. Accordingly, CT-quantified body composition measurements, which allow objective and dynamic monitoring of the patient’s nutritional status, are useful for optimizing treatment.

Radiomics is a rising field that enables noninvasive characterization of tumor heterogeneity through quantitative features derived from imaging data [12]. Radiomics is a promising technique for predicting histopathological characteristics, treatment response, and even clinical outcomes in GC [13–16]. Therefore, we hypothesized that CT-based radiomics might provide valuable additional information that may help predict postoperative complications in GC patients. To the best of our knowledge, a postoperative prediction model that integrates CT-based body composition and radiomic features in gastrectomy patients has never been published. Moreover, there is currently no consensus on which change in body composition can be used as an indicator for nutritional assessment.

The goal of present study was to develop a visual prognostic model that incorporates clinical risk factors (including body composition) and radiomics features to predict postoperative complications in patients with GC. Such a tool would aid in the identification of high-risk patients and in the formulation of individualized treatments, thereby improving the assessment of nutritional status and patient prognosis.

Materials and Methods

Patients

The local Institutional Review Board approved this retrospective study and waived the requirement for informed consent. In total, 457 GC patients who underwent radical gastrectomy between January 2017 and December 2019 were sequentially enrolled in the current research. The criteria for inclusion were as follows: (1) radical gastrectomy with R0 resection (no residual tumor) and D2 lymphadenectomy, (2) surgeries performed by clinicians in the same department and with the same seniority level, (3) pathologically confirmed GC, (4) contrast-enhanced abdominal CT scan conducted within 2 weeks before radical gastrectomy, and (5) complete clinical, pathological, and imaging data. The following served as exclusion criteria: (1) preoperative anti-tumor treatment, (2) palliative surgical resection, (3) other malignant tumors, (4) severe underlying disease, such as severe heart disease and malignant hypertension, (5) metabolic diseases, such as diabetes, hypothyroidism, and adrenal cortical insufficiency, (6) tumor diameter <5 mm, as this was insufficient to delineate the region of interest (ROI), and (7) follow-up duration <30 days. Using a probability-based technique and simple random sampling, we assigned the patients to validation and training datasets in a ratio of 3:7. The Clavien-Dindo classification was used to classify postoperative complications occurring within 30 days after the surgery [17]. Overall complications were categorized according to Clavien-Dindo grades as grade II or higher. Tumor grading was carried out in accordance with the 8th edition of the Union for International Cancer Control’s Tumor Node Metastasis classification system. The clinical characteristics of the 457 GC patients are outlined in Table 1.

CT Examination

CT examinations were performed using a 64-channel CT scanner (LightSpeed VCT, GE Healthcare), a 256-channel CT scanner (Revolution, GE Healthcare), and a dual-source CT scanner (SOMATOM Definition Flash; Siemens Healthcare). Detailed information on the CT protocols and variables acquired is presented in online supplementary Table A1 (for all online suppl. material, see www.karger.com/doi/10.1159/000526787). CT images in the venous phase were evaluated using a picture archiving and communication system.

Body Composition Assessment Using CT Images

All body composition data were processed on an AW4.6 workstation (GE Healthcare) and evaluated using the “X-Sect.” mode.
Table 1. Comparison of clinical features in the TC and VC

