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# Radiomics and prognostic nutritional index for predicting postoperative survival in esophageal carcinoma

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## Abstract

**Background** Surgery offers the potential for a radical cure and prolonged survival in individuals diagnosed with esophageal squamous cell carcinoma (ESCC). However, survival rates exhibit significant variability among patients. Accurately assessing surgical outcomes remains a critical challenge. This study aimed to evaluate the predictive value of preoperative radiomics and the prognostic nutritional index for individuals with ESCC and to develop a comprehensive model for estimating postoperative overall survival (OS) in these patients.

**Methods** A retrospective analysis was conducted on 466 patients with ESCC from two medical centers. The dataset was randomly divided into a training cohort (TC, hospital 1, 246 cases), an internal validation cohort (IVC, hospital 1, 106 cases), and an external validation cohort (EVC, hospital 2, 114 cases). Radiological features were extracted after delineating the region of interest, followed by the application of the least absolute shrinkage and selection operator (LASSO) regression to identify optimal radiomics features and compute the radiomics score (RS). Independent prognostic factors identified via Cox regression analysis were incorporated with the RS to construct a combined nomogram. The predictive performance of the model was evaluated using the concordance index, time-dependent receiver operating characteristic (ROC) curves, calibration plots, and decision curve analysis.

**Results** The predictive model, which integrated preoperative radiomics, the prognostic nutritional index, and tumor–node–metastasis (TNM) staging to estimate the 3 year OS rate, achieved area under the ROC curve (AUC) values of 0.812, 0.786, and 0.810 in the TC, IVC, and EVC, respectively, demonstrating excellent prognostic accuracy. These values surpassed the AUCs of the TNM staging model in the TC, IVC, and EVC, which were 0.717, 0.612, and 0.699, respectively. The combined model's concordance indexes in the TC, IVC, and EVC were 0.780, 0.760, and 0.764, respectively. Calibration and decision curves highlighted the nomogram's superior calibration and clinical utility.

**Conclusion** This study developed a predictive model by combining radiomics with the prognostic nutritional index, enabling the estimation of OS in postoperative patients with ESCC. This model holds promise as a tool for preoperative risk stratification.

**Keywords** Esophageal carcinoma, Hematologic parameter, Nomogram, Overall survival, Prognosis, Radiomics

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## Introduction

Esophageal carcinoma (EC) ranks among the deadliest malignancies globally, with the majority of individuals in Asia being affected by squamous cell carcinoma [1, 2]. Early-stage EC is typically asymptomatic, resulting in numerous patients being diagnosed at advanced or late stages of the disease during their initial medical evaluation [3]. Multimodal therapeutic strategies, such as surgical intervention combined with chemotherapy or chemoradiotherapy, constitute the standard treatment regimen, offering the best prospects for resectable cancers. However, the prognosis for patients aiming for curative outcomes remains poor. The 5 year overall survival (OS) rate stands at 45.0–46.5%, while the median survival duration following disease progression is merely 13 months [4, 5]. Currently, clinical tumor–node–metastasis (TNM) staging is instrumental in guiding therapeutic decisions. Nonetheless, its predictive accuracy for concurrent pathological staging in early-stage cancer is suboptimal, and certain limitations are evident in its prognostic utility [6, 7]. Thus, identifying novel and dependable biomarkers to assess tumor heterogeneity, evaluate treatment efficacy, and enhance prognostic accuracy is imperative.

Radiological features derived from contrast-enhanced computed tomography images offer significant data for predictive models. Non-invasive radiological techniques, including computed tomography (CT), magnetic resonance imaging, and positron emission tomography, enable the extraction of high-throughput quantitative features from images, thereby supporting diagnosis, evaluation of treatment response, and prognosis in various cancers, including EC [8–10]. Radiomics has demonstrated utility in prognostic analysis, facilitating the prediction of postoperative recurrence in EC patients who have achieved a pathological complete response following neoadjuvant chemoradiotherapy, lymph node metastasis, and resectability [11]. Furthermore, radiomics-based nomograms have shown potential in predicting radiation pneumonitis, assessing the expression of programmed death-ligand 1, and evaluating treatment outcomes for radiotherapy and chemotherapy. Such tools can assist in identifying patients who derive limited benefit from radiotherapy and chemotherapy, as well as in determining the efficacy of neoadjuvant radiotherapy and chemotherapy [11, 12]. Additionally, the integration of CT-based radiomics with clinical factors has further improved the predictive performance of ESCC [13].

In addition to radiomics, which extracts features from local tumors, hematological indicators are instrumental in evaluating the systemic inflammatory state, a factor associated with recurrence and prognosis in various cancers [14]. Previous studies have highlighted the impact of the prognostic nutritional index (PNI) on recurrence and prognosis in patients with EC [15, 16]. Although previous studies have examined the effects of radiomics and hematological parameters on prognosis, limited investigations have combined these factors to predict survival outcomes. Consequently, this multi-institutional study aimed to construct a combined prognostic model for patients with ESCC undergoing radical surgery by integrating PNI with CT radiological features and validating the model's effectiveness.

## Material and methods

### Information collection and follow-up

According to the guidelines established by the Chinese Society of Clinical Oncology, surgical treatment is prioritized for individuals diagnosed with clinical stage cT1b-2N0M0, regardless of lesion length and differentiation degree [17].

