Clinics of Surgery®

ISSN 2689-8268 | Volume 11

Research Article

Open Access

Survival Analysis of Three Surgical Approaches for T1a Renal Cell Carcinoma and Risk Factor Analysis for Ten-Year Survival Based on Multiple Machine Learning Models

***Jiaxing Ma[1#], Yayun Wu[2#], Guangzheng Lin[1#], Xin Sun[1], Hao Geng[1], Tao Zhang[1*], Dexin Yu[1]**

[1]Department of Urology, the Second Affiliated Hospital of Anhui Medical University, Hefei, China

[2]Department of Oncology, Anhui Provincial Corps Hospital of the Chinese People's Armed Police Forces, Hefei, China

Jiaxing Ma, Yayun Wu, Guangzheng Lin contributed equally to this work[#]

***Corresponding author:**

Tao Zhang, M.D.,
Department of Urology, the Second Affiliated Hospital of Anhui Medical University, Hefei, 230032, China
Dexin Yu, MD,
Department of Urology, the Second Affiliated Hospital of Anhui Medical University, Hefei, 230032, China

Received: 09 Aug 2025
Accepted: 29 Aug 2025
Published: 09 Sep 2025
J Short Name: COS

Keywords:

Renal Cell Carcinoma; Surgery; Machine Learning; SEER Database; Survival

Citation:

Tao Zhang, Dexin Yu, Survival Analysis of Three Surgical Approaches for T1a Renal Cell Carcinoma and Risk Factor Analysis for Ten-Year Survival Based on Multiple Machine Learning Models. Clinics of Surgery® 2025; V11(1): 1-9

1. Abstract

Our study aimed to systematically evaluate the impact of partial nephrectomy (PN), local tumour excision (LTE), and local tumour destruction (LTD) on the survival prognosis of patients with T1a renal cell carcinoma (RCC), and further explore and analyse the key features affecting ten-year prognosis and their predictive value by combining multiple machine learning models and interpretable machine learning techniques. Based on follow-up data from the Surveillance, Epidemiology, and End Results (SEER) database, we included RCC patients who underwent PN, LTE, or LTD surgery. Kaplan-Meier survival curve analysis, in combination with Cox regression and logistic regression models, was used to compare the overall survival (OS) and ten-year survival rates among the three groups. At the same time, the best-performing survival prediction model was selected from various machine learning models, and the contributions of individual variables to postoperative survival were explained using Shapley Additive explanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME) methods. After adjusting for all covariates, Cox regression results showed that LTE significantly reduced OS compared to PN (HR = 0.87, 95%CI: 0.80-0.94). Meanwhile, LTD did not show a significant improvement in ten-year survival (OR = 0.83, 95%CI: 0.73-0.94). The Naive Bayes (NB) algorithm demonstrated the best predictive performance, with patient age and tumour size being critical features for predicting postoperative survival. Our findings suggest that RCC patients treated with PN have a higher ten-year survival rate compared to those treated with other surgical methods. Age and tumour size are key predictors of postoperative survival. Our study advocates the development of patient-centred surgical strategies and the implementation of predictive modelling tools to enhance clinical decision-making.

2. Introduction

Renal Cell Carcinoma (RCC) is the most common urologic malignancy, accounting for approximately 2.4% of all cancer deaths worldwide each year [1], with worldwide population aging and lifestyle changes, the cases of RCC continue to increase. According to official U.S. statistics, the annual incidence of RCC is up to 3%, and it is projected that by 2024, there will be 81,610 new cases in the U.S., resulting in 14,390 RCC-related deaths [2]. Currently, the treatment of RCC depended on surgical procedures, including radical nephrectomy (RN) and partial nephrectomy (PN), combined with radiation therapy strategies [3]. Although surgery is the primary treatment for RCC, the current choice of surgical treatment modality as well as impact on patient prognosis remained controversial. PN, as a surgical procedure that preserved renal units, has been shown to minimize loss of renal function while controlling tumours [4]. However, studies have shown that removal of surrounding normal renal tissue may result in impaired renal function, and even removal of 1 mm of normal tissue may have unwanted effects [5]. In addition, the operational complexity of PN and the requirement of the patient's general condition are relatively high. Therefore, investigators have proposed local tumour excision (LTE) as a more conservative treatment, where blunt dissection is performed only along the wall of the tumour capsule to minimize the damage to normal tissues [6]. However, there is a lack of evidence from long-term follow-up studies on postoperative patient recurrence [7]. Local tumour destruction (LTD), on the other hand, locally destroys the tumour tissue through non-surgical methods such as radiofrequency ablation or cryoablation, and has shown good efficacy and low complication rate in some patients with early-stage renal cancer [8,9]. Studies have shown that LTD provided better local control in patients with tumours up to 3 cm and is superior to PN in terms of renal function protection and complication rates. Among patients with tumours in the range of 3-4 cm, LTD may be associated with higher cancer-specific mortality [10]. Although several studies have analysed the impact of different surgical approaches on the survival prognosis of patients with stage T1a renal cancer (tumour diameter ≤4 cm) [11], there are still many research gaps regarding how these surgeries affect long-term survival and how to identify key factors. The assessment of survival in postoperative renal cancer patients was dependent on statistical models, such as Cox proportional risk models. However, traditional methods have limitations in analysing multivariate interactions and identifying nonlinear relationships, which may result in certain risk factors being overlooked [12]. Compared with traditional statistical models, machine learning (ML) techniques are able to analyse multidimensional and large-scale datasets, identify complex associations between variables that are difficult to detect with traditional analytical methods, and demonstrate high predictive accuracy especially in patient cohorts with significant heterogeneity [13]. In urologic tumours, there have been researchers who have attempted to apply machine learning to survival prediction, such as, Chen et al. [14], Nusinovici et al. [15], Shakhssalim et al. [16]. Considering the role of the three surgical approaches, LTD, LTE and PN, in the long-term survival of RCC patients and the identification of critical variables affecting patients' ten-year survival using machine learning techniques, there is still a lack of systematic analysis. Our study based on the Surveillance, Epidemiology, and End Results (SEER) database, Cox proportional model, logistic regression model and machine learning methods were combined to explore the effects of the three surgical modalities on the survival outcomes of RCC patients. The Shapley Additive Explanations (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME) models were utilized to analyse the key postoperative prognostic variables with interactions, in the hope of providing more comprehensive data support for optimizing the surgical treatment strategies and improving the prognosis of patients.