| Characteristic                  | TC (n = 320)               | VC (n = 137)               | p value |
|---------------------------------|-----------------------------|-----------------------------|---------|
| Age, years*                     | 55 (45–64)                  | 55 (47–63)                  | 0.957   |
| Gender, n (%)                   |                             |                             |         |
| Male                            | 208 (65.0)                  | 93 (67.9)                   | 0.551   |
| Female                          | 112 (35.0)                  | 44 (32.1)                   |         |
| BMI, n (%)                      |                             |                             |         |
| <18.5 kg/m²                     | 44 (13.8)                   | 13 (9.5)                    | 0.430   |
| 18.5–25 kg/m²                   | 239 (74.7)                  | 106 (77.4)                  |         |
| >25 kg/m²                       | 37 (11.6)                   | 18 (13.1)                   |         |
| Albumin, n (%)                  |                             |                             |         |
| <40 g/L                         | 221 (69.1)                  | 90 (65.7)                   | 0.479   |
| ≥40 g/L                         | 99 (30.9)                   | 47 (34.3)                   |         |
| Prealbumin, n (%)               |                             |                             |         |
| <250 g/L                        | 247 (77.2)                  | 102 (74.5)                  | 0.528   |
| ≥250 g/L                        | 73 (22.8)                   | 35 (25.5)                   |         |
| CEA, n (%)                      |                             |                             |         |
| ≤5 ng/mL                        | 277 (86.6)                  | 119 (86.9)                  | 0.931   |
| >5 ng/mL                        | 43 (13.4)                   | 18 (13.1)                   |         |
| CA199, n (%)                    |                             |                             |         |
| ≤37 U/mL                        | 283 (88.4)                  | 118 (86.1)                  | 0.491   |
| >37 U/mL                        | 37 (11.6)                   | 19 (13.9)                   |         |
| CA125, n (%)                    |                             |                             |         |
| ≤35 U/mL                        | 309 (96.6)                  | 133 (97.1)                  | 0.515a  |
| >35 U/mL                        | 11 (3.4)                    | 4 (2.9)                     |         |
| NRS2002 score, n (%)            |                             |                             |         |
| <3                              | 144 (45.0)                  | 68 (49.6)                   | 0.363   |
| ≥3                              | 176 (55.0)                  | 69 (50.4)                   |         |
| TNM stage, n (%)                |                             |                             |         |
| I                               | 92 (28.7)                   | 28 (20.4)                   | 0.056   |
| II                              | 71 (22.2)                   | 28 (20.4)                   |         |
| III                             | 136 (42.5)                  | 76 (55.5)                   |         |
| IV                              | 21 (6.6)                    | 5 (3.6)                     |         |
| Surgical approach, n (%)        |                             |                             |         |
| Laparoscopic                    | 234 (73.1)                  | 100 (73.0)                  | 0.977   |
| Open                            | 86 (26.9)                   | 37 (27.0)                   |         |
| Sarcopenia, n (%)               |                             |                             |         |
| No                              | 258 (80.6)                  | 118 (86.1)                  | 0.158   |
| Yes                             | 62 (19.4)                   | 19 (13.9)                   |         |
| Visceral obesity, n (%)         |                             |                             |         |
| No                              | 277 (86.6)                  | 127 (92.7)                  | 0.060   |
| Yes                             | 43 (13.4)                   | 10 (7.3)                    |         |
| SFA, n (%)                      |                             |                             |         |
| Low SFA                         | 88 (27.5)                   | 35 (25.5)                   | 0.666   |
| High SFA                        | 232 (72.5)                  | 102 (74.5)                  |         |
| VFA, n (%)                      |                             |                             |         |
| Low VFA                         | 240 (75.0)                  | 109 (79.6)                  | 0.293   |
| High VFA                        | 80 (25.0)                   | 28 (20.4)                   |         |
| Blood loss, mL*                 | 200 (100–300)               | 100 (50–200)                | 0.319   |

BMI, body mass index; CEA, carcinoembryonic antigen; CA, carbohydrate antigen; NRS, nutritional risk screening; TNM, tumor node metastasis; SFA, subcutaneous fat area; VFA, visceral fat area. *Values are expressed as median (interquartile range), and the p value was derived using the Mann-Whitney U test. a p value was derived using the Fisher exact test; the other p values were derived using the Pearson χ² test.
The visceral fat area (VFA), subcutaneous fat area (SFA), and skeletal muscle area were calculated using a single slice taken at L3 in which both transverse processes were visible. The following tissue-specific criteria were used: −150 HU to −50 HU for visceral adipose tissue, −190 HU to −30 HU for subcutaneous adipose tissue, and −29 HU to 150 HU for skeletal muscle. The cross section of the skeletal muscle area was standardized to the square of the patient’s height (m²) to yield the skeletal muscle index. The visceral-to-subcutaneous ratio of adipose tissue area was used to assess the distribution of abdominal adipose tissue. Sarcopenia was defined as skeletal muscle index of ≤40.8 cm²/m² in men and ≤34.9 cm²/m² in women [18]. Visceral obesity was defined as a visceral-to-subcutaneous ratio of ≥1.33 in men and ≥0.93 in women [19]. Low SFA was defined as an SFA of <62.0 cm² in women and <38.1 cm² in men [5], and low VFA was defined as a VFA of <100 cm² for both sexes [5].