This study involved 446 patients with ESCC who underwent radical surgical intervention at the First Affiliated Hospital of Anhui Medical University and the Fudan University Shanghai Cancer Center between June 2010 and June 2023. Preoperative chest CT images of EC were simultaneously collected. The investigation was conducted in adherence to the World Medical Association Declaration of Helsinki. Approval for this investigation was granted by the Ethics Committee of the First Affiliated Hospital of Anhui Medical University (Approval Number: quick-PJ 2024-04-57). As the study was retrospective in nature, the requirement for informed consent from patients was waived.

The selection criteria included: (1) individuals aged 18 to 80 years; (2) histological confirmation of ESCC obtained through biopsy; (3) diagnosis of non-metastatic EC using preoperative standard contrast-enhanced CT; and (4) complete availability of clinical and pathological characteristics. All patients were staged in accordance with the eighth edition of the TNM staging system of the American Joint Committee on Cancer for EC [18]. The exclusion criteria were defined as follows: (1) absence of clinical data, loss to follow-up, or suboptimal-quality CT images; (2) coexistence of other malignant tumors; and (3) patients who received preoperative chemotherapy, immunotherapy, or radiotherapy. A total of 352 individuals from the First Affiliated Hospital of Anhui Medical University were randomly allocated, at a ratio of 7:3, to the training cohort (TC, $N=246$) and the internal validation cohort (IVC, $N=106$). Additionally, data from 114 patients at the Fudan University Shanghai Cancer Center were used for the external validation cohort (EVC). The patient recruitment and selection process is illustrated in Fig. 1.

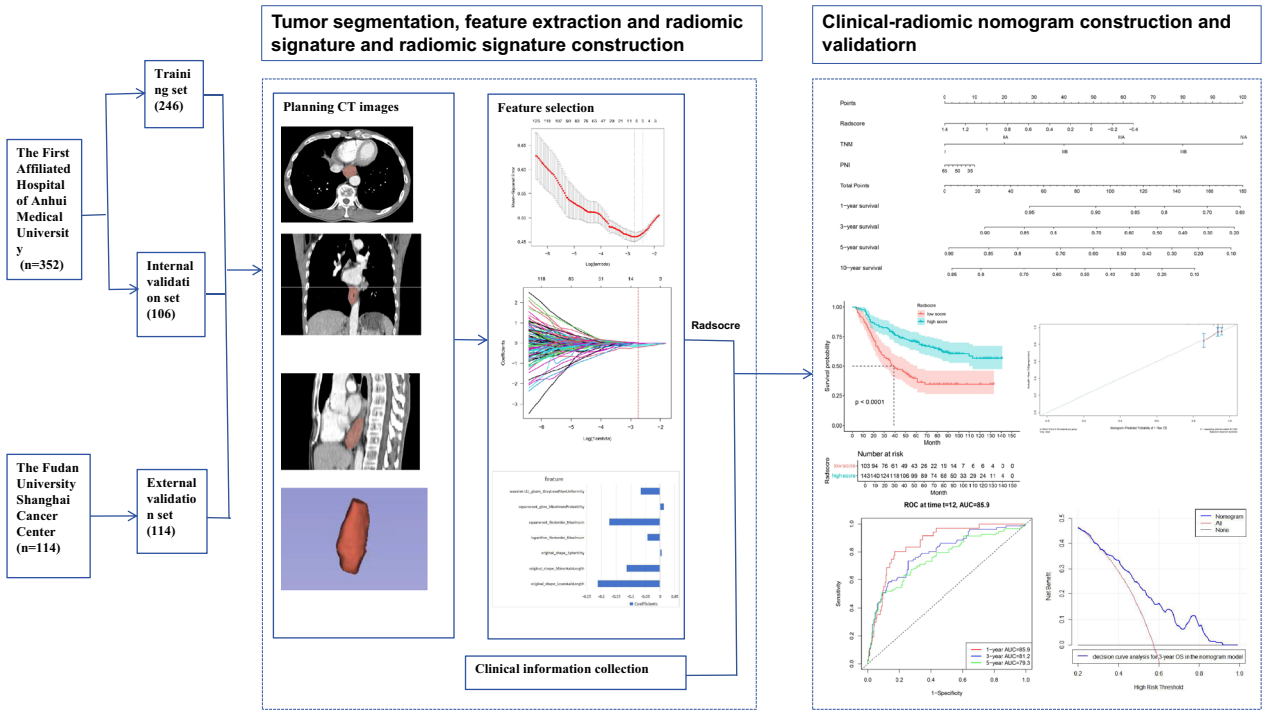


**Fig. 1** The study procedure of this research. *ROC* receiver operator characteristic

All clinical characteristics in the preoperative stage, including age, gender, body mass index, smoking status, alcohol consumption, differentiation status, tumor location, TNM stage, surgical approach, and PNI, were retrieved. The PNI was determined using the formula: serum albumin + 5 × total lymphocyte count. CT examinations were conducted three weeks prior to surgery, while hematological tests were performed one week before the procedure.

During the postoperative period, follow-up was conducted at intervals of 3 to 6 months from the 1st to the 2nd year, every 6 months from the 3rd to the 5th year, and annually thereafter. The follow-up endpoint was established as June 1, 2024. OS was defined as the time from surgical intervention to death from any cause. Postoperative follow-up included esophageal radiography, contrast-enhanced CT scans, and routine hematological examinations.