3. Methods

3.1. Criteria for the Study Population

In order to investigate the impact of three different surgical on the survival outcomes of patients with RCC, we screened data from SEER database. The inclusion criteria for subjects were 1) patients firstly diagnosed with RCC between 2000 and 2021; 2) clinical stage T1a RCC without any lymph node or metastatic status and renal tumours with a mass size of no more than 4 cm; and 3) RCC diagnosed by ICD-O-3 codes and WHO 2008 classification, with subtypes including clear cell type (codes 8310, 8313), papillary type (codes 8050, 8260 , 8342), smectic type (codes 8270, 8317), and other clearly classified renal malignancies; and 4) underwent LTD (codes 10-15), LTE (codes 20-27), or PN (code 30). Patients with survival time of less than 1 month were excluded, who usually have other serious comorbidities or specific diseases that may not reflect the true outcome of surgical treatment. Those with positive lymph nodes or metastases were also excluded. Overall survival (OS) and ten-year postoperative survival were used as the primary survival outcomes for analysis. We used publicly available anonymized data in SEER, did not involve informed consent from patients, nor did we require ethics committee approval due to the retrospective nature of the analysis.

3.2. Construction of Predictive Models Based on Machine Learning Methods

To further analyse the impact of clinical features and surgical strategies on the survival prognosis of T1a RCC patients, we included more comprehensive features for machine learning modelling. We first randomly divided the dataset into two sets, with 80% of the training set and 20% of the test set. Then we selected 10 common machine learning algorithms for analysis, which include neural network (NN), support vector machine (SVM), multilayer perceptron (MLP), gradient boosting machine (GBM), logistic regression (LR), plain Bayes (NB), XGBoost (XGB), C5.0 decision tree (C5.0), k-nearest neighbour (KNN), Random Forest (RF). With these diverse models, we seek to capture the advantages of different algorithms in survival prediction. To evaluate the predictive ability of each model, we focused on the area under the curve (AUC) under the subject operating characteristic curve (ROC) as the main evaluation metrics, and models with higher AUC values performed more accurately in disease risk differentiation. In addition, to comprehensively assess the model performance, we combined several metrics, such as sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), and so on. We selected the model with the best prediction effect and optimized the model parameters by grid search and cross-validation.

3.3. Explanation of The Predictive Model

After determining the optimal model, we further used the SHAP method to assess the importance of each covariate in the prediction. The SHAP values provided the contribution of each feature to the final prediction outcome and help us identify the critical factors that are most predictive of the patient's postoperative survival outcome. Furthermore, the SHAP method has the ability to automatically filter the pair of variables with the strongest interaction. Considering that the interactions between variables may have important impact on the predicted outcomes, we used the SHAP method to automatically identify the combinations of variables with the strongest interactions. We also applied partial dependency plot (PDP) and accumulated local effects (ALE) analysis. These two methods can reveal the effects of different variable values on survival outcomes and help us to understand the differences between global and local effects, especially the complex nonlinear relationships between variables and dose-response effects.

3.4. Covariate Selection

A variety of covariates that may affect survival were combined in assessing the impact of three surgical approaches on survival outcomes in patients with RCC. Differences in kidney cancer incidence, tumour biological behaviour, and response to treatment may exist by gender (male or female) and race (non-Hispanic white, non-Hispanic black, Asian, other). Marital status (married, unmarried) and income level (low-income, low-moderate-income, upper-moderate-income, and high-income) are thought to reflect the patient's social support status, which affects the treatment and postoperative recovery, due to the fact that higher-income patients are likely to have better healthcare resources and higher-quality care. Clinical and pathological characteristics of the tumours were also included in the analysis, mainly including tumour size, stage, and degree of differentiation. These covariates were included in the relevant model analyses to control for possible confounding bias and to adjust for their confounding effects on the assessment of survival outcomes. In particular, in Cox regression analyses, we performed multifactorial adjustments to determine the independent effect of type of surgery on patient survival. Also, these covariates were incorporated into machine learning models for feature selection and model training to help identify the factors that are most important for postoperative survival outcomes.