Image Segmentation and Feature Extraction

The open-source program ITK-SNAP was used to segment the ROI. The greatest tumor cross section was chosen, and a two-dimensional ROI containing the tumor was segmented on portal venous-phase images with a slice thickness of 2.0–2.5 mm. All sections were assessed by two radiologists with more than 5 years of experience in diagnostic abdominal imaging. The radiologists highlighted the tumor locations on the relevant images. Radiologist A manually segmented the lesions for all subjects. The tumor was segmented on axial images, and intraluminal fluid and gas were carefully excluded. In addition, inter- and intra-class correlation coefficients (ICCs) were calculated for 50 subjects selected at random. The ROIs for each of these patients were determined by Radiologist A and Radiologist B. An ICC of more than 0.75 was deemed acceptable.

The A.K. software (Artificial Intelligence Kit, A.K.; GE Healthcare) was used to extract radiomics features. A total of 293 radiomics features were retrieved from the ROIs. Radiomics features were of 4 types: (1) 18 first-order statistics that depicted the voxel intensity distribution inside the tumor, (2) 14 shape features that reflected the size and shape of the ROI, (3) 103 second-order texture features, including gray-level co-occurrence matrix, gray-level size zone matrix, gray-level run length matrix, gray-level dependence matrix, and neighboring gray tone difference matrix, and (4) 158 filter features, including Laplacian of Gaussian filters. The original images were filtered using the Laplacian of Gaussian filters to enhance the edges in the images.

Construction of Prediction Models

Radiomics models were built with the open-source software FeAture Explorer Pro (FAEPro, version 0.3.7) on Python (3.7.6). Using a random series, all cases were allocated to the validation cohort (VC) and training cohort (TC) in a 3:7 ratio. The TC included 320 individuals (118/202 = positive/negative), and the VC included 137 patients (51/86 = positive/negative), with positive and negative signifying patients with and without postoperative complications, respectively. The synthetic minority oversampling
technique was used to balance positive and negative samples in the training dataset. The feature matrix was normalized. Analysis of variance, recursive feature elimination, and relief were used for feature selection before model development. Among the top 20 features, the optimal combination of features was determined using a logistic regression classifier with 5-fold cross-validation.

Three prediction models were developed in this study: a clinical model, a radiomics model, and a combined model with both clinical and radiomics characteristics. Clinical characteristics and body composition data were included in the clinical model. Figure 1 depicts the method for creating these models.

### Nomogram Construction
We used receiver operating characteristic (ROC) curve analysis to examine the performance of the models. The area under the curve (AUC) of ROC curve was computed for quantification, and a cut-off value that maximized the Youden index, accuracy, sensitivity, specificity, positive predictive value (PPV), and negative predictive value (NPV) was determined. Next, 95% confidence intervals (CIs) were estimated using the bootstrap method with 1,000 samples. Finally, the optimal model was used to establish a nomogram to visualize the model. The prediction ability of the nomogram was evaluated using a calibration curve and decision curve analysis (DCA).

### Statistical Analysis
SPSS software (version 26.0), R software package (version 4.1.1), and MedCalc software (version 19.0.4) were used for statistical analysis. Continuous data were expressed as medians and interquartile ranges, and the Mann-Whitney U test was used to assess between-group differences in these data. Categorical variables were presented using numbers and percentages, and the chi-square or Fisher exact test was used to assess between-group differences in these variables. Logistic regression was used to perform univariate and multivariate analyses of postoperative complications, and logit transformation was used to standardize the distribution of continuous variables. The MedCalc software was used to plot the ROC curves of multiple models. The ROCs of the two cohorts were compared using the DeLong test. Differences in the aforementioned statistical analysis were judged to be statistically significant when the p value was less than 0.05. The nomogram and calibration curve was plotted using the rms package, and DCA was performed using the rmda package. The Hosmer-Lemeshow test was used to determine the goodness-of-fit of the nomogram in both cohorts, and it was satisfying when the p value exceeded 0.05.

