

P8108 Final Project

Group 6

2025-11-16

Data Import

```
lung_df <- survival::lung %>%
  janitor::clean_names() %>%
  mutate(
    inst = as.factor(inst),
    time = as.numeric(time),
    status = as.factor(status),
    event = status == 2,
    age = as.numeric(age),
    sex = factor(sex, levels = c(1, 2), labels = c("Male", "Female")),
    ph_ecog = factor(ph_ecog, ordered = TRUE),
    ph_karno = as.numeric(ph_karno),
    pat_karno = as.numeric(pat_karno),
    meal_cal = as.numeric(meal_cal),
    wt_loss = as.numeric(wt_loss)
  )
```

We create a new variable called `event` to indicate survival status, where 1 represents death and 0 represents censoring.

The variable `ph_ecog` (ECOG performance score, 0–3) is treated as an ordinal variable. For descriptive and Kaplan–Meier analyses, it is handled as a categorical factor to visualize group differences. It might be modeled as an ordinal numeric variable in Cox model.

Check NAs

```
summary(lung_df)
```

```
##      inst        time      status       age         sex     ph_ecog
## 1: 36   Min. : 5.0  1: 63  Min. :39.00  Male :138  0 : 63
## 12: 23  1st Qu.:166.8  2:165  1st Qu.:56.00 Female: 90  1 :113
## 13: 20   Median :255.5           Median :63.00          2 : 50
## 3: 19   Mean   :305.2           Mean   :62.45          3 :  1
## 11: 18  3rd Qu.:396.5           3rd Qu.:69.00         NA's:  1
## (Other):111 Max.   :1022.0           Max.   :82.00
## NA's : 1
##      ph_karno      pat_karno      meal_cal      wt_loss
## Min. : 50.00  Min. : 30.00  Min. : 96.0  Min. :-24.000
## 1st Qu.: 75.00 1st Qu.: 70.00 1st Qu.:635.0 1st Qu.: 0.000
## Median : 80.00  Median : 80.00  Median :975.0  Median : 7.000
## Mean   : 81.94  Mean   : 79.96  Mean   :928.8  Mean   : 9.832
## 3rd Qu.: 90.00 3rd Qu.: 90.00 3rd Qu.:1150.0 3rd Qu.: 15.750
```

```

##   Max.    :100.00  Max.    :100.00  Max.    :2600.0  Max.    : 68.000
##   NA's     :1          NA's     :3          NA's     :47         NA's     :14
##   event
##   Mode :logical
##   FALSE:63
##   TRUE :165
##
##
##
##lung_cc <- lung_df %>%
#  filter(complete.cases(time, event, age, sex, ph_ecog,
#                        ph_karno, pat_karno, meal_cal, wt_loss, inst))
#summary(lung_cc)

##      inst       time      status       age       sex       ph_ecog
## 1     :28   Min.   : 5.0  1: 47  Min.   :39.00  Male  :103  0:47
## 12    :16   1st Qu.:174.5 2:120  1st Qu.:57.00 Female: 64  1:81
## 11    :13   Median :268.0           Median :64.00           2:38
## 13    :13   Mean   :309.9           Mean   :62.57           3: 1
## 22    :13   3rd Qu.:419.5           3rd Qu.:70.00
## 3     :12   Max.   :1022.0          Max.   :82.00
## (Other):72
##      ph_karno      pat_karno      meal_cal      wt_loss
##  Min.   : 50.00  Min.   : 30.00  Min.   : 96.0  Min.   :-24.000
##  1st Qu.: 70.00  1st Qu.: 70.00  1st Qu.: 619.0  1st Qu.: 0.000
##  Median : 80.00  Median : 80.00  Median : 975.0  Median : 7.000
##  Mean   : 82.04  Mean   : 79.58  Mean   : 929.1  Mean   : 9.719
##  3rd Qu.: 90.00  3rd Qu.: 90.00  3rd Qu.:1162.5  3rd Qu.: 15.000
##  Max.   :100.00  Max.   :100.00  Max.   :2600.0  Max.   : 68.000
##
##      event
##      Mode :logical
##      FALSE:47
##      TRUE :120
##
##
##
##
```

There are NAs in this data, so we will also create another dataset that observations with missing values will be excluded to ensure that all variables used in the analysis had complete information.

