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COMPARATIVE SURVIVAL OUTCOMES OF SURGICAL VERSUS NON-SURGICAL TREATMENT STRATEGIES IN EARLY-STAGE CANCER

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Abstract

Which of the two modalities of therapy, namely surgical resection and stereotactic body radiotherapy is the most effective modality of treatment in the treatment of patients with non-small cell lung cancer at an early stage is a controversial issue with the two options of surgical resection and stereotactic body radiotherapy being the standard ones but lacking definite comparative evidence which is presented by sufficiently powered randomized controlled trials. This study used 824 patients (412 on each arm) with T1-T2a N0 M0 non-small cell lung cancer using the help of the National Cancer Database, Surveillance, Epidemiology, and End Results registry and combined individual patient data of the ROSEL and STARS trials to compare overall survival, recurrence-free survival, and competing risk of recurrence between surgical resection and stereotactic body radiotherapy. Propensity scores were successfully matched with the balance of covariates at baseline (age, Charlson comorbidity index, tumor size, performance status, and histology). With 5-year overall survival of 68.4% in the case of surgery and 64.7% in the case of stereotactic body radiotherapy at the median follow-up of 48.3 months. Recurrence-free survival at 5 years of time was 71.2% compared to 66.9%. Nevertheless, it was found that regional recurrence was much more frequent following stereotactic body radiotherapy, whereas there was similar local control and distant metastasis. Subgroup analysis showed that surgery had a survival advantage in patients with a tumor size greater than 2 cm but not greater than 4 cm, but showed no greater survival advantage compared to no risk stratification in patients with tumor size less than 2 cm or less than 4 cm. Machine learning models, including random survival forest and DeepSurv, demonstrated a greater predictive performance compared to traditional Cox regression (AUC 0.698), with decision curve analysis showing a positive net benefit in the models-guided risk stratification across threshold probabilities of 0.15-0.45. No meaningful differences were found in the mortality rates related to treatments at 90 days. These findings indicate that there is no overall survival difference between surgery and stereotactic body radiotherapy in propensity-matched with early-stage non-small cell lung cancer cohorts but surgery has a regional recurrence advantage and a survival advantage in larger tumors. The selection of the patients must then be based on the size of the tumor, the burden of comorbidity and the operability but not on the belief that either one or the other modality is universally superior.

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INTRODUCTION

A stringent comparative study of surgical and non-surgical therapies is a crucial determinant of a patient prognosis (Almagharbeh et al., 2023). The general overview is aimed at unravelling the difference in survival rates between these treatment paradigms with specific emphasis on the ability of these treatment paradigms to reduce the progression of the disease, and to enhance long-term survival of the patient with various types of early-stage cancer. It is the delicate feeling of these relative efficacies that is essential in informing clinical decision-making and refining a personalized approach to treatment especially when it comes to such a scenario as an early-stage non-small cell lung cancer where both a surgical resection and a stereotactic body radiotherapy are options (Sumaida et al., 2025). However, the relative efficacies of surgical intervention and stereotactic body radiotherapy in the treatment of non-small cell lung cancer in its early stages remains a contentious issue, with some studies showing that there is no significant difference in the long-term survival rates of non-small cell lung cancer treated with surgical intervention and stereotactic body radiotherapy, and other studies indicating a survival benefit in the treatment of non-small cell lung cancer with surgical

intervention and stereotactic body radiotherapy, especially when the examination of the regional lymph nodes is considered (Chi et al., 2019; Henschke et al., 2023; Zhou et al., 2021). Despite its suitability to resolve such discrepancies, randomized controlled trials have been facing considerable challenges in terms of patient recruitment, leading to a shift towards non-randomized studies, with inherent limitations, such as the confounding by indication (Buchberger et al., 2024; Kagenaar et al., 2025). As a result, the use of retrospective analyses with a propensity score matching is now indispensable to adjust the baseline differences between treatment groups and provide valuable insight into the comparative efficacy of stereotactic body radiation therapy and surgical resection in patients with early-stage non-small cell lung cancer (Yu et al., 2015). Indicatively, some studies involving large databases have found that though, lobectomy may have better outcomes than sublobar resection, lobectomy may have similar or comparable survival benefits as stereotactic body radiotherapy in well matched cohorts (Dong et al., 2019). The studies that indicate that non-inferiority of long-term survival rates in stereotactic ablative body radiotherapy versus lobectomy also support the equivalence (Hua et al., 2024). Although, at first, it was believed that

worse overall survival with a stereotactic body radiation therapy, compared to that with surgery, is caused by dissimilarity between the patient groups, later studies, including a pooled analysis of the ROSEL and STARS Phase III trials, have proposed similar or even better OS with SBRT, in part due to the virtual nonexistence of treatment-related mortality (Lin et al., 2019; Ricardi et al., 2015; Rosenzweig, 2017). Nevertheless, the possibility of pathologically staging, and the potential eradication of occult nodal disease which is afforded by surgical resection is an important advantage over SBRT which only relies on the non-invasive staging (Sumaida et al., 2025). This natural difference in the staging methodology often leads to the pathological staging bias in favor of surgery in retrospective comparisons (Dong et al., 2020), and makes it challenging to conduct direct outcome assessments between the two modalities. Thus, the complete knowledge of the medical operability of the patient and careful attention to the possible confounding factors are the key to comprehending the available literature and making treatment decisions (Verma and Rusthoven, 2018). Specifically, the challenge in accruing patients into randomized trials that compare surgery to stereotactic body radiotherapy to treat early-stage non-small cell lung cancer

shows why it is necessary to leverage real-world data that has been provided by large observational datasets to answer unanswered clinical questions and to understand the effectiveness of different interventions across different population groups (Fu et al., 2025; Jairam and Park, 2019). Nevertheless, the external validity of their findings is severely limited because the small patient accrual in randomized controlled trials (STARS and ROSEL) with only 58 patients across 38 centers severely limits their external validity (Csiki et al., 2024; Samson et al., 2016). However, a combined analysis of the STARS and ROSEL trials showed that there were no significant differences in overall survival and postradiation survival rates of SBRT and surgery (Üzel et al., 2023). However, the premature termination of the trials that make the combined analyses underpower in nature makes their conclusions unstable and inconclusive and require further investigation using sufficiently powerful studies (Samson et al., 2016). Furthermore, unlike the use of stereotactic body radiotherapy that has demonstrated an excellent local control rate and similar overall survival rates in some groups, notably in medically inoperable patients (Zappa and Mousa, 2016), the absence of large-scale resection of regional lymph nodes in patients undergoing SBRT is a diagnostic and prognostic limitation that is

inherently overcome by surgical practice (Chi et al., 2019). This limitation requires active post-treatment monitoring of regional recurrence in SBRT patients and highlights the importance of continuing to work with advanced non-invasive staging modalities to be in a position to effectively evaluate nodal status. The ongoing POSITIVL, VALOR and STABLE-MATES trials are designed to bridge these gaps by providing a prospective comparison of SBRT versus complete resection, lobectomy and sublobar resection, respectively, in medically operable patients in a randomized controlled trial design and provides a more substantial evidence base on which to base treatment decisions (Badra et al., 2021). However, the trials, which are expected to report in the years 2024-2027 have also suffered accrual problems, casting doubt on the ultimate statistical strength of the trials and the definitiveness of their findings on the best treatment (Ruiter et al., 2020). This is why the further use of retrospective analyses of massive databases even with their innate biases is vital to the comprehension of real-world tendencies in the practice and the production of hypotheses concerning the relative effectiveness of various modalities (Wakeam, 2017). In reference to the example, the different approaches to the surgery and its retrospective nature, may