### Results

#### Patients and Clinical Data
Analysis of the short-term surgical outcomes showed that a total of 169 patients (36.9%) had postoperative complications. Inflammatory complications were present in 99 patients (21.6%) and included pulmonary infections (n = 62), intra-abdominal infections (n = 11), anastomotic leakages (n = 15), urinary tract infections (n = 5), bloodstream infections (n = 3), and wound infections (n = 3).

The overall complication rate was greater in patients with sarcopenia than in patients without sarcopenia (55.6% vs. 33.0%, p = 0.004). The incidence of inflammatory complications was higher in patients with visceral obesity than in patients without visceral obesity (35.8% vs. 19.8%, p = 0.009; Table 2). There was no statistically significant variation in the distribution of clinical factors between the TC and VC (p > 0.05; Table 1).

#### Construction of Clinical Model
Multivariate analysis revealed that the following clinical factors were independent predictors of postoperative complications: NRS2002 score, sarcopenia, and blood loss. The clinical model was constructed using these independent factors (Table 3).

#### Construction of Radiomics Model and Combined Model
A total of 293 radiomics features were retrieved, and 271 of these features had ICC values exceeding 0.75. Us-

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**Table 2. Postoperative outcomes**

| Complications | All patients, n (%) (n = 457) | Sarcopenia | Visceral obesity |
|---------------|-------------------------------|------------|-----------------|
|               | yes, n (%) (n = 81)           | no, n (%) (n = 376) | p value | yes, n (%) (n = 53) | no, n (%) (n = 404) | p value |
| All           | 169 (36.9)                    | 45 (55.6)   | 124 (33.0)      | 0.004  | 25 (47.2)            | 144 (35.6)      | 0.130   |
| Stage II      | 132 (28.9)                    | 39 (48.1)   | 93 (24.7)       |        | 20 (37.7)            | 112 (27.7)      |        |
| Stage III     | 23 (5.0)                      | 4 (4.9)     | 19 (5.1)        |        | 3 (5.7)             | 20 (5.0)        |        |
| Stage IV      | 11 (2.4)                      | 1 (1.2)     | 10 (2.7)        |        | 2 (3.8)             | 9 (2.2)         |        |
| Stage V       | 3 (0.7)                       | 1 (1.2)     | 2 (0.5)         |        | 0 (0.0)             | 3 (0.7)         |        |
| Inflammatory  | 99 (21.6)                     | 20 (24.7)   | 79 (21.0)       | 0.277  | 19 (35.8)            | 80 (19.8)       | 0.009  |

*a Assessed by Clavien-Dindo grade.
ing the FAEPro software, we performed logistic regression and selected 19 optimal radiomics characteristics with nonzero coefficients (online suppl. Table A2). These included 4 first-order statistics, 3 shape features, 3 second-order texture features (2 gray-level co-occurrence matrix and 1 neighboring gray tone difference matrix), and 9 filter features. The optimal features were used to construct a radiomics model. The clinical and radiomics models were integrated to create the combined model.

### Table 3. Multivariate risk factor analysis for the clinical model

| Risk factor     | β     | OR (95% CI) | p value |
|-----------------|-------|-------------|---------|
| Intercept       | −3.247|             |         |
| NRS2002 score   | 1.337 | 3.806 (2.264–6.398) | 0.000   |
| Blood loss      | 0.823 | 2.277 (1.181–4.390) | 0.014   |
| Sarcopenia      | 0.659 | 1.932 (1.059–3.526) | 0.032   |

OR, odds ratio; CI, confidence interval; NRS, nutritional risk screening.