Both the original dataset and the complete-case dataset were retained for further analyses to allow comparisons and sensitivity checks.

EDA

Descriptive Table

```

lung_cc %>%
  select(time, event, age, sex, ph_ecog, ph_karno, pat_karno, meal_cal, wt_loss) %>%
 tbl_summary(
  by = sex,
  missing = "no",

```

Characteristic	Overall N = 167 ¹	Male N = 103 ¹	Female N = 64 ¹	p-value ²
Survival time (days)	310 (209)	291 (208)	340 (209)	0.069
Death indicator	120 (72%)	82 (80%)	38 (59%)	0.005
Age (years)	63 (9)	63 (9)	61 (9)	0.10
ECOG performance status				>0.9
0	47 (28%)	28 (27%)	19 (30%)	
1	81 (49%)	52 (50%)	29 (45%)	
2	38 (23%)	22 (21%)	16 (25%)	
3	1 (0.6%)	1 (1.0%)	0 (0%)	
Physician Karnofsky score				0.8
50	4 (2.4%)	3 (2.9%)	1 (1.6%)	
60	16 (9.6%)	8 (7.8%)	8 (13%)	
70	24 (14%)	16 (16%)	8 (13%)	
80	47 (28%)	28 (27%)	19 (30%)	
90	50 (30%)	32 (31%)	18 (28%)	
100	26 (16%)	16 (16%)	10 (16%)	
Patient Karnofsky score				0.3
30	2 (1.2%)	1 (1.0%)	1 (1.6%)	
40	2 (1.2%)	1 (1.0%)	1 (1.6%)	
50	3 (1.8%)	2 (1.9%)	1 (1.6%)	
60	23 (14%)	15 (15%)	8 (13%)	
70	30 (18%)	24 (23%)	6 (9.4%)	
80	37 (22%)	20 (19%)	17 (27%)	
90	44 (26%)	24 (23%)	20 (31%)	
100	26 (16%)	16 (16%)	10 (16%)	
Meal calories	929 (413)	985 (428)	840 (374)	0.027
Weight loss (kg)	10 (13)	12 (13)	7 (13)	0.015

¹Mean (SD); n (%)