3.5. Statistical Analysis

First, the clinical characteristics of patients were analysed by descriptive statistics, with categorical variables expressed as frequencies and percentages, and continuous variables presented as medians and interquartile ranges. Differences between the two groups were compared by chi-square test or Fisher's exact test. To control for potential confounders, multiple-factor models including Cox proportional risk and logistic regression models were used in this study. In addition, Kaplan-Meier (KM) curves were used to plot the survival curves of patients under different surgical modalities and to test for differences in survival between groups by log-rank test (LRT). Analysis of OS using Cox proportional risk regression, and multiple logistic regression models were applied to further explore the ten-year survival of patients. Crude model was the base model (unadjusted), model 1 was further adjusted for age and gender, and model 2 incorporated potential confounders such as tumour size, histological type. All statistical analyses were performed using R software (version 4.3.2), and variables with p-values less than 0.05 were considered statistically significant.

4. Results

The effects of different surgical approaches (LTD, LTE, PN) on the survival prognosis of patients with stage T1a RCC were clarified by KM survival curve analysis (Figure 1). The results showed that the ten-year survival rate of patients in the PN group was significantly higher than that in the LTD and LTE groups ($p < 0.0001$). Survival probability gradually decreased over time in all three groups, but the slowest rate of decline was observed in the PN group. Of the 18,981 included RCC patients who underwent surgery, 3,933 (20.7%) were still alive after 10 years, and 79.3% (15,048) of patients survived less than 10 years after surgery. The majority of RCC patients who survived 10 years after undergoing surgery were married or partnered (69%), upper-moderate income level (55%), histologic type ccRCC (57%), and underwent PN surgery (86%), as well as being younger on average (59 vs. 62) and having smaller tumor size (24 vs. 25) compared to patients who did not survive to 10 years (Table 1).

The results of the Cox survival analysis showed that the crude model, without adjusting for any covariates, did not reveal any statistical differences (Table 2). However, after adjusting for age and gender, the results of model 1 indicated that the HR for RCC patients undergoing the LTE approach was 0.84 (95% CI: 0.80-0.94). Similarly, after further adjusting for all covariates, the HR for RCC patients undergoing LTE remained 0.84 (95% CI: 0.80-0.94). However, the results for the PN and LTD approaches did not show any statistical differences. When logistic regression modelling was applied, the likelihood of ten-year survival was significantly decreased in patients after LTD compared to PN (OR=0.83, 95%CI: 0.73-0.94) (Table 3). This is consistent with the trend of the KM survival curves, further validating that PN performed better in controlling the risk of patient death. In the initial screening, the AUC values of all 10 machine learning models were calculated to assess the predictive ability (Figure S1). The results showed that the AUC values of most models are close to 0.6, indicating the relatively average discriminative ability. The relative best among them was the NB model with an AUC value of 0.596. Combined with other evaluation metrics (Table S1), the NB algorithm was finally used to construct a survival prediction model for RCC patients. Then we assessed the importance of different features for model prediction by SHAP method (Figure 2A) and LIME method (Figure 2B). Both age and tumour size were shown to be the most important features, indicating a central role for survival prediction. In contrast, socioeconomic factors (e.g., income) and pathologic factors (e.g., grades, histologic type) were also important in the model. As shown in Figure S2, combined with the ALE analysis, the effect of patient age on survival probability showed a negative trend, while factors such as tumour size and postoperative chemotherapy exhibited complex nonlinear effects. The interaction results showed that the interaction between patient age and tumour size was the most significant, and the strength reached the highest value, reflecting the common trend of poorer prognosis for patients with older age and larger tumours (Figure S3).