### Delineation of the region of interest (ROI) and derivation of radiomics features (RFs)

This study acquired arterial phase CT images of preoperative patients with ESCC from two medical center systems, employing a 5 mm slice interval. Details regarding the scanner equipment and the protocol for intravenous contrast agent administration are provided in Table S1. In quantitative imaging analysis, the primary tumor was defined as a lesion with esophageal wall thickening exceeding 5 mm or a lumen occlusion diameter greater than 1 cm. Intraluminal gas and oral contrast agents were disregarded, and the lesion was selected as the ROI, while normal structures and metastatic lymph nodes were excluded [19]. Patient information was anonymized, and the initial tumor segmentation was performed by two radiologists with over 6 years of professional experience. The segmentation was subsequently reviewed and adjusted as necessary by a radiologist with more than 12 years of experience. None of the physicians had access to patient-specific information. ROI delineation was carried out using 3D Slicer (version 5.7.0). A total of 1409 RFs were extracted from the ROIs using PyRadiomics (version 3.6.2). The RFs, derived through wavelet filtering, included first-order statistics, neighboring gray-tone difference matrix (NGTDM), gray-level size zone matrix (GLSZM), gray-level dependence matrix (GLDM), gray-level run-length matrix (GLRLM), gray-level co-occurrence matrix (GLCM), and shape features.

The RF values underwent normalization through Z-score analysis, with their reproducibility assessed using the intraclass correlation coefficient (ICC) evaluation. Features identified with a *P*-value below 0.05 and an ICC ≥ 0.8 were chosen for subsequent analysis. Thereafter, the least absolute shrinkage and selection operator (LASSO) regression was implemented in R software

(version 4.4.1) to identify features associated with OS, and optimal parameters (λ) were determined via tenfold cross-validation. During the feature selection procedure, LASSO regression employed L1 regularization, which utilized gradient-based optimization to refine parameter coefficients, balancing their respective weights and mitigating overfitting and collinearity issues. Finally, the selected features were assigned weights and linearly combined through non-zero coefficients derived in this process, enabling the calculation of the radiomics score (rad-score) for each patient.

#### Establishment and validation of the nomogram for the combined model

Prognostic factors associated with OS were identified using univariate Cox regression analysis. Subsequently, these parameters were analyzed through multivariate Cox regression analysis, with factors demonstrating $P<0.05$ considered independent prognostic factors (IPFs) for OS. Following this, a nomogram was constructed by integrating the rad-score and IPFs. The clinical applicability and predictive accuracy of the model were evaluated through calibration curves, time-dependent area under the curve (AUC), and decision curve analysis (DCA).

#### Statistical analysis

Statistical analyses were performed using SPSS software (version 29.0, International Business Machines Corporation, Armonk, NY, USA), R software (version 4.4.1, R Foundation for Statistical Computing, Vienna, Austria), and Python software (version 3.6.7, http://www.python.org/). The cut-off values were determined with X-tile software (version 3.6.1, Yale University School of Medicine, New Haven, USA). Patient categories and continuous baseline characteristics were represented as frequency (percentage) and mean ± standard deviation, respectively. Survival curves were constructed using the Kaplan–Meier (KM) method, and survival differences were assessed via the Log-rank test. Univariate and multivariate analyses were conducted through the Cox proportional hazards regression model to identify factors independently associated with survival. A $P$-value < 0.05 was regarded as statistically significant.

## Results

#### Patient characteristics

This study included 352 participants from the First Affiliated Hospital of Anhui Medical University and 114 patients from the Shanghai Cancer Center of Fudan University. Of these, the TC group comprised 246 cases, the IVC group included 106 cases, and the EVC group consisted of 114 cases. The median follow-up duration for the First Affiliated Hospital of Anhui Medical University was 55 months (range: 3–141 months), while for the Shanghai Cancer Center of Fudan University, it was 51 months (range: 3–156 months). By June 1, 2024, 166 patients from Institution 1 and 68 patients from Institution 2 had passed away. Table 1 demonstrates that no significant differences in clinical pathological data were observed between the three cohorts.

#### Univariable analysis and multivariable analysis

After excluding redundant RFs and those with unsatisfactory ICC values, 1,078 of the 1,409 features were retained for LASSO regression analysis, resulting in the selection of seven RFs: Original_shape_least axis length, original_shape_minor axis length, original_shape_sphericity, logarithm_first order_maximum, square root_first order_maximum, square root_glcm_maximum probability, and wavelet-LLL_glszm_gray level non-uniformity (Fig. 2). By integrating the rad-score with clinical features and conducting an analysis via X-tile software, the optimal cut-off value for the rad-score was identified as −0.45, while that for PNI was determined to be 47.1. The Schoenfeld residual plot indicated that the PH assumption of the Cox regression model was valid ($P>0.05$, Fig. 3). The univariate analysis of the TC revealed that age (hazard ratio [HR]: 0.649, 95% confidence interval CI 0.426–0.988, $P<0.001$), TNM stage (HR: 0.317, 95% CI 0.212–0.474, $P<0.001$), rad-score (HR: 3.080, 95% CI 2.024–4.687, $P<0.001$), and PNI (HR: 1.729, 95% CI 1.171–2.552, $P=0.006$) were significant prognostic factors for OS (Table 2). The multivariate analysis of the TC identified TNM stage (HR: 0.404, 95% CI 0.267–0.612, $P<0.001$), rad-score (HR: 1.849, 95% CI 1.258–2.716, $P=0.002$), and PNI (HR: 1.576, 95% CI 1.058–2.348, $P=0.025$) as IPFs for OS. KM survival analysis demonstrated significant differences in OS based on rad-score, PNI, and TNM stage within the TC, IVC, and EVC groups (Fig. 4). Individuals exhibiting high rad-score, high PNI, and stage I–II tumors displayed markedly higher 1-, 3-, and 5 year OS rates.