²Wilcoxon rank sum test

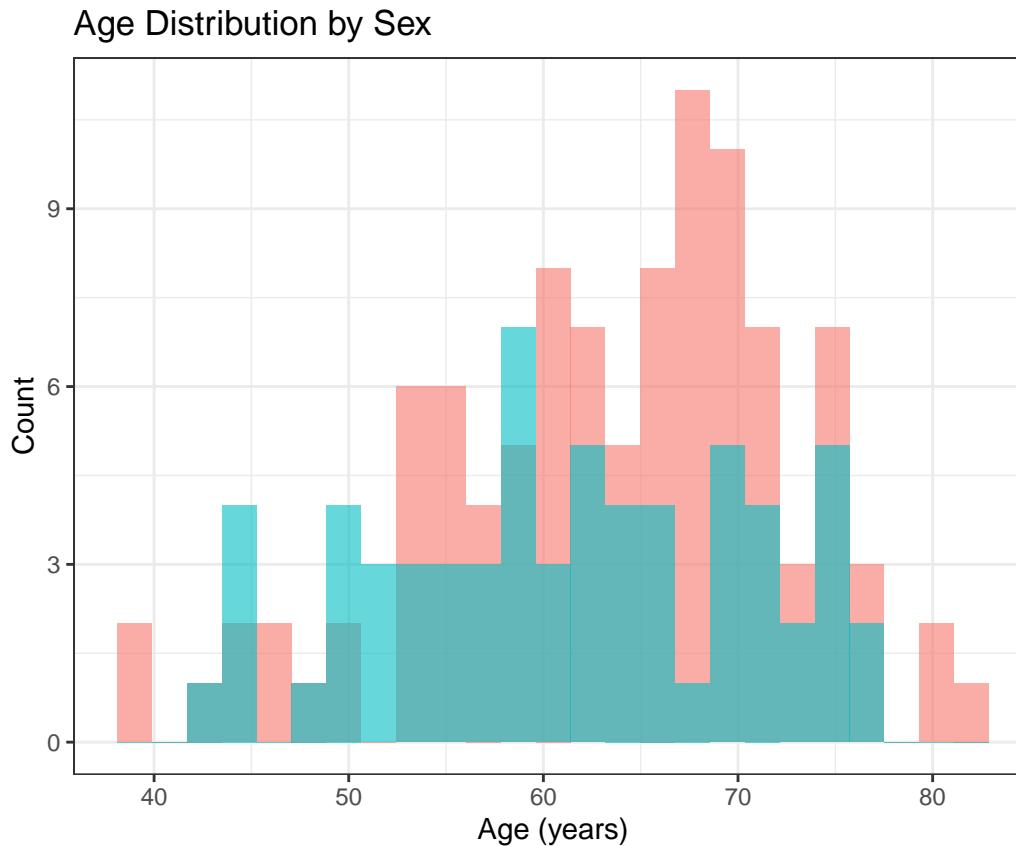
```

statistic = list(all_continuous() ~ "{mean} ({sd})", all_categorical() ~ "{n} ({p}%)",
label = list(
  time ~ "Survival time (days)",
  event ~ "Death indicator",
  age ~ "Age (years)",
  ph_ecog ~ "ECOG performance status",
  ph_karno ~ "Physician Karnofsky score",
  pat_karno ~ "Patient Karnofsky score",
  meal_cal ~ "Meal calories",