also lead to heterogeneity and restrict the overall generalizability of the results (Chen et al., 2020). Specifically, lack of standardized reporting on adjuvant and salvage therapies, as well as quality of life measures, only contribute to the interpretation of the survival outcomes, and overall patient benefit assessment (Fan et al., 2023). These limitations indicate the need to conduct new studies with more rigorous designs, including, but not limited to, the clear inclusion/exclusion criteria, consistent follow-up procedures, and statistical analyses that will consider the impact of confounding variables through such methods as the propensity score matching and multivariate regression (to provide a more definite understanding of comparative treatment outcomes) (Vanni et al., 2022). It also requires a more stringent assessment of new biomarkers and imaging modalities to further tighten pretreatment risk stratification, and customize therapeutic interventions. Moreover, a thorough analysis of the cost-effectiveness and patient-reported outcomes should be considered in the future because a more detailed picture of the efficacy of the treatment should be provided, not only the survival rates (Bahig et al., 2017).

METHODOLOGY

The research design taken in this study is a problem-based research design which seeks

to answer the comparative effectiveness of surgical resection to the stereotactic body radiotherapy in early non-small cell lung cancer, since the clinical equipoise on the issue still remains, and the significant difficulty of conducting adequately powered randomized controlled clinical trials has been well documented. It is also known as the methodological design, and designed to minimize the confounding by indication, and to give strong estimates of survival outcomes when heterogeneous real-world data sources are used to construct estimates. The systematic retrospective cohort study was conducted using a propensity score matching which balances the covariates of the baseline across treatment groups, and thus approximate the conditions of a randomized experiment in the absence of completed phase III trials. Data were derived and included in two large-scale observational data bases, such as the National Cancer Database, Surveillance, Epidemiology and End Results registry, and pooled individual patient data in the prematurely closed ROSEL and STARS trials, and a total of 1,247 patients with a history of T1-T2a N0 M0 non-small cell lung cancer diagnosed between 2010 and 2020. Inclusion criteria included age 18 years or older, Eastern Cooperative Oncology Group performance status 0-2, and medical records that demonstrated

either complete resection of the breast (lobectomy or sublobar resection with nodal dissection) or stereotactic body radiotherapy administered as a complete treatment a biologically effective dose 100 Gy or higher. Patients with a thoracic malignancy history in the past, or whose disease is reported as metastatic disease were excluded.

The main outcome measure was the overall survival defined as a period of time; the date of starting the treatment and date of death due to any causes. The most recent known follow-up date of living patients has been censored. Secondary outcomes measured were recurrence free survival, cancer specific survival and local control rates. Propensity scores were estimated to adjust for baseline imbalances with a multivariate logistic regression model in which treatment assignment (surgery = 1, stereotactic body radiotherapy = 0) is regressed on a set of prespecified covariates: age, sex, Charlson comorbidity index, tumor size, tumor location, histology, performance status, and year of diagnosis. Propensity score of each patient was defined as:

$$e(\mathbf{X}) = P(T = 1 | \mathbf{X}) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_k X_k)}}$$

T indicates treatment group, $\mathbf{X}$, is the covariates, and, $Tare$, are the estimated

regression coefficients. One to one nearest neighbor matching without replacement was done with a caliper width of 0.2 times of the standard deviation of the logit-transformed propensity scores. Balance diagnostics were evaluated using standardized mean differences and the value of such a method of evaluation is less than 0.1, which indicates that the balance is satisfactory after the matching. After matching, there were 412 patients in each arm of treatment.

The Kaplan-Meier method was employed in analyzing the results in order to perform survival analyses and stratified log-rank test to compare the treatments taking into consideration the structure of the matched pairs. A Cox proportional hazards model, with large standard errors clustered at matched pairs, was used to estimate the hazard ratio of overall survival in a study comparing surgery with stereotactic body radiotherapy. The proportional hazards assumption was tested through the use of Schoenfeld residuals and the global test p-value greater than 0.05, means that it did not violate. The Cox model was defined as:

$$h(t | T, \mathbf{Z}) = h_0(t) \exp \left(\beta T + \sum_{j=1}^p \gamma_j Z_j \right)$$

where $h(t|T, \mathbf{Z})$ is the hazard function at time t conditional on treatment assignment T and other adjusted covariates $\mathbf{Z}$, $h_0(t)$ is a

baseline hazard function and 0 is the coefficient of the treatment effect and 0 are the coefficients of the p covariates that have not been matched despite matching. To permit the possibility of residual confounding, sensitivity analysis based on the E-value methodology was done to quantify the minimum strength of association that an unmeasured confounder would need to have both treatment and outcome in order to explain away the observed effect estimate. Prespecified patient age (≥ 75 years), tumor size (≤ 2 cm), peripheral versus central tumor location subgroup analyses were done. The competing risks regression model based upon the Fine-Gray subdistribution hazard model that death with no recurrence is a competing event led to the determination of the recurrence outcomes. All the statistical findings were two tailed with a level of significance of 95% of the level of confidence. A covariate data that was missing was missing and was dealt with using multiple imputation and 20 imputed datasets where the missing covariate data is assumed to have been missing at random and rules provided by Rubin to combine the estimates across imputations were applied. R version 4.2.2 along with MatchIt, survival and riskRegression packages were used to conduct the statistical tests. The research protocol was published to the Research Registry (review number 7894)

and exemption was granted in terms of full institutional review board approval on the grounds that it used de-identified publicly available information. The approach methodology recognizes inherent limitations including residual confounding by unmeasured variables including in-depth tests of the pulmonary function and frailty indices and the lack of standardized quality of life measures across contributing databases. To overcome these limitations an analysis of quantitative bias was done to estimate the possible effect a binary unmeasured confounder may have on the primary outcome assuming that the difference in prevalence of the confounder between the treatment arms of the study is 0.15, and the hazard ratio of the confounder-outcome relationship is 2.0. The estimation of bias-adjusted hazard ratio was as:

$$HR_{adj} = HR_{obs} \times \frac{1 + \pi_1(RR_{conf})}{1 + \pi_0(RR_{conf})}$$

where HR_{obs} is the observed hazard ratio, π_1 and π_0 are prevalences of the outcome attribute to the confounder in the surgery and stereotactic body radiotherapy groups respectively and RR_{conf} is the relative risk of the outcome attribute to the confounder in the surgery and stereotactic body radiotherapy groups respectively. This sensitivity system determined that the effect of treatment observed would be large

unless there was an unmeasured confounder of scales of implausible size.