#### Establishment of models to predict OS

This study utilized rad-score, PNI, and TNM to construct a model for OS prediction. The c-index values of the TNM staging model in the TC, IVC, and EVC cohorts were 0.635 (95% CI 0.595–0.675), 0.611 (95% CI 0.529–0.693), and 0.607 (95% CI 0.029–1.185), respectively. In comparison, the c-index values of the integrated model in the TC, IVC, and EVC cohorts were 0.780 (95%

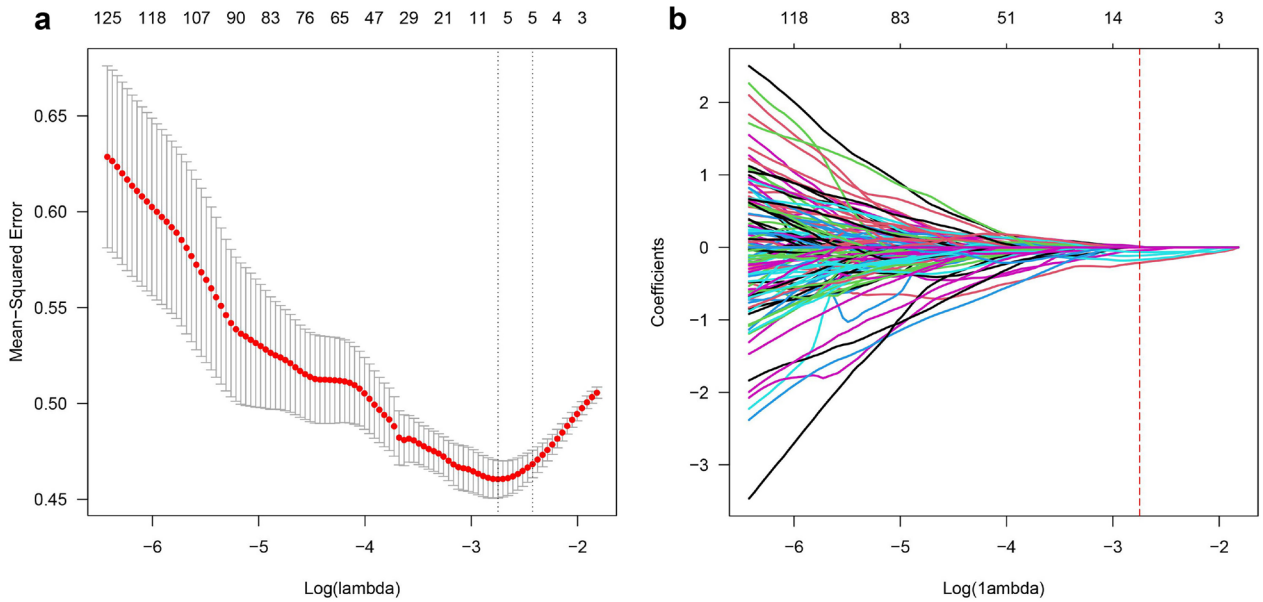


**Fig. 2** In the TC, radiomic features linked to OS were identified via the LASSO regression model. **a**: The cross-validation curve. **b**: Coefficient curves for radiomic features

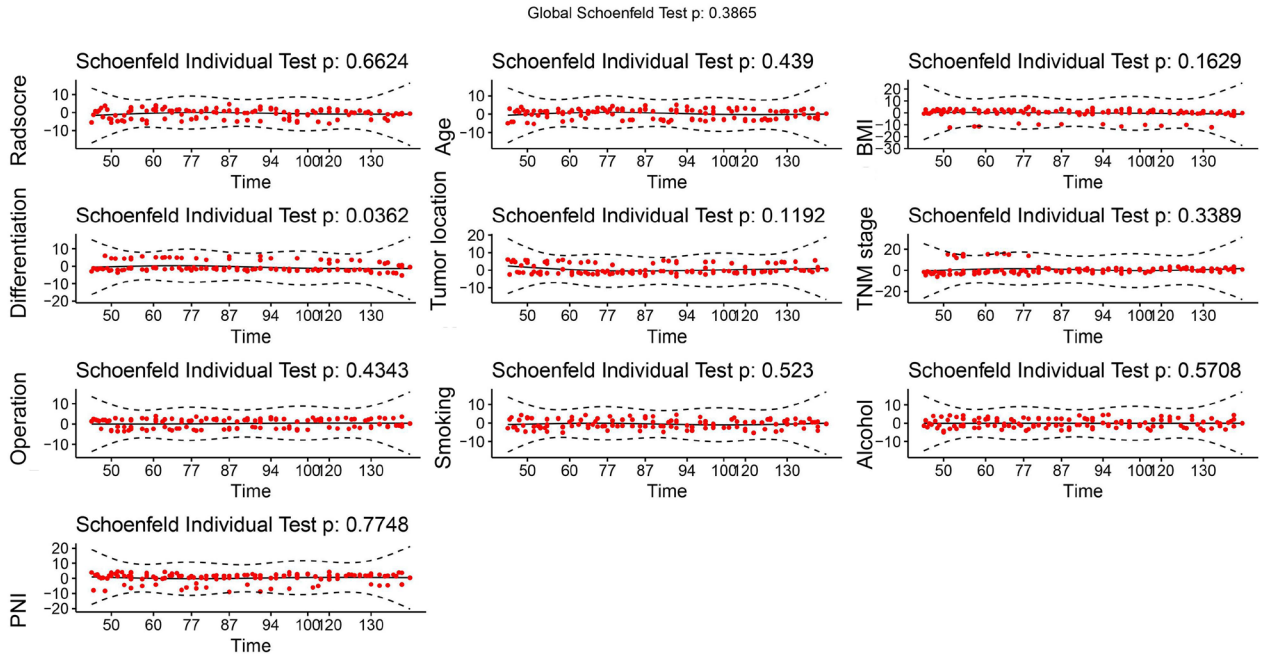


**Fig. 3** Schoenfeld residual plot of the Cox proportional-hazards regression model. *BMI* Body mass index; *PNI* Prognostic nutritional index