  wt_loss ~ "Weight loss (kg)"
)
) %>%
add_overall() %>%
add_p(test = everything() ~ "wilcox.test") %>%
bold_labels()

```

Age Distribution by Sex

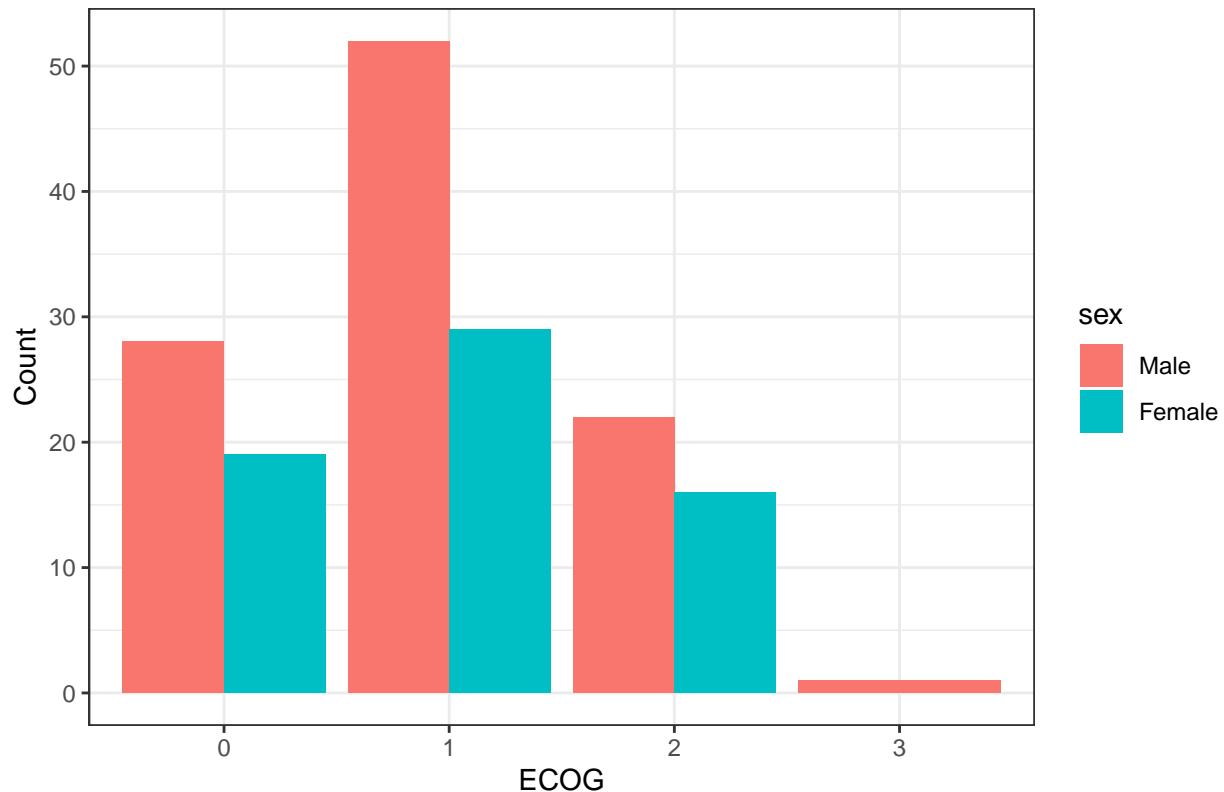
```
ggplot(lung_cc, aes(x = age, fill = sex)) +
  geom_histogram(bins = 25, position = "identity", alpha = 0.6) +
  theme_bw() +
  labs(title = "Age Distribution by Sex", x = "Age (years)", y = "Count")
```