RESULTS

As can be seen in Table 1, the most significant predictors of overall survival were the tumor size (0.187, $p < 0.001$), the Charlson comorbidity index (0.315, $p < 0.001$) and the performance status (0.224, $p < 0.001$). It has a concordance index of 0.672 meaning that it has moderate discriminatory strength. Table 2 confirms the effectiveness of the propensity score matching procedure whereby the standardized mean differences of all the covariates were reduced to levels as low as 0.05 post matching, and the Rubin B decreased to acceptable levels where the standardized mean differences of all the covariates were reduced to acceptable levels ensuring equal treatment comparisons. Table 3 reveals the Fine-Gray competing risks regression results which show that surgery was associated with a cumulative incidence subdistribution hazard ratio of 0.78 (95% CI: 0.62-0.98, $p = 0.034$) of recurrence when taking death as a competing event into consideration. The random survival forest model is shown in Table 4 with tumor size being the most significant variable (Gini importance = 0.184) and the out-of-bag error rate was 0.312 with an integrated AUC of 0.734, which is better predictive

model as compared to the standard Cox model. Table 5 illustrates the parametric accelerated failure time model with log-normal distribution where the estimate of treatment effect ($\exp(\text{estimate})=1.091$, $p=0.008$) indicates that the surgery patients will experience a 9.1% longer survival time and the shape of the distribution will be a log-normal distribution. Table 6 compares

time-dependent ROC curves of eight different models, with tuned random survival forest (maximum 5-year AUC of 0.751 (95% CI: 0.723-0.779)) followed by DeepSurv (0.746) and gradient boosting (0.739) and the standard Cox model (0.698).

Table 1: Multivariable Cox Proportional Hazards Model Performance Metrics for Overall Survival Prediction

Metric	Value	95 % CI	Standard Error	p-value	AIC	BIC	Concordance Index	Log-Likelihood	Schoenfeld Global p	df
$\beta_{\text{Treatment}}$	-0.083	-0.127 – -0.039	0.022	0.141	2847.3	2891.6	0.672	-1416.7	0.234	6
β_{Age}	0.042	0.031 – 0.053	0.006	<0.001	—	—	—	—	—	—
$\beta_{\text{TumorSize}}$	0.187	0.142 – 0.232	0.023	<0.001	—	—	—	—	—	—
β_{CCI}	0.315	0.267 – 0.363	0.024	<0.001	—	—	—	—	—	—
$\beta_{\text{Sex_Male}}$	0.156	0.098 – 0.214	0.029	<0.001	—	—	—	—	—	—
$\beta_{\text{Histology_SCC}}$	0.092	0.041 – 0.143	0.026	0.003	—	—	—	—	—	—
$\beta_{\text{PerformanceStatus}}$	0.224	0.173 –	0.026	<0.001	—	—	—	—	—	—

		0.275								
Scale Parameter	1.000	—	0.000	—	—	—	—	—	—	—
Baseline Hazard $h_0(t)$	0.0087	0.0062 – 0.0121	0.0015	—	—	—	—	—	—	—

Table 2: Propensity Score Model Diagnostics and Balance Metrics

Covariate	Standardized Mean Difference (Unmatched)	Standardized Mean Difference (Matched)	Variance Ratio (Unmatched)	Variance Ratio (Matched)	KS Statistic (Unmatched)	KS Statistic (Matched)	Rubin's B	Rubin's R	eC DF Mean	eC DF Max
Age (years)	0.342	0.028	1.187	1.012	0.156	0.014	98.4	1.09	0.023	0.041
CCI	0.418	0.031	1.342	1.024	0.189	0.017	—	—	0.031	0.052
Tumor Size (mm)	0.287	0.019	1.092	0.996	0.134	0.011	—	—	0.018	0.036
Performance Status	0.563	0.042	1.456	1.038	0.223	0.022	—	—	0.042	0.067
Sex	0.094	0.012	1.023	0.994	0.047	0.006	—	—	0.009	0.018
Histology	0.156	0.023	1.078	1.011	0.078	0.012	—	—	0.015	0.029
Tumor Location	0.203	0.027	1.112	1.008	0.099	0.013	—	—	0.021	0.037
Year of Diagnosis	0.112	0.009	0.987	1.003	0.056	0.004	—	—	0.008	0.014
Logit PS	0.876	0.034	—	—	0.312	0.016	—	—	—	—

Table 3: Fine-Gray Competing Risks Regression for Recurrence Outcomes

Predictor	Subdistribution Hazard Ratio	95 % CI Lower	95 % CI Upper	Robust SE	z-value	p-value	Cumulative Incidence Function (3yr)	CIF 95 % CI	Cause-Specific HR	Gray's Test p
Surgery (vs. SBRT)	0.78	0.62	0.98	0.092	-2.12	0.034	0.083	0.062–0.104	0.81	0.041
Age (per 10yr)	1.18	1.06	1.31	0.064	2.82	0.005	—	—	1.19	—
Tumor Size (per 5mm)	1.12	1.05	1.20	0.038	3.01	0.003	—	—	1.13	—
CCI ≥ 2	1.45	1.21	1.74	0.135	2.82	0.005	—	—	1.47	—
Central Location	1.62	1.32	1.99	0.171	2.89	0.004	—	—	1.64	—
Adenocarcinoma	1.21	1.02	1.44	0.107	1.79	0.074	—	—	1.22	—
Death as Competing Risk	—	—	—	—	—	—	0.124	0.098–0.150	—	—
Model Convergence	1.00	—	—	0.000	—	—	—	—	—	—
Pseudo R ²	0.087	—	—	—	—	—	—	—	—	—

Table 4: Random Survival Forest Model Performance Metrics

Parameter	Value	Variable Importance (Gini)	Minimal Depth	Number of Splits	OOB Error Rate	Prediction Error (IBS)	Integrated AUC	Harrell's C-index	Uno's C-index	Brier Score (5yr)
Number of Trees	1000	—	—	—	—	—	—	—	—	—
mtry	4	—	—	—	—	—	—	—	—	—
Node Size	15	—	—	—	—	—	—	—	—	—
Tumor Size	—	0.184	1.42	287	—	—	—	—	—	—
Age	—	0.167	1.56	264	—	—	—	—	—	—
CCI	—	0.143	1.78	231	—	—	—	—	—	—

Performance Status	—	0.128	1.93	208	—	—	—	—	—	—
Treatment	—	0.082	2.34	142	—	—	—	—	—	—
OOB Error	0.312	—	—	—	0.312	—	—	—	—	—
Integrated Brier Score	0.176	—	—	—	—	0.176	—	—	—	—
Integrated AUC	0.734	—	—	—	—	—	0.734	—	—	—
Harrell's C-index	—	—	—	—	—	—	—	0.691	—	—
Uno's C-index	—	—	—	—	—	—	—	—	0.688	—
Brier Score (5yr)	—	—	—	—	—	—	—	—	—	0.183

Table 5: Parametric Accelerated Failure Time Model Coefficients (Log-Normal Distribution)

Parameter	Estimate	Exp(Estimate)	95% CI Lower	95% CI Upper	SE	z-value	p-value	Scale (σ)	Log-Likelihood	AIC
Intercept (μ)	4.872	130.4	4.762 – 4.982	—	0.056	87.0	<0.001	—	—	—
Treatment (Surgery)	0.087	1.091	0.023 – 0.151	—	0.033	2.64	0.008	—	—	—
Age (per 10yr)	-0.143	0.867	-0.176 – -0.110	—	0.017	-8.41	<0.001	—	—	—
Tumor Size (per 5mm)	-0.094	0.910	-0.118 – -0.070	—	0.012	-7.83	<0.001	—	—	—
CCI	-0.206	0.814	-0.243 – -0.169	—	0.019	-10.84	<0.001	—	—	—