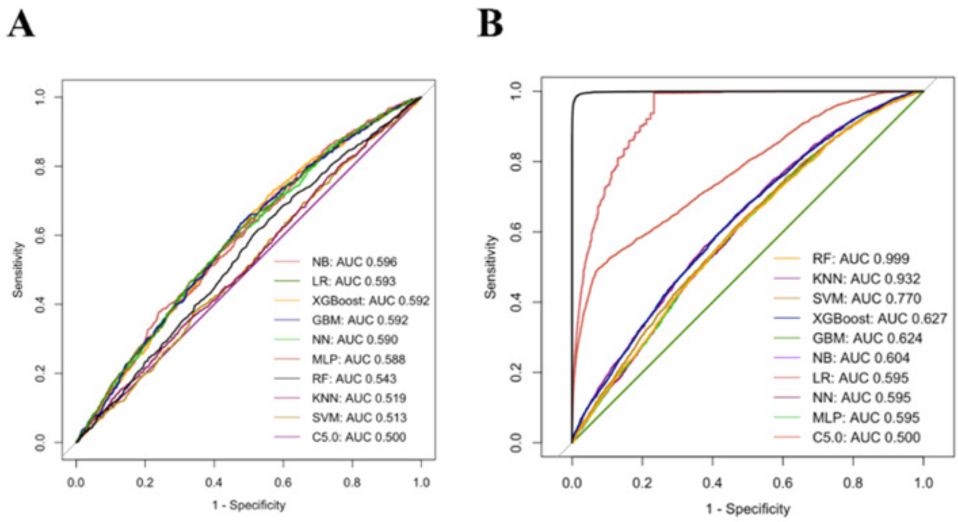

Figure S1: ROC curve of A) test set and B) train set.

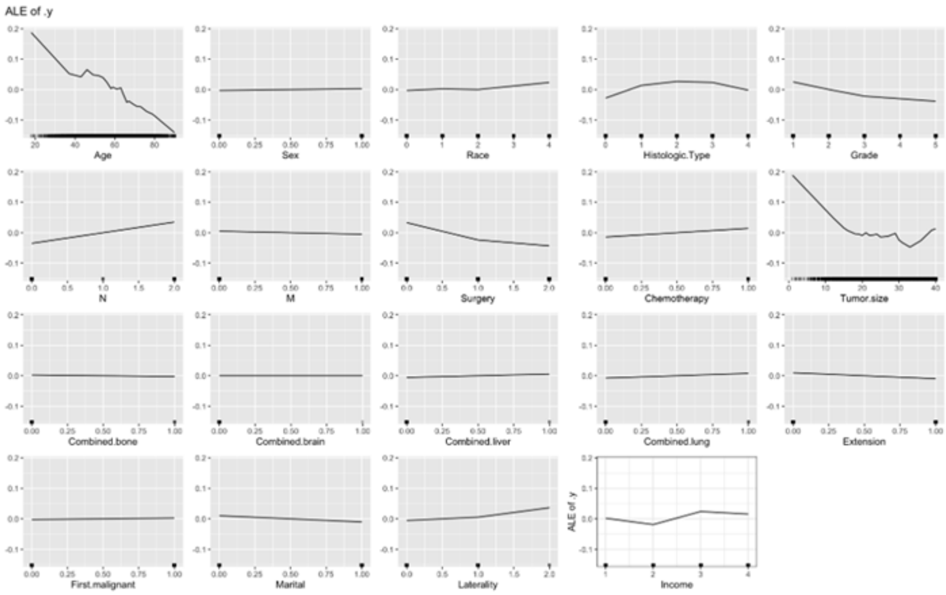

Figure S2: Accumulative local effects analysis of survival prognosis in T1a RCC patients after thermal ablation.

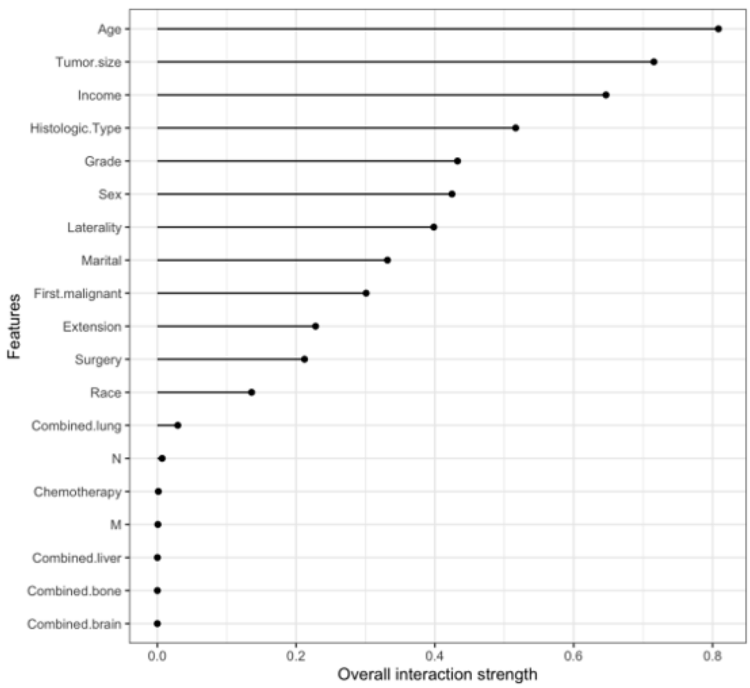

Figure S3: Interaction analysis of critical variables in T1a RCC patients.

Table S1: Predicting performance of ten machine learning models in test set.