ECOG Performance Status by Sex

```
ggplot(lung_cc, aes(x = ph_ecog, fill = sex)) +
  geom_bar(position = "dodge") +
  theme_bw() +
  labs(title = "ECOG Performance Status by Sex", x = "ECOG", y = "Count")
```

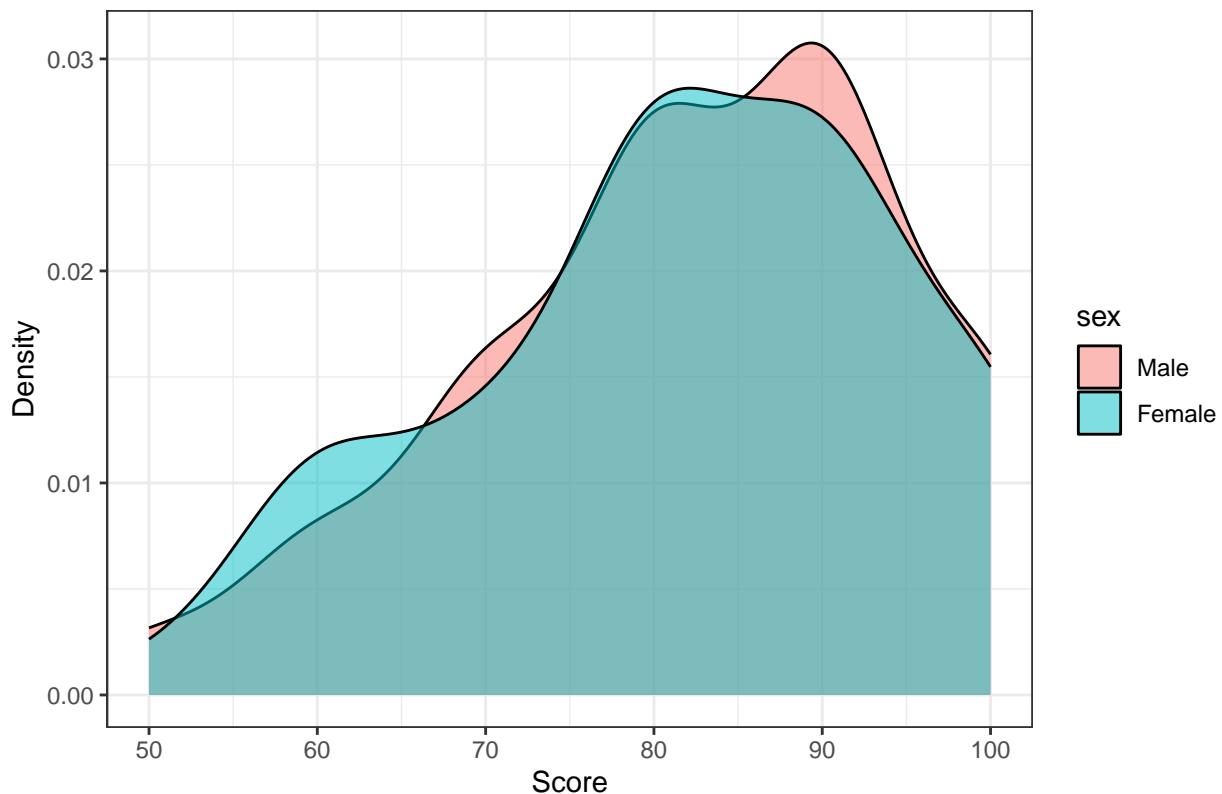
ECOG Performance Status by Sex



Physician-rated Karnofsky Score by Sex

```
ggplot(lung_cc, aes(x = ph_karno, fill = sex)) +  
  geom_density(alpha = 0.5) +  
  theme_bw() +  
  labs(title = "Physician-rated Karnofsky Score by Sex", x = "Score", y = "Density")
```