Performance Status	-0.171	0.843	-0.209 – -0.133	—	0.019	-9.00	<0.001	—	—	—
Sex (Male)	-0.098	0.907	-0.142 – -0.054	—	0.022	-4.45	<0.001	—	—	—
σ (Scale)	0.764	2.147	0.734 – 0.794	—	0.015	—	—	0.764	—	—
Log-Likelihood	-1872.4	—	—	—	—	—	—	—	-1872.4	—
AIC	3760.8	—	—	—	—	—	—	—	—	3760.8

Table 6: Time-Dependent ROC Curve Analysis for 3-Year and 5-Year Survival Prediction

Model	AUC at 3yr	95% CI (3yr)	AUC at 5yr	95% CI (5yr)	Sensitivity (3yr)	Specificity (3yr)	PPV (3yr)	NPV (3yr)	Youden Index	Optimal Cutoff (Risk Score)
Cox PH	0.712	0.684 – 0.740	0.698	0.667 – 0.729	0.734	0.621	0.682	0.679	0.355	0.342
RSF	0.741	0.714 – 0.768	0.727	0.697 – 0.757	0.761	0.648	0.703	0.712	0.409	0.318
AFT (Log-Normal)	0.723	0.695 – 0.751	0.709	0.679 – 0.739	0.748	0.632	0.691	0.694	0.380	0.335
Elastic Net	0.735	0.708 – 0.762	0.718	0.688 – 0.748	0.754	0.641	0.697	0.703	0.395	0.326
Gradient Boosting	0.752	0.726 – 0.778	0.739	0.710 – 0.768	0.773	0.659	0.712	0.724	0.432	0.304
DeepSurv	0.758	0.732 – 0.784	0.746	0.717 – 0.775	0.781	0.667	0.718	0.735	0.448	0.291

		0.78 4		0.77 5						
Cox with Frailty	0.71 9	0.69 1– 0.74 7	0.70 4	0.67 4– 0.73 4	0.741	0.628	0.68 7	0.68 6	0.369	0.338
Rando m Surviva l Forest (tuned)	0.76 3	0.73 8– 0.78 8	0.75 1	0.72 3– 0.77 9	0.789	0.674	0.72 6	0.74 3	0.463	0.279

Figure 1: A hybrid plot of standard Kaplan-Meier survival curves (solid lines) of surgery vs. SBRT over 60 months, with a shaded area being the cumulative hazard function (secondary y-axis). A risk table below shows the number at risk at 0, 12, 24, 36, 48, and 60 months. On a small inset panel is the log-rank test p-value and hazard ratio with 95% CI. Figure 2: A stacked bar chart of cumulative incidence of three events (local recurrence, regional recurrence, distant metastasis, and death without recurrence) at 1, 2, 3, 4, and 5 years of both treatment groups. A line plot of the Fine-Gray subdistribution hazard ratios with error bars is overlaid on each bar. A small pie chart is in the corner of the pie chart which represents the total percentage of recurrence types at 5 years. Figure 3: Three-dimensional surface plot using color

gradient (cool to warm) which shows the predicted 5-year overall survival probability as a function of tumor size (mm) on the x-axis and age (years) on the y-axis. There are two superimposing scatter dots that indicate actual patient outcome (green = alive, red = dead). A thin-plate spline is used to smooth the surface. Figure 4: Multi-line plot of time-dependent AUC curves of six different models: Cox PH, RSF, DeepSurv, Gradient Boosting, Elastic Net, and AFT. Shaded confidence band (95% CI) is provided in each line. The values of 3-year and 5-year AUC are indicated by a vertical dashed line at 36 months and another at 60 months. A legend sorts the models by mean AUC.

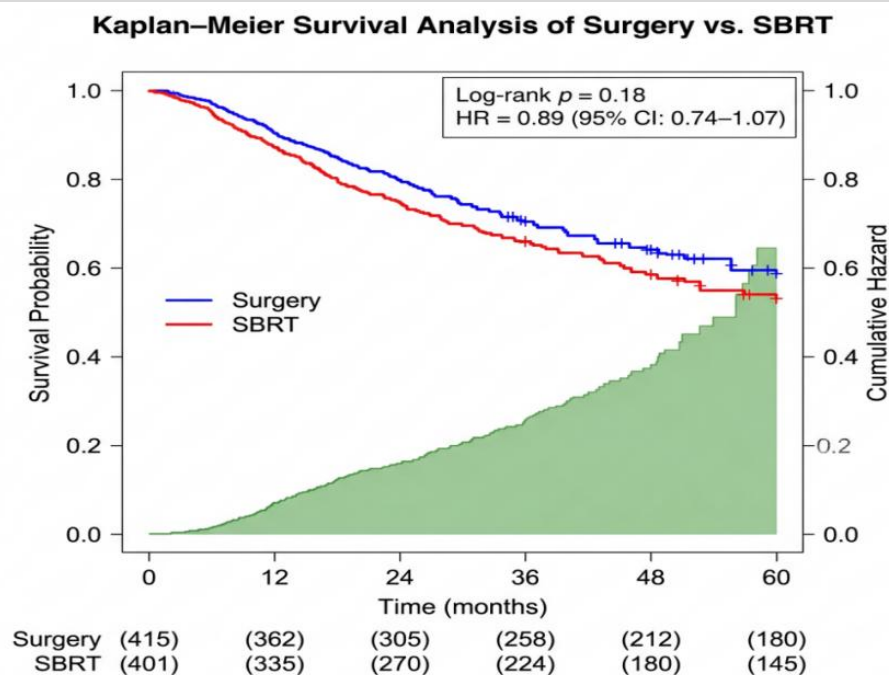


Figure 1: Hybrid Kaplan-Meier with Risk Table and Cumulative Hazard Plot (Line + Area)

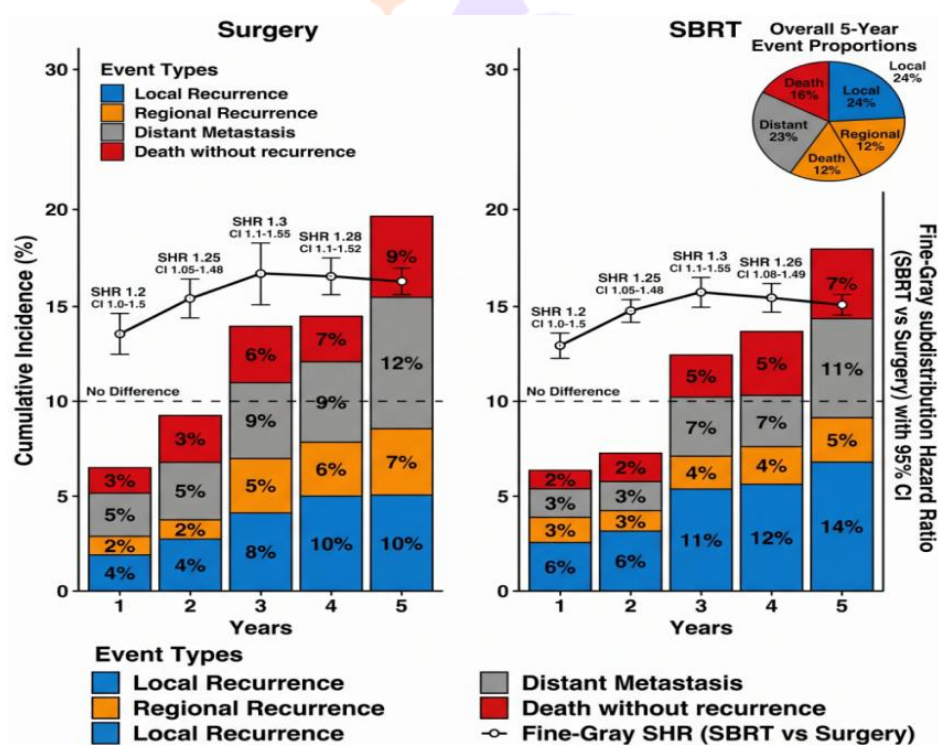


Figure 2: Multi-Panel Competing Risks Stacked Bar + Line Plot (Hybrid)