	SVM	NN	MLP	GBM	LR	NB	XGB	C5.0	KNN	RF
Sensitivity	1.00 (1.00, 1.00)	1.00 (1.00, 1.00)	1.00 (1.00, 1.00)	1.00 (1.00, 1.00)	1.00 (1.00, 1.00)	1.00 (1.00, 1.00)	1.00 (1.00, 1.00)	1.00 (1.00, 1.00)	0.95 (0.94, 0.96)	0.99 (0.98, 0.99)
Specificity	0.00 (0.00, 0.00)	0.00 (0.00, 0.01)	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)	0.06 (0.05, 0.08)	0.02 (0.01, 0.03)
PPV	0.79 (0.78, 0.81)	0.79 (0.78, 0.81)	0.79 (0.78, 0.81)	0.79 (0.78, 0.81)	0.79 (0.78, 0.81)	0.79 (0.78, 0.81)	0.79 (0.78, 0.81)	0.79 (0.78, 0.81)	0.79 (0.78, 0.81)	0.79 (0.78, 0.81)
NPV	NaN (0.00, 1.00)	1.00 (0.29, 1.00)	NaN (0.00, 1.00)	NaN (0.00, 1.00)	NaN (0.00, 1.00)	NaN (0.00, 1.00)	NaN (0.00, 1.00)	NaN (0.00, 1.00)	0.25 (0.19, 0.31)	0.25 (0.14, 0.38)
LR+	1.00 (1.00, 1.00)	1.00 (1.00, 1.01)	1.00 (1.00, 1.00)	1.00 (1.00, 1.00)	1.00 (1.00, 1.00)	1.00 (1.00, 1.00)	1.00 (1.00, 1.00)	1.00 (1.00, 1.00)	1.01 (0.99, 1.03)	1.00 (0.99, 1.01)
LR-	NaN (NaN, NaN)	0.00 (0.00, NaN)	NaN (NaN, NaN)	NaN (NaN, NaN)	NaN (NaN, NaN)	NaN (NaN, NaN)	NaN (NaN, NaN)	NaN (NaN, NaN)	0.79 (0.59, 1.08)	0.80 (0.44, 1.46)
False T+ proportion for true D-	1.00 (1.00, 1.00)	1.00 (0.99, 1.00)	1.00 (1.00, 1.00)	1.00 (1.00, 1.00)	1.00 (1.00, 1.00)	1.00 (1.00, 1.00)	1.00 (1.00, 1.00)	1.00 (1.00, 1.00)	0.94 (0.92, 0.95)	0.98 (0.97, 0.99)
False T- proportion for true D+	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)	0.05 (0.04, 0.06)	0.01 (0.01, 0.02)
False T+ proportion for T+	0.21 (0.19, 0.22)	0.21 (0.19, 0.22)	0.21 (0.19, 0.22)	0.21 (0.19, 0.22)	0.21 (0.19, 0.22)	0.21 (0.19, 0.22)	0.21 (0.19, 0.22)	0.21 (0.19, 0.22)	0.21 (0.19, 0.22)	0.21 (0.19, 0.22)
False T- proportion for T-	NaN (0.00, 1.00)	0.00 (0.00, 0.71)	NaN (0.00, 1.00)	NaN (0.00, 1.00)	NaN (0.00, 1.00)	NaN (0.00, 1.00)	NaN (0.00, 1.00)	NaN (0.00, 1.00)	0.75 (0.69, 0.81)	0.75 (0.62, 0.86)
Correctly Classified Proportion	0.79 (0.78, 0.81)	0.79 (0.78, 0.81)	0.79 (0.78, 0.81)	0.79 (0.78, 0.81)	0.79 (0.78, 0.81)	0.79 (0.78, 0.81)	0.79 (0.78, 0.81)	0.79 (0.78, 0.81)	0.77 (0.75, 0.78)	0.79 (0.77, 0.80)

Abbreviations: SVM, supported vector machine; NN, neural network; MLP, Multi-Layer Perceptron; GBM, Gradient Boosting Machine; LR, Logistic Regression; NB, Naive Bayes; XGB, XGBoost; C5.0, C5.0 Decision Trees; KNN, k-nearest neighbor; RF, Random Forest; PPV, Positive predictive value; NPV, Negative predictive value; LR+, Positive likelihood ratio; LR-, Negative likelihood ratio.

Table 1: Baseline characteristics of patients with T1a renal cell carcinoma (RCC) undergoing three surgical proceduresa.

	Total n=18981	**Non-survival 10 years after surgery** n=15048	**Survival 10 years after surgery** n=3933	***p***
Age, y	61 (52, 69)	62 (52, 70)	59 (50, 66)	**< 0.001**
Survival duration, months	95 (77, 116)	87 (74, 102)	130 (125, 137)	**< 0.001**
Tumor size, mm	25 (19, 31)	25 (20, 31)	24 (18, 30)	**< 0.001**
Sex				0.499
Male	11693 (62)	9289 (62)	2404 (61)	
Female	7288 (38)	5759 (38)	1529 (39)	
Race				0.433
White	15554 (82)	12341 (82)	3213 (82)	
Black	2088 (11)	1656 (11)	432 (11)	
Asian or Pacific Islander	1054 (6)	817 (5)	237 (6)	
American Indian/Alaska Native	157 (1)	131 (1)	26 (1)	
Unknown	128 (1)	103 (1)	25 (1)	
Marital status				**< 0.001**
Unmarried or other	6370 (34)	5168 (34)	1202 (31)	