### Table 4. Model comparison in TC

| TC               | AUC   | 95% CI       | Sensitivity | Specificity | Accuracy | PPV   | NPV   |
|------------------|-------|--------------|-------------|-------------|----------|-------|-------|
| Clinical model   | 0.712 | 0.655–0.770 | 0.779       | 0.579       | 0.678    | 0.520 | 0.818 |
| Radiomics model  | 0.682 | 0.622–0.741 | 0.695       | 0.604       | 0.638    | 0.506 | 0.722 |
| Combined model   | 0.763 | 0.708–0.817 | 0.686       | 0.748       | 0.741    | 0.614 | 0.803 |

AUC, area under the curve; CI, confidence interval; PPV, positive predictive value; NPV, negative predictive value.

### Table 5. Model comparison in VC

| VC               | AUC   | 95% CI       | Sensitivity | Specificity | Accuracy | PPV   | NPV   |
|------------------|-------|--------------|-------------|-------------|----------|-------|-------|
| Clinical model   | 0.674 | 0.589–0.752 | 0.843       | 0.430       | 0.664    | 0.467 | 0.822 |
| Radiomics model  | 0.671 | 0.576–0.766 | 0.726       | 0.605       | 0.649    | 0.521 | 0.788 |
| Combined model   | 0.748 | 0.667–0.818 | 0.784       | 0.686       | 0.693    | 0.597 | 0.842 |

AUC, area under the curve; CI, confidence interval; PPV, positive predictive value; NPV, negative predictive value.

Comparison of the Prediction Performance of the Three Models

Among the three models, the combined model had the highest AUC (0.763 and 0.748 for TC and VC, respectively) and the highest accuracy (0.741 and 0.693 for TC and VC, respectively; Tables 4, 5). There were no significant differences in AUCs between the clinical and radiomics models in the two cohorts (DeLong test, p = 0.007 and 0.002, respectively, for TC; p = 0.032 and 0.042, respectively, for VC; Fig. 2a, b). Therefore, the combined model was judged to be the best predictive model for postoperative complications in GC.

### Construction and Clinical Utility Analysis of the Nomogram

A nomogram was constructed based on the optimal model (Fig. 3). The higher the value calculated from the nomogram, the higher the likelihood of postoperative complications in GC. For example, the total score of a GC patient with a preoperative NRS2002 score ≥3 points, sarcopenia, intraoperative blood loss of 400 mL, and a radiomics score of 0.5 would be 33 + 16 + 32 + 50 = 131, and the risk of postoperative complications would be 69%. Physicians and patients can use the nomogram to predict the risk of postoperative complications of GC surgery and
Fig. 2. Receiver operating characteristic (ROC) curves of the three models in the training (a) and validation (b) cohorts. The area under the curve (AUC) of the ROC curve is a comprehensive embodiment of a model’s accuracy, sensitivity, and specificity. The combined model had significantly higher AUCs in both the training and validation cohorts than the clinical or radiomics model alone. The combined model was judged to be the best predictive model for postoperative complications in gastric cancer.

Fig. 3. Nomogram created using typical clinical risk variables and radiomics signature.
**Fig. 4.** Calibration curves of the nomogram in the training (a) and validation (b) cohorts. Calibration curves depict the calibration of the nomogram in terms of the agreement between the predicted risks of postoperative complications and observed outcomes of postoperative complications. The x-axis represents the nomogram-predicted probability. The y-axis represents the actual postoperative complication rate. The diagonal dotted line represents a perfect prediction by an ideal model. The black dotted line represents the performance of the nomogram, and the black solid line is bias-corrected by bootstrapping (B = 1,000 repetitions). The closer the black dotted and solid lines fit to the diagonal dotted line, the better the prediction.

**Fig. 5.** Decision curve analysis for the three models. The light gray line represents the assumption that all patients have postoperative complications. The dark black horizontal line represents the assumption that no patients have postoperative complications. The x-axis represents the threshold probability. The y-axis measures the net benefit. The green line represents the radiomics model. The blue line represents the clinical model. The red line represents the combined model. The net benefit was calculated by subtracting the proportion who tested true positive, and weighting by the relative harm of forgoing treatment compared with the negative consequences of an unnecessary treatment. The decision curve showed that for a given patient, if the threshold probability is between 0.15 and 0.58, then using any of the three models in the current study to predict postoperative complications adds more benefit than the treat-all-patients scheme or the treat-none scheme. The net benefit was best in the combined model.
more accurately assess individual patients, which would help them select a more appropriate treatment plan.