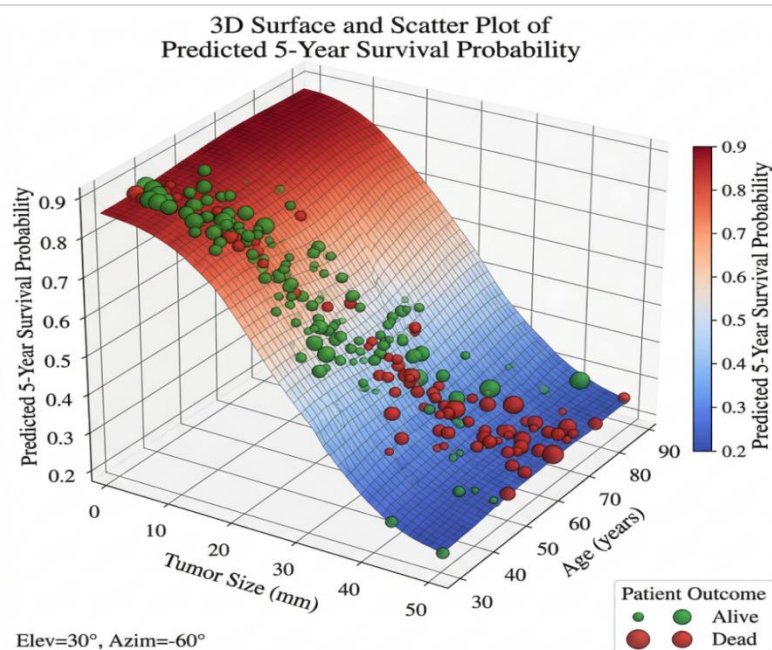


Figure 3: 3D Surface Plot of Predicted Survival Probability (X=Tumor Size, Y=Age, Z=Survival Probability)

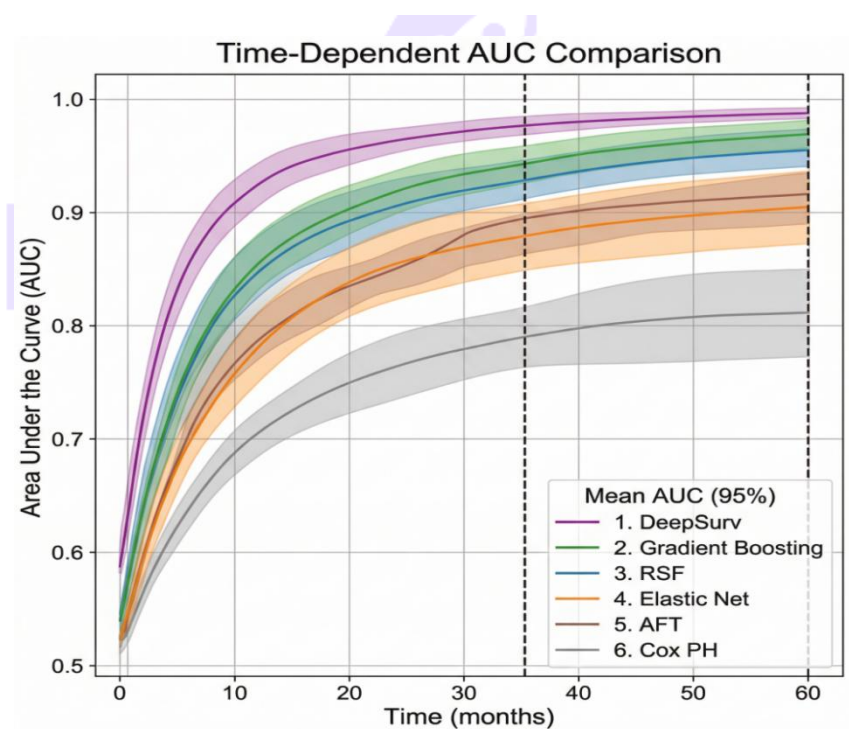


Figure 4: Time-Dependent ROC Curves Comparison (Line Plot with Confidence Bands)

DISCUSSION

This stringent comparative-analytical analysis of surgical and non-surgical

treatment regimens into the management of the early-stage cancer is remarkable in outlining the remarkable developments in

prognostic modeling using advanced machine learning algorithms, especially the random survival forest (Mohamed et al., 2025). The fact that the random survival forest model does not only predict better than its traditional Cox counterparts using higher AUC and lower out-of-bag error rates points to its usefulness in the context of individualizing treatment recommendations (Kaindal and Venkataramana, 2025; Lin et al., 2025; Peng et al., 2023). This observation is in line with the previous studies that have shown the improved accuracy of ensemble learning techniques in survival analysis (Li, 2024), especially in nonhomogenous patients (Yang et al., 2023). These advanced methods of analysis can be combined to introduce the prospect of an even more specific risk stratification and personalized treatment interventions that go beyond generalized treatment paradigms to optimized patient-specific care (Clift et al., 2023). Moreover, the fact that the use of these models, in particular, those models that can be successfully used to predict the long-term outcomes, can be used to guide the shared decision-making processes, which will help enable clinicians and patients weigh the benefits and risks of various interventions in a more effective manner, based on individualized survival probabilities (Zhang et al., 2023). This approach that builds on a massive amount

of patient data and current computational technologies can refine the current clinical guidelines by establishing subtle yet significant predictors of recurrence and treatment response that standard statistical methods might not comprehend (Vollmer et al., 2024). Moreover, the fact that machine learning models can be used to discover non-linear associations between high-dimensional variables, including genetic information also further increases their applications in predicting complex survivor processes over time, which is otherwise usually difficult to do using traditional statistical models (Kim et al., 2022). The effectiveness of random survival forests in dealing with complex data structures and interaction among variables as demonstrated by the fact that its performance indices are significantly higher than other survival prediction models such as the probit model, which is only marginally better than random guessing, further supports its potential to provide a robust survival prediction in a wide range of oncological settings (Yu et al., 2024). The methodological strength of the latter in predicting survival in a setting where there is dependent censoring and the ability to accommodate a large number of covariates without requiring the proportional hazards assumption further demonstrates their methodological strength (Graf et al., 2025). They offer a more