Physician-rated Karnofsky Score by Sex



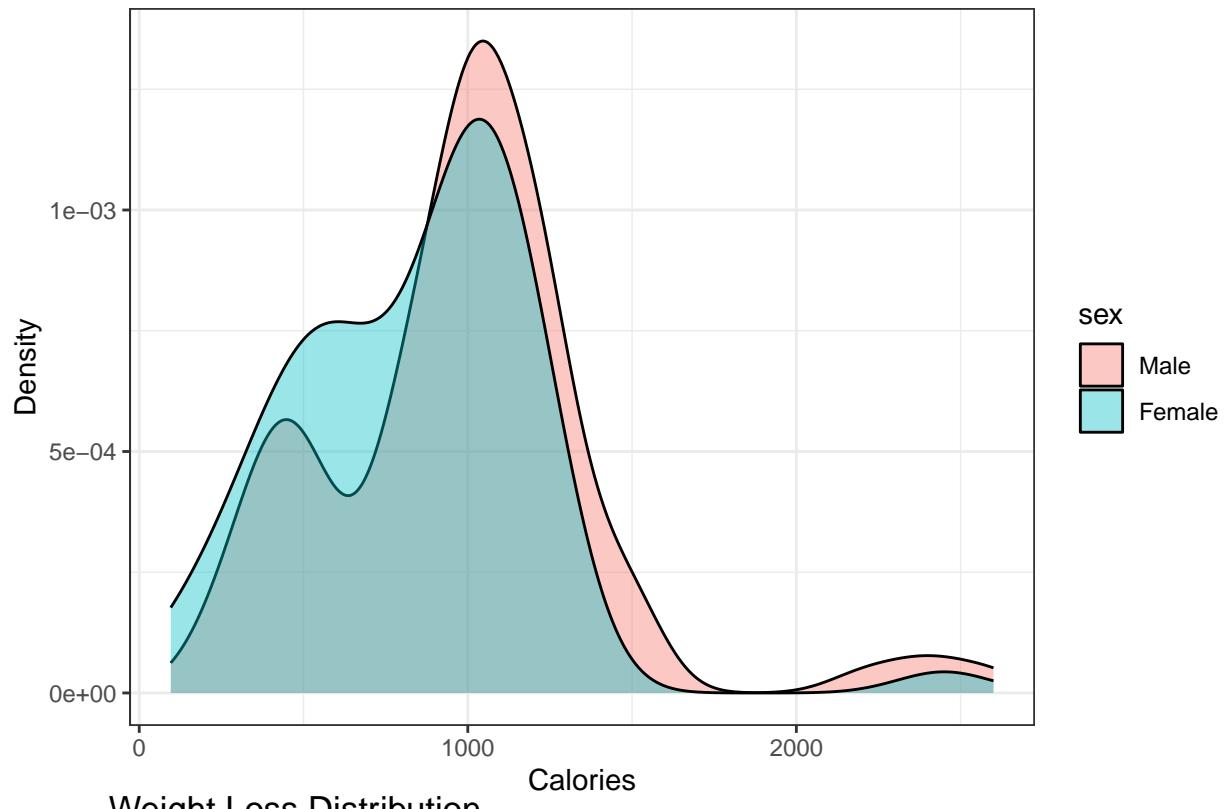
Meal Calories and Weight Loss Distributions

```
p1 <- ggplot(lung_cc, aes(x = meal_cal, fill = sex)) +
  geom_density(alpha = 0.4) +
  labs(title = "Meal Calories Distribution", x = "Calories", y = "Density") +
  theme_bw()

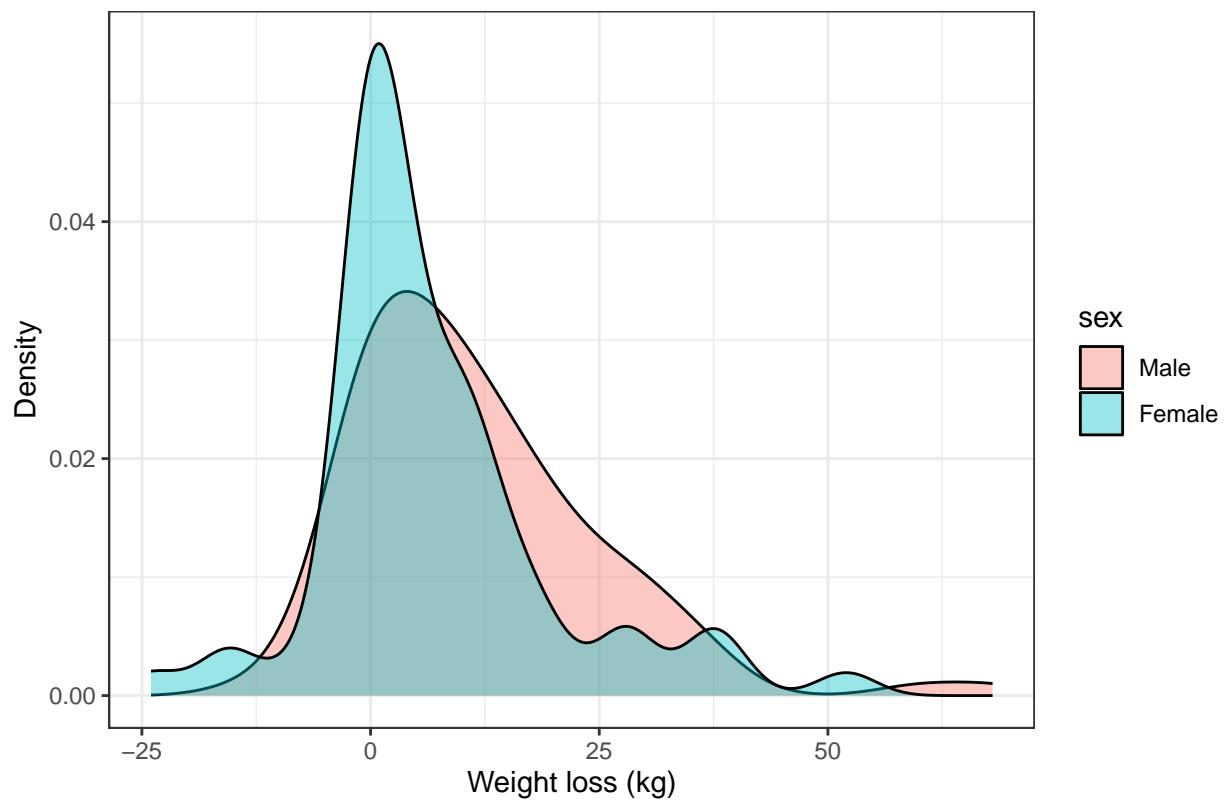
p2 <- ggplot(lung_cc, aes(x = wt_loss, fill = sex)) +
  geom_density(alpha = 0.4) +
  labs(title = "Weight Loss Distribution", x = "Weight loss (kg)", y = "Density") +
  theme_bw()

p1; p2
```