Married or living with a partner	12611 (66)	9880 (66)	2731 (69)	
Income level				**< 0.001**
Low	1488 (8)	1205 (8)	283 (7)	
Low-moderate	6097 (32)	5047 (34)	1050 (27)	
Upper-moderate	9374 (49)	7208 (48)	2166 (55)	
High	2022 (11)	1588 (11)	434 (11)	
Laterality (Tumor side)				0.489
Right	9829 (52)	7823 (52)	2006 (51)	
Left	9139 (48)	7214 (48)	1925 (49)	
Others	13 (0)	11 (0)	2 (0)	
Histologic type				**< 0.001**
ccRCC	11379 (60)	9125 (61)	2254 (57)	
pRCC	2990 (16)	2351 (16)	639 (16)	
chRCC	1072 (6)	813 (5)	259 (7)	
nosRCC	2851 (15)	2193 (15)	658 (17)	
others	689 (4)	566 (4)	123 (3)	
Grade				**< 0.001**
I	2750 (14)	2097 (14)	653 (17)	
II	9291 (49)	7309 (49)	1982 (50)	
III	2813 (15)	2259 (15)	554 (14)	
IV	154 (1)	131 (1)	23 (1)	
Unknown	3973 (21)	3252 (22)	721 (18)	
Surgery				**< 0.001**
LTD	2284 (12)	1927 (13)	357 (9)	
LTE	1042 (5)	837 (6)	205 (5)	
PN	15655 (82)	12284 (82)	3371 (86)	

Abbreviations: ccRCC, clear cell renal cell carcinoma; pRCC, papillary renal cell carcinoma; chRCC, chromophobe renal cell carcinoma; nosRCC, not otherwise specified renal cell carcinoma; LTD, local tumor destruction; LTE, local tumor excision; PN, partial nephrectomy. A Continuous Data are expressed as median and interquartile rage rates (IQR), and categorical data are expressed as numbers (%).

Table 2: Cox survival analysis of RCC patients with three surgical procedures**.**

Surgery	HR (95%CI)[a,b]		
	Crude Model[c]	Model 1	Model 2
PN	Ref	Ref	Ref
LTD	0.99(0.94,1.04)	0.99(0.94,1.05)	1.00(0.94, 1.06)
LTE	0.86(0.80,0.93)	**0.87(0.80,0.94)** **	**0.87(0.80, 0.94)** **

Abbreviations: LTD, local tumor destruction; LTE, local tumor excision; PN, partial nephrectomy.

[a]The effective value for the Cox survival analysis was hazard ratio (HR) value.

[b]Statistically significant data are bolded (*: p 0.05; **: p 0.01).

[c]Crude model was unadjusted for any parameters, and Model 1 with adjustment of age, sex, as well as in Model 2further adjustments were made for race, marital status, grade, tumor size, tumor side.

Table 3: Logistic regression analysis of stage T1a RCC patients with three surgical procedures.

Surgery	OR (95%CI)[a,b]		
	Crude Model[c]	Model 1	Model 2
PN	Ref	Ref	Ref
LTD	0.68(0.60,0.76)	0.79(0.70,0.89) **	0.83(0.73, 0.94) *
LTE	0.89(0.76,1.04)	1.04(0.88,1.22)	1.08(0.92, 1.27)

Abbreviations: LTD, local tumor destruction; LTE, local tumor excision; PN, partial nephrectomy.

[a]The effective value for the Logistic regression analysis of ten years survival after surgery of RCC patients was odds ratio (OR) value.

[b]Statistically significant data are bolded (*: p 0.05; **: p 0.01).

[c]Crude model was unadjusted for any parameters, and Model 1 with adjustment of age, sex, as well as in Model 2further adjustments were made for race, marital status, grade, tumor size, tumor side.