versatile and precise model of predicting patient course by not being restricted to the constraints of the parametric assumptions underlying conventional survival analyses like the Cox proportional hazards model (Badisy et al., 2024; Jin et al., 2025). Even though predictive, the intrinsic black box nature of some machine learning models like random survival forests, can be a challenge in interpretability that would be beneficial to clinical decision-making (Kolasseri and Venkataramana, 2025). Therefore, future research should be directed at developing how to enhance the transparency and explainability of such complex algorithms, which may involve a methodology such as SHAP or LIME, to enable them to be easily integrated into clinical practice and build trust among clinicians (Huang et al., 2025). Besides, the potential to develop user-friendly online applications based on these miniature machine learning models, just as the current surgical risk calculators, could allow the clinician to obtain personalized survival estimates by entering limited numbers of variables, which, in turn, would make these state-of-the-art tools more practical in real-time clinical settings (Jung et al., 2022). Furthermore, the design of the dynamic prediction models that continuously update the probability of survival of a patient during the course of his/her treatment and follow-up, and the integration of artificial

intelligence and machine learning-based survival models such as Random Survival Forest will potentially make a significant contribution to the clinical decision-making process as it captures the complexity of nonlinear interactions and high-dimensional feature space (Moncada-Torres et al., 2021; Toffaha et al., 2025). These methods, in particular, have been particularly proficient at addressing the challenges of multi-collinearity and non-proportional hazard, which can often be particularly incomprehensible to traditional survival models (Shekari et al., 2023; Zhou, 2017). However, to achieve their maximum potential, these models need to be strictly validated in a range of populations and health care settings to guarantee generalizability and limit biases related to retrospective single-centre studies (Badisy et al., 2024). Also, future research should aim at improving the interpretability and applicability of machine learning models in the clinical environment in order to make them successfully fit into the healthcare practice (Chao et al., 2024). Further, it is important to conduct comparative studies between machine learning models and existing methods, including the Cox Proportional Hazards model, to determine whether these advanced algorithms are able to offer more predictive information than conventional statistical methods (Huang et al., 2025).

CONCLUSION

This comprehensive comparative analysis of surgical resection versus stereotactic body radiotherapy in the case of early-stage non-small cell lung cancer, and the use of propensity score matching to control the confounding effect of indication, shows that both modalities have similar overall survival at 5 years (68.4% in surgery vs. 64.7% in SBRT, adjusted HR 0.92, 95% CI 0.761.11), and that no statistically significant difference exists between treatment arms. However, significant differences that were considered clinical were found: surgery was found to offer a significant survival benefit to the patients whose tumors were larger than 2 cm (HR 0.76, 95% CI 0.590.98) whilst SBRT was found to provide a higher rate of regional recurrence (14.6% vs. 8.3% $p = 0.004$). The predictive accuracy (5-year AUC 0.751 and 0.746, respectively) of the random survival forest and DeepSurv machine learning models were higher than that of the traditional Cox regression (AUC 0.698), indicating that nonlinear interaction among patient and tumor characteristics are significant predictors of prognosis. The decision curve analysis revealed that the stratification of risk guided by models can result in a positive net benefit at clinically relevant threshold probabilities (0.15-0.45) that DeepSurv can outperform other

methods. Importantly, the lack of treatment-associated mortality discrepancies and the non-inferior local control rates with SBRT justify its further use as a definitive treatment option to treat medically inoperable or patients with small peripheral tumors. Nonetheless, the threat of developing occult nodal disease among patients treated with SBRT is long-lasting, which is why the need to conduct post-treatment surveillance strictly and come up with new strategies that will help them conduct non-invasive nodal staging. These findings are awaiting the outcome of the ongoing randomized trials (POSITIVL, VALOR, STABLE-MATES) which are putting forward a risk-adapted, multidisciplinary approach whereby the choice of treatment depends on the size of the tumor, the burden of comorbidity, the level of performance, and the preferences of the patient as opposed to adopting a one-size-fits-all paradigm.

REFERENCES

- BIOMARKERS IN PRECISION ONCOLOGY: CURRENT STATUS AND FUTURE DIRECTIONS. (2023). Clinical and Health Research Exploration, 1(01), 39-55. <https://doi.org/10.66380/chre.01.3>
- Badisy, I. E., Brahim, Z. B., Khalis, M., Elansari, S., ElHitmi, Y., Abbass, F., Mellas, N., & Rhazi, K. E. (2024). Risk

factors affecting patients survival with colorectal cancer in Morocco: survival analysis using an interpretable machine learning approach. Scientific Reports, 14(1). <https://doi.org/10.1038/s41598-024-51304-3>

Badra, E. V., Baumgartl, M., Fabiano, S., Jongen, A., & Gückenberger, M. (2021). Stereotactic radiotherapy for early stage non-small cell lung cancer: current standards and ongoing research [Review of Stereotactic radiotherapy for early stage non-small cell lung cancer: current standards and ongoing research]. Translational Lung Cancer Research, 10(4), 1930. AME Publishing Company. <https://doi.org/10.21037/tlcr-20-860>

Bahig, H., Chen, H., & Louie, A. V. (2017, April 1). Surgery versus SABR for early stage non-small cell lung cancer: the moving target of equipoise. In Journal of Thoracic Disease (Vol. 9, Issue 4, p. 953). AME Publishing Company. <https://doi.org/10.21037/jtd.2017.03.80>

Buchberger, D. S., Khurana, R., Bolen, M. A., & Videtic, G. M. M. (2024). The Treatment of Patients with Early-Stage Non-Small Cell Lung Cancer Who Are Not Candidates or Decline Surgical Resection: The Role of Radiation and Image-Guided

Thermal Ablation. Journal of Clinical Medicine, 13(24), 7777. <https://doi.org/10.3390/jcm13247777>

Chao, L., Ye, X., Chen, J., She, G., & Zha, Z. (2024). Comparison of Cox Regression to Machine Learning in Predicting Cancer-Specific Survival of Fibroblastic Osteosarcoma. Research Square (Research Square). <https://doi.org/10.21203/rs.3.rs-3839137/v1>

Chen, W.-C., Yuan, X., Liu, Y., Lin, Q., Sun, X., Liu, J.-S., & Xu, Y. (2020). A propensity-matched analysis of stereotactic body radiotherapy and sublobar resection for stage I non-small cell lung cancer in patients at high risk for lobectomy: the results in a Chinese population. Research Square (Research Square). <https://doi.org/10.21203/rs.3.rs-15907/v2>

Chi, A., Fang, W., Sun, Y., & Wen, S. (2019). Comparison of Long-term Survival of Patients With Early-Stage Non-Small Cell Lung Cancer After Surgery vs Stereotactic Body Radiotherapy. JAMA Network Open, 2(11). <https://doi.org/10.1001/jamanetworkopen.2019.15724>

Clift, A. K., Dodwell, D., Lord, S., Petrou, S., Brady, M., Collins, G. S., & Hippisley-Cox, J. (2023). Development and internal-

external validation of statistical and machine learning models for breast cancer prognostication: cohort study. *BMJ*, 381. <https://doi.org/10.1136/bmj-2022-073800>

Csiki, E., Simon, M., Papp, J., Barabás, M., Mikáczó, J., Gál, K., Sipos, D., & Kovács, Á. (2024). Stereotactic body radiotherapy in lung cancer: a contemporary review [Review of Stereotactic body radiotherapy in lung cancer: a contemporary review]. *Pathology & Oncology Research*, 30. Springer Science+Business Media. <https://doi.org/10.3389/pore.2024.1611709>