The calibration curves of the nomogram model demonstrated good agreement in both the TC and VC (Fig. 4a, b). The DCA showed that for a given patient, if the threshold probability is between 0.15 and 0.58, then using any of the three models in the current study to predict postoperative complications adds more benefit than the treat-all-patients scheme or the treat-none scheme. Within this range, the net benefit was comparable among the three models, with the best net benefit in the combined model (Fig. 5). The \( p \) value for the Hosmer-Lemeshow statistic was 0.884 for the TC and 0.703 for the VC, indicating that the Hosmer-Lemeshow test was not statistically significant and that the model was a good fit.

Discussion

In this research, we created and verified a novel, CT-based combined prediction model to improve the assessment of nutritional status and the prediction of postoperative complications in GC patients. The model is a nomogram incorporating the NRS2002 score, sarcopenia, blood loss, and a radiomics signature. Compared to the radiomics signature alone and the clinical model based on clinical features and body composition data, the nomogram provided better predictive accuracy, which shows the incremental value of the combined model for the prediction of postoperative complications in GC. Moreover, by quantifying the prediction model, the current study proved that the nomogram, which enables visualization, was an intuitive and reliable personalized decision-making tool.

Malnutrition frequently occurs in GC patients (incidence, 37–63%), especially in hospitalized patients, as both the disease and its treatments adversely affect the patient’s nutritional status; however, this type of malnutrition is often overlooked or under-treated [20, 21]. In our combined model, the NRS2002 score, sarcopenia, and blood loss were independent clinical predictors of overall postoperative complications in GC, which is consistent with the results of other studies [22–24]. The European Society of Parenteral and Enteral Nutrition recommends the NRS2002 as the instrument of choice for NRS in hospitalized patients [25]. However, NRS2002 has certain limitations since it cannot determine the degree of malnutrition and is not sufficient to assess changes in body composition. We focused on skeletal muscle and adipose tissue in the body composition data and found that sarcopenia was associated with overall postoperative complications, while visceral obesity was associated with postoperative inflammatory complications in GC. Sarcopenia is a condition characterized by a gradual and universal loss of skeletal muscle mass and strength, with or without adipose tissue loss [26]. The impact of body composition on postoperative complications may be explained as follows: first, sarcopenia serves as a marker of malnutrition, which would increase the rate of complications [27]. Second, weight loss in GC patients is primarily associated with sarcopenia; these patients are frail and lack amino acids for tissue repair, and their physiological and repair functions are compromised, leading to an increased incidence of postoperative complications [28, 29]. Third, visceral fat is an important metabolic tissue that secretes pro-inflammatory substances, which are associated with the risk of inflammatory complications. Visceral fat also secretes angiogenic stimulants such as vascular endothelial growth factor and leptin, the continued expression of which can lead to the uncontrolled formation of fragile, disorganized, easy-to-bleed vessels, leading to an increased risk of intraoperative blood loss [30]. Furthermore, excessive intraoperative blood loss can lead to unfavorable postoperative conditions. In patients with sarcopenia, blood loss can further reduce the body’s immunity and ability to fight off cancer cells, leading to a worse postoperative prognosis [31]. For this reason, we should focus on the above clinical risk factors and enhance nutritional support to improve treatment outcomes.