CI 0.741–0.819), 0.760 (95% CI 0.695–0.825), and 0.764 (95% CI 0.710–0.818), respectively. These results suggest that the c-index of the combined model consistently exceeds that of the TNM staging model across the TC, IVC, and EVC. In the TC cohort, the AUC values of the combined model for predicting the 1-, 3-, and 5 year OS rates were 0.859, 0.812, and 0.793, respectively, while those of the TNM staging model were 0.760, 0.717, and

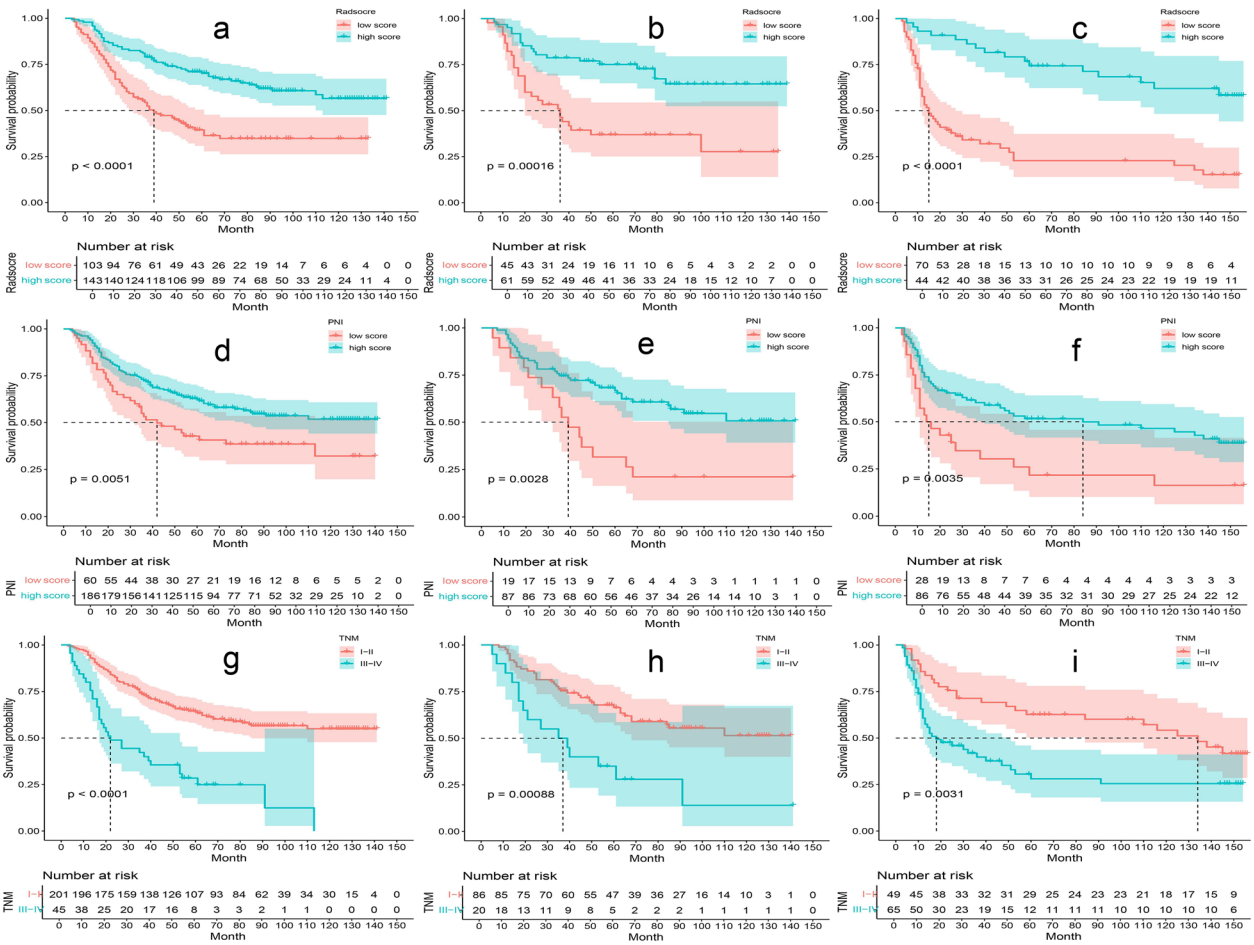


**Fig. 4** TC (**a**, **d**, and **g**), IVC (**b**, **e**, and **h**), and EVCs' (**c**, **f**, and **i**) KM survival curves. **a**, **b**, and **c**: KM survival curve based on rad-score; d, e, and f: KM survival curve based on PNI; g, h, and i: KM survival curve based on TNM