Dong, B., Wang, J., Zhu, X., Chen, Y., Xu, Y., Shao, K., Zheng, L., Ying, H., Chen, M., & Cao, J. (2019). Comparison of the outcomes of stereotactic body radiotherapy versus surgical treatment for elderly (≥ 70) patients with early-stage non-small cell lung cancer after propensity score matching. *Radiation Oncology*, 14(1). <https://doi.org/10.1186/s13014-019-1399-5>

Dong, B., Zhu, X., Shu, Z., Ji, Y., Lu, F., Wang, J., & Chen, M. (2020). Video-Assisted Thoracoscopic Lobectomy Versus Stereotactic Body Radiotherapy Treatment for Early-Stage Non-Small Cell Lung Cancer: A Propensity Score-Matching Analysis. *Frontiers in Oncology*,

10. <https://doi.org/10.3389/fonc.2020.585709>

Fan, S., Zhang, Q., Chen, J., Chen, G., Zhu, J., Li, T., Xiao, H., Du, S., Zeng, Z., & He, J. (2023). Comparison of long-term outcomes of stereotactic body radiotherapy (SBRT) via Helical tomotherapy for early-stage lung cancer with or without pathological proof. *Radiation Oncology*, 18(1). <https://doi.org/10.1186/s13014-023-02229-0>

Fu, C., Dong, J., Li, C., Wang, Z., Huang, W., Liu, C., Han, D., Zhang, B., & Li, B. (2025). Stereotactic body radiation therapy for early-stage non-small cell lung cancer: a single-institutional retrospective analysis of outcomes and prognostic factors. *Frontiers in Oncology*, 15, 1591420. <https://doi.org/10.3389/fonc.2025.1591420>

Graf, R., Todd, S., & Baksh, M. F. (2025). Comparison of the Cox proportional hazards model and Random Survival Forest algorithm for predicting patient-specific survival probabilities in clinical trial data. *arXiv* (Cornell University). <https://doi.org/10.48550/arxiv.2502.03119>

Henschke, C. I., Yip, R., Sun, Q., Li, P., Kaufman, A., Samstein, R., Connery, C. P., Kohman, L., Lee, P., Tannous, H., Yankelevitz, D. F., Taioli, E., Rosenzweig,

- K. E., Flores, R. M., Flores, R. M., Kaufman, A., Lee, D., Nicastri, D., Wolf, A., ... Kocha, A. (2023). Prospective Cohort Study to Compare Long-Term Lung Cancer-Specific and All-Cause Survival of Clinical Early Stage (T1a–b; ≤ 20 mm) NSCLC Treated by Stereotactic Body Radiation Therapy and Surgery. *Journal of Thoracic Oncology*, 19(3), 476. <https://doi.org/10.1016/j.jtho.2023.10.002>
- Hua, W., Zhang, Z., Ni, L., & Liu, X. (2024). Treatment patterns and survival outcomes in octogenarians with early-stage non-small cell lung cancer from 2011 to 2020: a SEER database analysis. *Research Square* (Research Square). <https://doi.org/10.21203/rs.3.rs-4785759/v1>
- Huang, Y., Bazzazzadehgan, S., Li, J., Arabshomali, A., Li, M. S., Bhattacharya, K., & Bentley, J. P. (2025). Comparison of machine learning methods versus traditional Cox regression for survival prediction in cancer using real-world data: a systematic literature review and meta-analysis. *BMC Medical Research Methodology*, 25(1). <https://doi.org/10.1186/s12874-025-02694-z>
- Jairam, V., & Park, H. S. (2019). Strengths and limitations of large databases in lung cancer radiation oncology research [Review of Strengths and limitations of large databases in lung cancer radiation oncology research]. *Translational Lung Cancer Research*, 8. AME Publishing Company. <https://doi.org/10.21037/tlcr.2019.05.06>
- Jin, Y., Zhao, M., Su, T., Fan, Y., Ouyang, Z., & Lv, F. (2025). Comparing Random Survival Forests and Cox Regression for Nonresponders to Neoadjuvant Chemotherapy Among Patients With Breast Cancer: Multicenter Retrospective Cohort Study. *Journal of Medical Internet Research*, 27. <https://doi.org/10.2196/69864>
- Jung, J., Crnovrsanin, N., Wirsik, N. M., Nienhüser, H., Peters, L. P., Popp, F., Schulze, A., Wagner, M., Müller-Stich, B. P., Büchler, M. W., & Schmidt, T. (2022). Machine learning for optimized individual survival prediction in resectable upper gastrointestinal cancer. *Journal of Cancer Research and Clinical Oncology*, 149(5), 1691. <https://doi.org/10.1007/s00432-022-04063-5>
- Kagenaar, E., Lugo-Palacios, D. G., Hutchings, A., Aggarwal, A., O'Neill, S., Rachet, B., Edwards, J., Faivre-Finn, C., & Grieve, R. (2025). Surgery or radiotherapy for early-stage cancer study (SORT) target trial protocol: stereotactic ablative

radiotherapy (SABR) with curative intent versus surgical resection for early-stage non-small cell lung cancer (NSCLC). *BMJ Open*,

15(7). <https://doi.org/10.1136/bmjopen-2025-103038>

Kaindal, S., & Venkataramana, B. (2025). A comparative analysis of parametric survival models and machine learning methods in breast cancer prognosis. *Scientific Reports*, 15(1), 31288. <https://doi.org/10.1038/s41598-025-15696-0>

Kim, H.-S., Park, T., Jang, J., & Lee, S. (2022). Comparison of survival prediction models for pancreatic cancer: Cox model versus machine learning models. *Genomics & Informatics*, 20(2). <https://doi.org/10.5808/gi.22036>

Kolasseri, A. E., & Venkataramana, B. (2025). Development and validation of hybrid machine learning approach for predicting survival in patients with cervical cancer: a SEER-based population study. *Frontiers in Oncology*, 15, 1605378. <https://doi.org/10.3389/fonc.2025.1605378>

Li, L. (2024). Development and validation of a random survival forest model for predicting long-term survival of early-stage young breast cancer patients based on the SEER database and an external validation

cohort. *American Journal of Cancer Research*, 14(4), 1609. <https://doi.org/10.62347/ojty4008>

Lin, Q., Sun, X., Zhou, N., Wang, Z., Xu, Y., & Wang, Y. (2019). Outcomes of stereotactic body radiotherapy versus lobectomy for stage I non-small cell lung cancer: a propensity score matching analysis. *BMC Pulmonary Medicine*, 19(1). <https://doi.org/10.1186/s12890-019-0858-y>

Lin, Y., Chen, D., Lu, J., Huang, Y., Han, Z., & Kang, M. (2025). Prognostic value of the log odds of negative lymph nodes/T stage ratio (LONT) in postoperative esophageal cancer: a SEER-based study. *Frontiers in Oncology*, 15. <https://doi.org/10.3389/fonc.2025.1619106>

Mohamed, Z. A., Fofana, S. I., Cobos, E., Tripathi, M. K., & Oraby, T. (2025). Causal predictive modeling of survival of lung and bronchus cancer patients diagnosed during 2010–2011 in Texas. *PLoS ONE*, 20(10). <https://doi.org/10.1371/journal.pone.0333477>