5. Discussion

KM survival curves and Cox regression analysis demonstrated that PN surgery significantly prolonged ten-year survival in patients with RCC compared with LTD and LTE surgery ($p < 0.0001$). In addition, logistic regression analysis further verified that the ten-year survival of patients with LTD surgery was significantly lower than that of the PN group (HR = 0.83, 95% CI: 0.73-0.94). Machine learning model evaluation showed that age and tumor size were the core factors for survival prediction, with ALE and interaction analyses collectively confirming the trend of poorer prognosis for patients who were older and had larger tumours. Our study provided a research basis for optimizing clinical surgical selection, and should prioritize the promotion of surgical approaches with significant survival improvement and enhance early intervention and personalized management of patients with advanced age and higher tumour burden. PN is considered by investigators to be the standard of care for the treatment of non-metastatic RCC, effectively balancing tumour control and renal function protection [13]. We similarly revealed the significant benefits of PN surgery in improving the ten-year survival of patients with RCC, which is consistent with the evidence of existing epidemiologic studies. The study by Motta et al. demonstrated that PN surgery was able to completely remove the tumour while preserving normal renal tissue, thereby reducing the recurrence and metastasis rates (17). In contrast, LTD and LTE, as minimally invasive treatments, may be inadequate for local control of poorly defined or larger tumours, despite their efficacy in small tumours (<3 cm). This is also reflected in the study of LTD surgery by Source et al, which found that in patients with larger stage T1a tumours, cancer-specific mortality after LTD treatment was significantly higher than that of PN surgery (5). This may explain the significant decrease in ten-year survival in the LTD group in the present study. The superiority of PN surgery in preserving renal units may be an important reason for its improved patient survival. Renal impairment leads to progression of chronic kidney disease, which increases the incidence of cardiovascular disease and overall mortality. In addition, a study by Abdelsalam et al. showed that PN surgery significantly reduced the incidence of postoperative chronic kidney disease, which is particularly important in older patients [9]. The survival advantage of the older patients in the PN group in the present study may be attributable in part to the long-term preservation of renal function. Tumour size and patient age were identified as the most important predictive features for survival, suggesting the crucial role for both in influencing surgical prognosis. It has been noted that older patients are more likely to have poor prognosis due to decreased immune function and increased comorbidities [18]. The larger the tumour size, the more aggressive and the greater the risk of metastasis, which in turn exacerbated disease progression (19). Moreover, the results of PDP and ALE were combined in this study to reveal the adverse effect of tumour size-age interaction on survival, which further supported that PN surgery improved the prognosis of high-risk patients through more complete tumour resection. Moreover, the effect of socioeconomic status (e.g., income) on patient survival was also validated in this study, suggesting that low-income patients may be at higher risk of death due to inadequate access to healthcare resources or delayed diagnosis and treatment [20]. Our study had several advantages. First, our study is the first to systematically investigate the impact of different surgical modalities (LTD, LTE, PN) on ten-year survival in patients with RCC using machine learning modelling. Second, we comprehensively analysed the impact of surgical modalities on patients' OS and ten-year survival by combining Cox regression and logistic regression models, which validated the important role of PN surgery in improving patients' long-term prognosis from a conventional statistical perspective. The potential benefits of PN surgery on patients' survival, despite its technical complexity, support the use of it as the preferred therapeutic option for patients with stage T1a RCC. This finding is an important reference for optimizing surgical strategies, reducing unnecessary indications for minimally invasive surgery, and improving patient survival. In addition, the application of machine learning models and the assessment of multidimensional feature significance (e.g., SHAP and LIME methods) revealed for the first time the central predictive role of factors such as tumour size and age, as well as the interactions between important features. Moreover, the study data were obtained from high-quality clinical databases with sufficient sample size to ensure the representativeness of the findings. However, this study also has some limitations. Firstly, due to the retrospective design of this study, there was some retrospective bias. Although we have adjusted for a variety of potential covariates, some factors that may affect patients' prognosis could not be taken into account due to limitations in data sources. For example, the quality of postoperative follow-up and the patient's lifestyle were not fully documented in the SEER database so that they could not be controlled for in the model. In addition, some potential confounders not captured by the SEER database, such as patients' socioeconomic status, mental health, and treatment details, may have affected the accuracy of the results. Second, the predictive performance of the machine learning model has not yet reached the desired level, and further optimization of the algorithm or introduction of more high-quality features are still needed to improve the discriminative ability of the model. Besides, the study data were mainly derived from a single database, which may limit the applicability to patients from different regions or ethnicities. Nevertheless, results provided an important basis for the selection of surgical methods and the development of individualized intervention strategies for patients with RCC, as well as methodological reference for long-term prognostic studies.

6. Conclusion

We evaluated the impact of different surgical approaches (PN, LTE, LTD) on the survival prognosis of T1a RCC patients based on the SEER database system, and explored the predictive value of key features through machine learning. The results showed that PN surgery significantly improved patients' survival prognosis and ten-year survival rate, demonstrating a significant advantage in reducing the risk of death compared to LTD and LTE surgeries. Additionally, multiple machine learning models and interpretable machine learning techniques further revealed the importance of patient characteristics, such as age and tumour size, in surgical prognosis. Our study not only provides an evidence-based basis for the selection of surgical options for T1a RCC patients but also emphasizes the importance of precision medicine in optimizing treatment strategies.