0.693, respectively ((Figs. 5a, d). In the IVC cohort, the AUC values of the combined model for forecasting the 1-, 3-, and 5 year OS rates were 0.780, 0.786, and 0.792, respectively, whereas the corresponding values for the TNM staging model were 0.705, 0.612, and 0.621 (Fig. 5b, e). In the EVC cohort, the AUC values of the combined model for predicting the probabilities of 1-, 3-, and 5 year OS (0.809, 0.810, and 0.792, respectively) surpassed those of the TNM staging model (0.690, 0.699, and 0.678, respectively) (Fig. 5c, f). The AUCs of individual radiomics features and the PNI model for predicting postoperative survival were shown in Figure S1. Across all three cohorts, the combined model's AUC values for forecasting the 1-, 3-, and 5 year OS rates consistently outperformed those of the TNM staging model. A nomogram was developed incorporating rad-score, PNI, and TNM (Fig. 6a). The calibration curves for OS showed that the predicted 1-, 3-, and 5-year OS rates closely aligned with the observed values (Fig. 6b–d). The DCA of the predictive model indicated a positive net benefit (Fig. 6e).

## Discussion

Conducting an individualized risk–benefit analysis facilitates the optimization of management decisions for resectable EC. Enhancing the accuracy of prognosis assessment remains a pivotal step. Preliminary imaging studies have demonstrated that RFs provide additional prognostic value [20, 21]. In this study, seven RFs strongly associated with OS were identified. Among them, GLCM is the most commonly observed statistical feature, while GLSZM captures variations in gray-level intensity values within the image [22, 23]. Relatively homogeneous, low-gray-level EC lesions have been linked to improved long-term survival. Other RFs considered in this study include

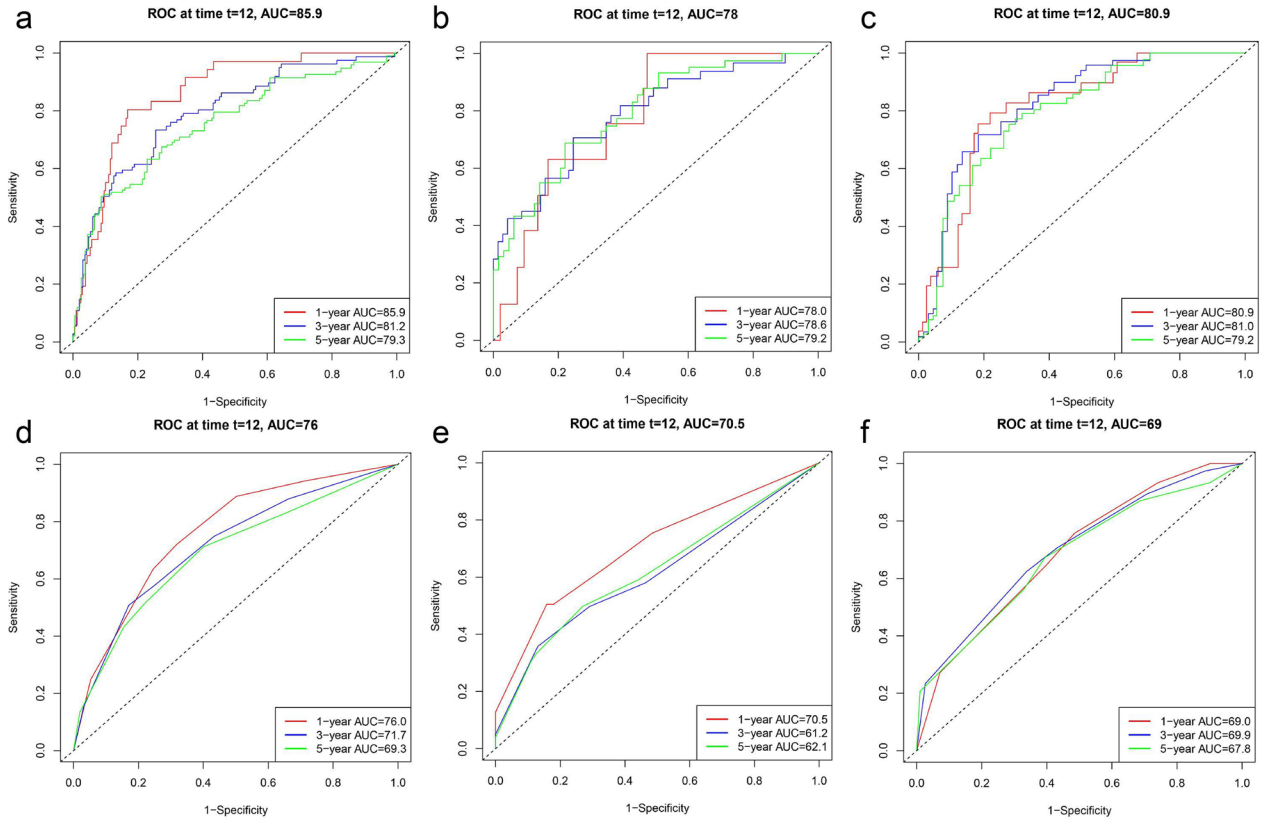


**Fig. 5** The predictive performances of the three models for patients with ESCC. ROC curves demonstrate the predictive performances of the TC (**a** and **d**), IVC (**b** and **e**), and EVC models (**c** and **f**). **a**, **b**, and **c** were combined models; d, e, and f were TNM prediction models

those related to least axis length, minor axis length, sphericity, and additional first-order features. Numerous studies have confirmed that radiomics can be employed to identify individuals at elevated risk of EC and refine clinical treatment strategies [24–26]. This investigation demonstrated that patients in the high rad-score cohort exhibited significantly longer median OS compared to those in the low rad-score cohort. Furthermore, it effectively stratified the pretreatment risk of ESCC patients.