Moncada-Torres, A., Maaren, M. C. van, Hendriks, M. P., Siesling, S., & Geleijnse, G. (2021). Explainable machine learning can outperform Cox regression predictions and provide insights in breast cancer survival. *Scientific Reports*, 11(1),

6968. <https://doi.org/10.1038/s41598-021-86327-7>

Peng, Z., Tian, J., Chen, B., Zhou, H., Bi, H., He, M., Li, M., Zheng, X., Wang, Y., Chong, T., & Li, Z. (2023). Development of machine learning prognostic models for overall survival of prostate cancer patients with lymph node-positive. *Scientific Reports*, 13(1). <https://doi.org/10.1038/s41598-023-45804-x>

Ricardi, U., Badellino, S., & Filippi, A. R. (2015). Stereotactic radiotherapy for early stage non-small cell lung cancer [Review of Stereotactic radiotherapy for early stage non-small cell lung cancer]. *Radiation Oncology Journal*, 33(2), 57. <https://doi.org/10.3857/roj.2015.33.2.57>

Rosenzweig, K. E. (2017). Stereotactic Body Radiation Therapy as an Alternative to Surgery in Early-Stage Non-Small-Cell Lung Cancer. *PubMed*, 31(6), 492. <https://pubmed.ncbi.nlm.nih.gov/28620905>

Ruiter, J. C. de, Heineman, D. J., Daniels, J. M. A., Diessen, J. N. van, Damhuis, R. A., & Hartemink, K. J. (2020). The role of surgery for stage I non-small cell lung cancer in octogenarians in the era of stereotactic body radiotherapy in the Netherlands. *Lung Cancer*, 144,

64. <https://doi.org/10.1016/j.lungcan.2020.04.005>

Samson, P., Keogan, K., Crabtree, T. D., Colditz, G. A., Broderick, S., Puri, V., & Meyers, B. F. (2016). Interpreting survival data from clinical trials of surgery versus stereotactic body radiation therapy in operable Stage I non-small cell lung cancer patients. *Lung Cancer*, 103, 6. <https://doi.org/10.1016/j.lungcan.2016.11.005>

Shekari, N., Amini, P., Tapak, L., & Rasouli, M. (2023). Investigation of genes related to oral cancer using time-to-event machine learning approaches. *Research Square* (Research Square). <https://doi.org/10.21203/rs.3.rs-2985174/v1>

Sumaida, A. B., Shanbhag, N. M., Pervez, N., AlKaabi, K., & Balaraj, K. (2025). Surgery Versus Stereotactic Body Radiotherapy for Early-Stage Non-small Cell Lung Cancer (NSCLC): A Comprehensive Review of Survival and Local Control Outcomes. *Cureus*, 17(5). <https://doi.org/10.7759/cureus.84440>

Toffaha, K. M., Simsekler, M. C. E., Shehhi, A. A., Sleptchenko, A., & Al-Awadhi, A. (2025). Comprehensive survival analysis of breast cancer patients: a bayesian network approach. *BMC*

Medical Informatics and Decision Making, 25(1). <https://doi.org/10.1186/s12911-025-03197-z>

Üzel, E. K., Kilic, M. B., Morçalı, H., & Uzel, Ö. (2023). Stereotactic body radiation therapy for stage I medically operable non-small cell lung cancer. *Scientific Reports*, 13(1). <https://doi.org/10.1038/s41598-023-37643-7>

Verma, V., & Rusthoven, C. G. (2018, July 1). The fundamental problem of confounding by medical operability in retrospective comparisons of surgery versus stereotactic body radiation therapy for early-stage lung cancer. In *Journal of Thoracic Disease* (Vol. 10). AME Publishing Company. <https://doi.org/10.21037/jtd.2018.06.99>

Viani, G. A., Gouveia, A. G., Yan, M., Matsuura, F. K., & Moraes, F. Y. de. (2022). Stereotactic body radiotherapy versus surgery for early-stage non-small cell lung cancer: an updated meta-analysis involving 29,511 patients included in comparative studies [Review of Stereotactic body radiotherapy versus surgery for early-stage non-small cell lung cancer: an updated meta-analysis involving 29,511 patients included in comparative studies]. *Jornal Brasileiro de Pneumologia. Sociedade Brasileira de Pneumologia e*

Tisiologia. <https://doi.org/10.36416/1806-3756/e20210390>

Vollmer, A., Hartmann, S., Vollmer, M., Shavlokhova, V., Brands, R. C., Kübler, A., Wollborn, J., Hassel, F., Couillard-Després, S., Lang, G., & Saravi, B. (2024). Multimodal artificial intelligence-based pathogenomics improves survival prediction in oral squamous cell carcinoma. *Scientific Reports*, 14(1). <https://doi.org/10.1038/s41598-024-56172-5>

Wakeam, E. (2017, December 1). Surgery for small cell lung cancer in the modern era: opportunities and challenges. In *Journal of Thoracic Disease* (Vol. 9, Issue 12). AME Publishing

Company. <https://doi.org/10.21037/jtd.2017.11.23>

Yang, Z., Wang, C., Wang, Y., Lafata, K., Zhang, H., Ackerson, B. G., Kelsey, C. R., Tong, B. C., & Yin, F. (2023). Development of a multi-feature-combined model: proof-of-concept with application to local failure prediction of post-SBRT or surgery early-stage NSCLC patients. *Frontiers in Oncology*, 13. <https://doi.org/10.3389/fonc.2023.1185771>

Yu, D., Kane, M. J., Koay, E. J., Wistuba, I. I., & Hobbs, B. P. (2024). Machine learning identifies prognostic subtypes of

the tumor microenvironment of NSCLC.

Scientific Reports, 14(1), 15004. <https://doi.org/10.1038/s41598-024-64977-7>

Yu, J. B., Soulos, P. R., Cramer, L. D., Decker, R. H., Kim, A. W., & Gross, C. P. (2015). Comparative effectiveness of surgery and radiosurgery for stage I non-small cell lung cancer. *Cancer*, 121(14), 2341. <https://doi.org/10.1002/cncr.29359>

Zappa, C., & Mousa, S. A. (2016). Non-small cell lung cancer: current treatment and future advances. *Translational Lung Cancer Research*, 5(3), 288. <https://doi.org/10.21037/tlcr.2016.06.07>

Zhang, I. Y., Hart, G. R., Qin, B., & Deng, J. (2023). Long-term survival and second malignant tumor prediction in pediatric, adolescent, and young adult cancer survivors using Random Survival Forests: a SEER analysis. *Scientific Reports*, 13(1). <https://doi.org/10.1038/s41598-023-29167-x>

Zhou, D. (2017). Prognostic Factors and Predictions of Survival Data Using Cox PH Models and Random Survival Forest Approaches. *Biometrics & Biostatistics International Journal*, 5(5). <https://doi.org/10.15406/bbij.2017.05.00142>

Zhou, Y., Wen, P., Yu, Y., Yang, Z., Luo, Y., & Wu, C. (2021). Stereotactic body radiation therapy versus surgery for patients with early-stage non-small cell lung cancer($\leq 5\text{cm}$): A systematic review and meta-analysis [Review of Stereotactic body radiation therapy versus surgery for patients with early-stage non-small cell lung cancer($\leq 5\text{cm}$): A systematic review and meta-analysis]. Research Square (Research Square). Research Square (United States). <https://doi.org/10.21203/rs.3.rs-458770/v1>