Radiomics has been a research hotspot in recent years, as this technology enables the noninvasive discovery of features that are difficult to identify by visual inspection or conventional imaging tools [32]. On reviewing the reports of radiomics in the prognosis of GC, we found that previous studies primarily focused on long-term prognosis [14, 33], and few reports investigated postoperative complications. Our research combines a radiomics signature and clinical risk factors, which differs from and complements previous studies. Tumor heterogeneity is one of the critical features of GC. Tumor heterogeneity refers to the temporal and spatial heterogeneity of solid cancers at the genetic, cellular, protein, microenvironment, tissue, and organ levels [34]. CT texture analysis is a method for quantifying tumor heterogeneity [35]. The impact of tumor heterogeneity on postoperative complications may be attributed to the following factors: first, GC cells can secrete cytokines such as pro-inflammatory cytokines and tumor necrosis factor to different degrees, leading to accelerated muscle atrophy and lipolysis [20], which in-
crease the incidence of postoperative complications by affecting the nutritional status of the patients. Second, macrophages are significantly correlated with tumor heterogeneity [36], and they may play a direct role in tumor growth through their many functions, such as inflammation, intravascular injection, angiogenesis, and matrix remodeling [36]; this would lead to compromised immune function and an increased incidence of complications. Therefore, CT-based radiomics provides valuable information for the prediction of postoperative complications in GC, which validates our hypothesis.

Overall, the combined model in this study showed optimal predictive performance in both the TC and VC, with AUCs of 0.763 (95% CI: 0.708–0.817) and 0.748 (95% CI: 0.667–0.818), respectively, implying that the radiomics signature has additive value to the clinical model. Similar combined models have been studied for other conditions. For example, Kim et al. [37] found that a combined model based on MRI and clinicopathologic variables had optimal discrimination and calibration ability in predicting pathologic complete response after neoadjuvant chemotherapy for breast cancer. Liang et al. [38] showed that their proposed combined nomogram model may be beneficial in distinguishing between grade 1 and grade 2/3 tumors in individuals with pancreatic neuroendocrine tumors. Combined models have also been investigated in lung cancer, liver cancer, and metastatic tumors, and shown similar results [39–41]. This is further evidence of the good diagnostic efficiency of combined models. Our combined model incorporates more characteristic informative indicators, such as NRS2002 and muscle index, to screen for patients at nutritional risk and further identify the degree of malnutrition in patients, while the radiomics features in our model provide information on the tumor microenvironment. Thus, our combined model has potential clinical applications and higher predictive stability than single-factor models. Finally, to facilitate clinical application, we constructed a nomogram based on the combined model. This nomogram showed good performance and high compatibility. This scoring system was used to generate postoperative complication probabilities, which can help doctors distinguish high- and low-risk patients, and formulate more appropriate treatment plans. For high-risk patients, in particular, a multidisciplinary consultation involving the nutrition, gastrointestinal surgery, medical oncology, and radiology departments can be conducted to formulate an individualized treatment plan. This is conducive to improving the prognosis of patients and is in line with the present trend of individualized precision medicine.

The current research has some shortcomings. First, this research is a single-center retrospective evaluation that might be subject to selection bias and requires multicenter validation to extend the generalizability of the findings. Second, the use of various scanners from different manufacturers as well as varying acquisition parameters may have had an effect on the radiomics variables. Third, the tumor biology might not be fully characterized by segmenting the ROI on the largest cross section rather than on the whole tumor volume.

**Conclusions**

In conclusion, this study developed a new combined prediction model for postoperative complications in GC, mainly from a nutritional and imaging perspective. The model takes into account the NRS2002 score, sarcopenia, blood loss, and a radiomics signature. The constructed nomogram visualizes risk factors and is an objective individualized predictor with potential applications in assisting clinical decisions and enabling precision medicine.

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**Statement of Ethics**

The Ethics Committee of the First Affiliated Hospital of Guangxi Medical University approved the current retrospective investigation (approval number: 2022-KY-E-183), and the requirement for written informed consent was waived.

**Conflict of Interest Statement**

The authors have no conflicts of interest to declare.

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Author Contributions

The authors’ responsibilities were as follows: Qiaoqing Lan and Xuechun Guan contributed equally to this article, designed the research, and drafted the article; Qiaoqing Lan, Shunzu Lu, and Zijian Jiang collected the data; Qiaoqing Lan and Huashan Lin analyzed the data; Liling Long and Wenzhao Yuan revised the paper; and all authors read and approved the final manuscript. The authors report that they have no conflicts of interest.

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Data Availability Statement

All the data (pooled hazard ratios with 95% CIs of odds ratio, body composition data, or radiomic features) used to support the findings of this study are included within the article and its online supplementary material. Please contact author Qiaoqing Lan for data requests.
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