The tumor microenvironment plays a pivotal role in facilitating tumor initiation and progression [27]. The catabolic effects of systemic inflammation and malnutrition on host metabolism promote tumor growth, exacerbate the vicious cycle of immune-nutritional deficiencies, and contribute to the worsening of cancer [28]. Consequently, systemic inflammation and malnutrition in tumors have garnered increasing attention from researchers [29]. Li et al. conducted a meta-analysis of nine studies to investigate the prognostic factors influencing ESCC. The findings revealed that a decreased PNI before treatment was strongly associated with recurrence-free survival and OS [30]. Zou et al. identified a significant correlation between low PNI levels and tumor stage in patients with EC, further corroborating the prognostic significance of PNI [31]. In this study, the optimal cut-off value of PNI was determined to be 47.1. The median OS in the high PNI cohort was significantly higher compared to the low PNI cohort, consistent with the findings of numerous prior studies [32–34].

Previous research has demonstrated that models integrating clinical factors and RFs achieve greater accuracy in prognostic assessments compared to clinical models alone [35]. In this study, the combined clinical-radiomics nomogram was shown to outperform the standalone TNM model in predicting OS, with C-index values for the TC, IVC, and EVCs recorded at 0.780, 0.760, and 0.764, respectively. The predictive outcomes of the combined model exhibited strong concordance with observed survival data, providing substantial clinical benefits to patients.

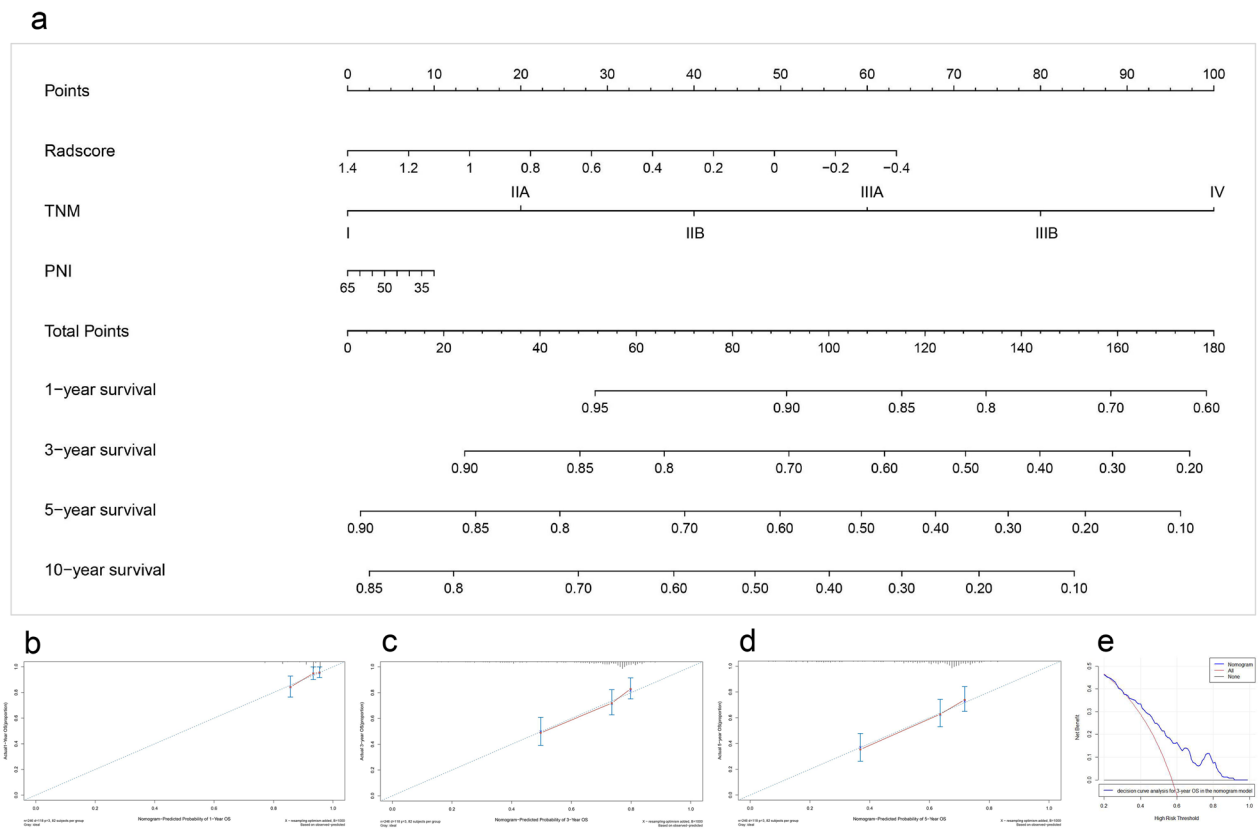


**Fig. 6** In the TC, the model's efficacy and verification for forecasting OS. The nomogram in the combined model (**a**), the calibration curve of the nomogram for predicting the 1- (**b**), 3- (**c**), and 5 year (**d**) OS. DCA for 3 year OS in the nomogram model (**e**)

This study has several limitations. Firstly, only patients diagnosed with ESCC were included, which restricts the applicability of the model to cases of adenocarcinoma. Secondly, patients who underwent neoadjuvant chemoradiotherapy prior to surgery were not incorporated. In clinical practice, a significant proportion of patients are at relatively advanced stages and receive neoadjuvant treatment before surgery. Thus, the applicability of this study to such populations remains unclear. Thirdly, data from only two centers were utilized. The dataset used to construct the predictive model was relatively small and geographically limited, inevitably introducing bias into the results. Consequently, expanding the scale and scope of research centers is necessary to further evaluate the feasibility of the predictive model.