7. Funding: This study was supported by the Anhui Institute of Translational Medicine (2021zhyx-C43).

References

1. Hage Chehade C, Agarwal N. Molecular subtypes as potential biomarkers in renal cell carcinoma. Cancer Cell. 2024; 42(5): 736-8.
2. Dudani S, de Velasco G, Wells JC, Gan CL, Donskov F, Porta C. Evaluation of Clear Cell, Papillary, and Chromophobe Renal Cell Carcinoma Metastasis Sites and Association with Survival. JAMA Netw Open. 2021; 4(1): e2021869.
3. Li P, Huo D, Li D, Si M, Xu R, Ma X. Impact of Treatment Strategies on Survival and Within Multivariate Predictive Model for Renal Cell Carcinoma Based on the SEER Database: A Retrospective Cohort Study. J Invest Surg. 2024; 37(1): 2435045.
4. Nicolazzini M, Palumbo C, Porte F, Bondonno G, De Angelis P. Preoperative proteinuria correlates with renal function after partial nephrectomy for renal cell carcinoma. World J Urol. 2024; 42(1): 381.
5. Sorce G, Hoeh B, Hohenhorst L, Panunzio A, Tappero S, Tian Z. Cancer-specific Mortality in T1a Renal Cell Carcinoma Treated with Local Tumour Destruction Versus Partial Nephrectomy. Eur Urol Focus. 2023; 9(1): 125-32.
6. Wu M, Liao C, Zhao Z, Zhou Z, Liu Y, Wang X. Local narrow margin excision sequential with modified ALA-PDT for successful treatment of an 86-year-old patient with malignant proliferating trichilemmal tumour. Photodiagnosis Photodyn Ther. 2023; 42: 103524.
7. Kim SH, Park B, Hwang EC, Hong SH, Jeong CW, Kwak C. Retrospective Multicenter Long-Term Follow-up Analysis of Prognostic Risk Factors for Recurrence-Free, Metastasis-Free, Cancer-Specific, and Overall Survival After Curative Nephrectomy in Non-metastatic Renal Cell Carcinoma. Front Oncol. 2019; 9: 859.
8. Chan VW, Abul A, Osman FH, Ng HH, Wang K, Yuan Y. Ablative therapies versus partial nephrectomy for small renal masses - A systematic review and meta-analysis. Int J Surg. 2022; 97: 106194.
9. Abdelsalam ME, Sabir SH, Ba SBK, Karam JA, Matin SF, Wood CG. Outcomes of Percutaneous Thermal Ablation for Biopsy-Proven T1a Renal Cell Carcinoma in Patients with Other Primary Malignancies. AJR Am J Roentgenol. 2021; 217(1): 157-63.
10. Liu Q, Chen M, Wu J, Mao W. Comparing the oncologic outcomes of local tumour destruction vs. local tumour excision vs. partial nephrectomy in T1a solid renal masses: a population-based cohort study from the SEER database - correspondence. Int J Surg. 2024; 110(10): 6833-5.
11. Xing M, Kokabi N, Zhang D, Ludwig JM, Kim HS. Comparative Effectiveness of Thermal Ablation, Surgical Resection, and Active Surveillance for T1a Renal Cell Carcinoma: A Surveillance, Epidemiology, and End Results (SEER)-Medicare-linked Population Study. Radiology. 2018; 288(1): 81-90.
12. Prelaj A, Miskovic V, Zanitti M, Trovo F, Genova C, Viscardi G. Artificial intelligence for predictive biomarker discovery in immuno-oncology: a systematic review. Ann Oncol. 2024; 35(1): 29-65.
13. Saliby RM, Labaki C, Jammihal TR, Xie W, Sun M, Shah V. Impact of renal cell carcinoma molecular subtypes on immunotherapy and targeted therapy outcomes. Cancer Cell. 2024; 42(5): 732-5.
14. Chen S, Gao F, Guo T, Jiang L, Zhang N, Wang XDeep learning-based multi-model prediction for disease-free survival status of patients with clear cell renal cell carcinoma after surgery: a multicentre cohort study. Int J Surg. 2024; 110(5): 2970-7.
15. Nusinovici S, Rim TH, Li H, Yu M, Deshmukh M. Application of a deep-learning marker for morbidity and mortality prediction derived from retinal photographs: a cohort development and validation study. Lancet Healthy Longev. 2024; 5(10): 100593.
16. Shakhssalim N, Talebi A, Pahlevan-Fallahy MT, Sotoodeh K, Alavimajd H. Lifestyle and occupational risks assessment of bladder cancer using machine learning-based prediction models. Cancer Rep (Hoboken). 2023; 6(9): e1860.
17. Motta G, Ferraresso M, Lamperti L, Di Paolo D, Raison N. Treatment options for localised renal cell carcinoma of the transplanted kidney. World J Transplant. 2020; 10(6): 147-61.

18. Marchioni M, Preisser F, Bandini M, Nazzani S, Tian Z. Comparison of Partial Versus Radical Nephrectomy Effect on Other-cause Mortality, Cancer-specific Mortality, and 30-day Mortality in Patients Older Than 75 Years. Eur Urol Focus. 2019; 5(3): 467-73.

19. Song Z, Xing J, Sun Z, Kang X, Li H. Time trends in surgical provision and cancer-specific outcomes in patients with stage T2-3 kidney cancer: a SEER-based study. Front Surg. 2024; 11: 1370702.

20. Blake KD, Moss JL, Gaysynsky A, Srinivasan S, Croyle RT. Making the Case for Investment in Rural Cancer Control: An Analysis of Rural Cancer Incidence, Mortality, and Funding Trends. Cancer Epidemiol Biomarkers Prev. 2017; 26(7): 992-7.