This study represents the first attempt to integrate the inflammatory factor PNI with radiomics to evaluate the postoperative prognosis of patients with ESCC. The findings indicate that a high PNI is correlated with an improved prognosis. The nomogram developed based on PNI and radiomics demonstrates robust predictive accuracy for assessing the postoperative prognosis of ESCC patients. Furthermore, as a straightforward and practical tool, it holds significant potential for enhancing prognosis evaluation and guiding treatment decisions. This preliminary investigation offers valuable insights and

**Table 1** The clinical baseline characteristics of the patients

| Variable | Training cohort(n = 246) | Internal validation cohort (n = 106) | External validation cohort(n = 114) | *P*-value |
|---|---|---|---|---|
| Age | | | | 0.617 |
| < 60 | 73 | 29 | 38 | |
| ≥ 60 | 173 | 77 | 76 | |
| Gender, case (%) | | | | |
| Male | 191 | 86 | 98 | 0.176 |
| Female | 55 | 20 | 16 | |
| Body mass index (kg/m$^2$) | | | | 0.656 |
| < 18.5 | 36 | 12 | 14 | |
| ≥ 18.5 | 210 | 94 | 100 | |
| Smoking | | | | 0.656 |
| Yes | 115 | 43 | 74 | |
| No | 131 | 63 | 40 | |
| Alcohol | | | | 0.488 |
| Yes | 140 | 53 | 63 | |
| No | 106 | 53 | 51 | |
| Differentiation (Well + moderate vs. poor) | | | | 0.423 |
| Well + moderate | 179 | 81 | 90 | |
| Poor | 67 | 25 | 24 | |
| Location | | | | 0.454 |
| Upper + middle | 183 | 79 | 78 | |
| Lower | 63 | 27 | 36 | |
| TNM stage (I + II vs. III + IV) | | | | 0.228 |
| T1 + 2 | 181 | 73 | 74 | |
| T3 + 4 | 65 | 33 | 40 | |
| Operation (thoracoscopic vs. non-thoracoscopic) | | | | 0.149 |
| Yes | 114 | 44 | 62 | |
| No | 132 | 62 | 52 | |

**Table 2** OS-related univariate and multivariate analyses in the TC

| | Univariate analysis | | | Multivariate analysis | | |
|---|---|---|---|---|---|---|
| | HR | 95% CI | *P*-value | HR | 95% CI | *P*-value |
| Age (< 60 vs. ≥ 60) | 0.649 | 0.426–0.988 | 0.044 | 0.706 | 0.461–1.080 | 0.109 |
| Sex (male vs. female) | 1.324 | 0.980–1.788 | 0.067 | | | |
| Body mass index (kg/m$^2$, < 18.5 vs. ≥ 18.5) | 1.147 | 0.737–1.784 | 0.544 | | | |
| Smoking (no vs. yes) | 1.218 | 0.847–1.753 | 0.287 | | | |
| Alcohol (no vs. yes) | 0.968 | 0.671–1.397 | 0.864 | | | |
| Tumor location (upper + middle vs. lower) | 1.182 | 0.784–1.783 | 0.424 | | | |
| Differentiation (Well + moderate vs. poor) | 0.913 | 0.610–1.365 | 0.656 | | | |
| TNM stage (I + II vs. III + IV) | 0.317 | 0.212–0.474 | < 0.001 | 0.404 | 0.267–0.612 | < 0.001 |
| Operation (thoracoscopic vs. non-thoracoscopic) | 1.037 | 0.723–1.489 | 0.842 | | | |
| Rad-score (≤ 0.22 vs. > 0.22) | 3.080 | 2.024–4.687 | < 0.001 | 1.849 | 1.258–2.716 | 0.002 |
| PNI (≤ 47.1 vs. > 47.1) | 1.729 | 1.171–2.552 | 0.006 | 1.576 | 1.058–2.348 | 0.025 |

establishes a foundation for future large-scale retrospective and prospective clinical trials.

## Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s40001-025-02358-0.

Supplementary material 1

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**Author contributions**
Author WW L, contributed to designe the experiments. Author JD D, JY D, T T, contributed to analyze and interprete the data, data curation, prepared Table 1, 2 and. Author XX C write the manuscript and analyzed results, reviewed literature, participated in production of Fig. 1 and Fig. 2. Author YC W contributed to data analysis, participated in production of Fig. 3, Fig. 4 and Fig. 5. Author F W, LY Z, ensured the compliance of this study with ethical standards and conducted a detailed review of the manuscript. Every author examined and verified the final version.

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**Data availability**
No datasets were generated or analysed during the current study.

## Declarations

**Ethics approval and consent to participate**
This investigation was approved by the Ethics Committee of the First Affiliated Hospital of Anhui Medical University (Approval Number: quick-PJ 2024-04-57). Given the retrospective nature of this study, the Ethics Committee waived the requirement for obtaining informed consent from the patients.

**Consent for publication**
In accordance with the legislative requirements of our country and the approval granted by the Ethics Committee of the First Affiliated Hospital of Anhui Medical University, the need for written informed consent from the participants was waived for this study.

**Competing interests**
The authors declare no competing interests.

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