Meal Calories Distribution

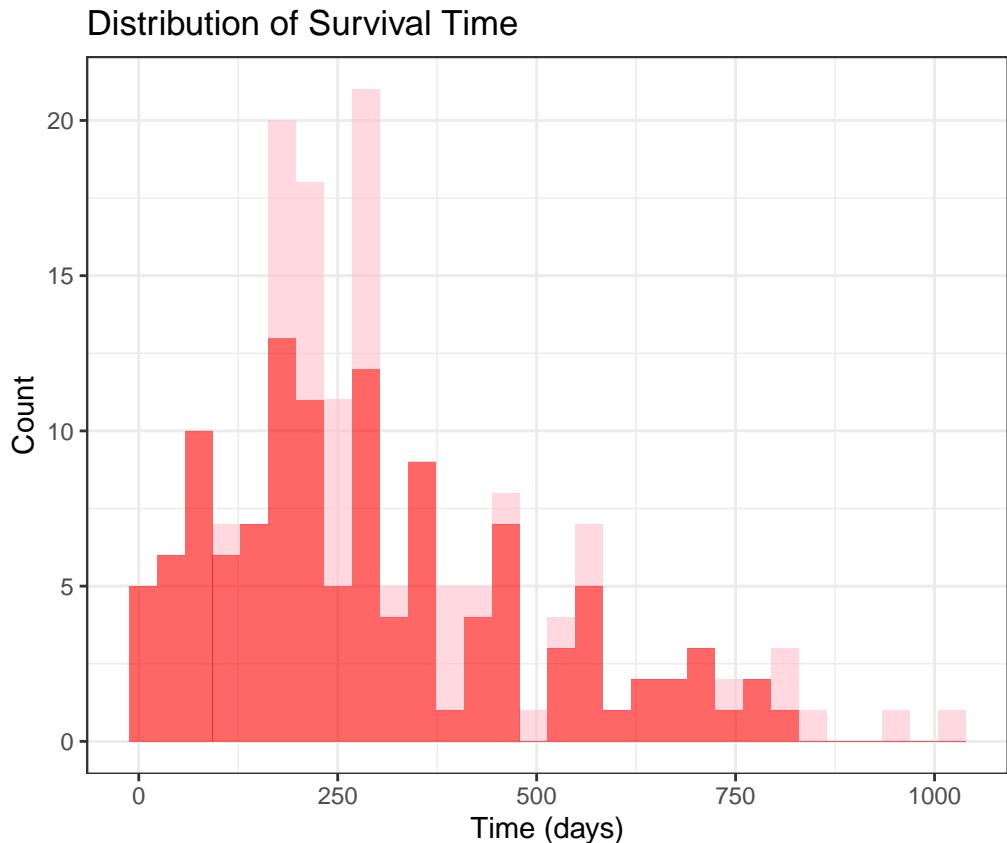


Weight Loss Distribution



Distribution of Survival Time

```
ggplot(lung_cc, aes(x = time, fill = event)) +
  geom_histogram(bins = 30, alpha = 0.6) +
  theme_bw() +
  labs(title = "Distribution of Survival Time", x = "Time (days)", y = "Count") +
  scale_fill_manual(values = c("PINK", "RED"), name = "Event", labels = c("Censored", "Death"))
```



Comparison of Survival Curves

```
# Create a survival object, which bundles the time and event data
surv_object <- Surv(time = lung_cc$time, event = lung_cc$event)

# Fit the Overall Kaplan-Meier Model
km_overall_fit <- survfit(surv_object ~ 1, data = lung_cc)

print(km_overall_fit)

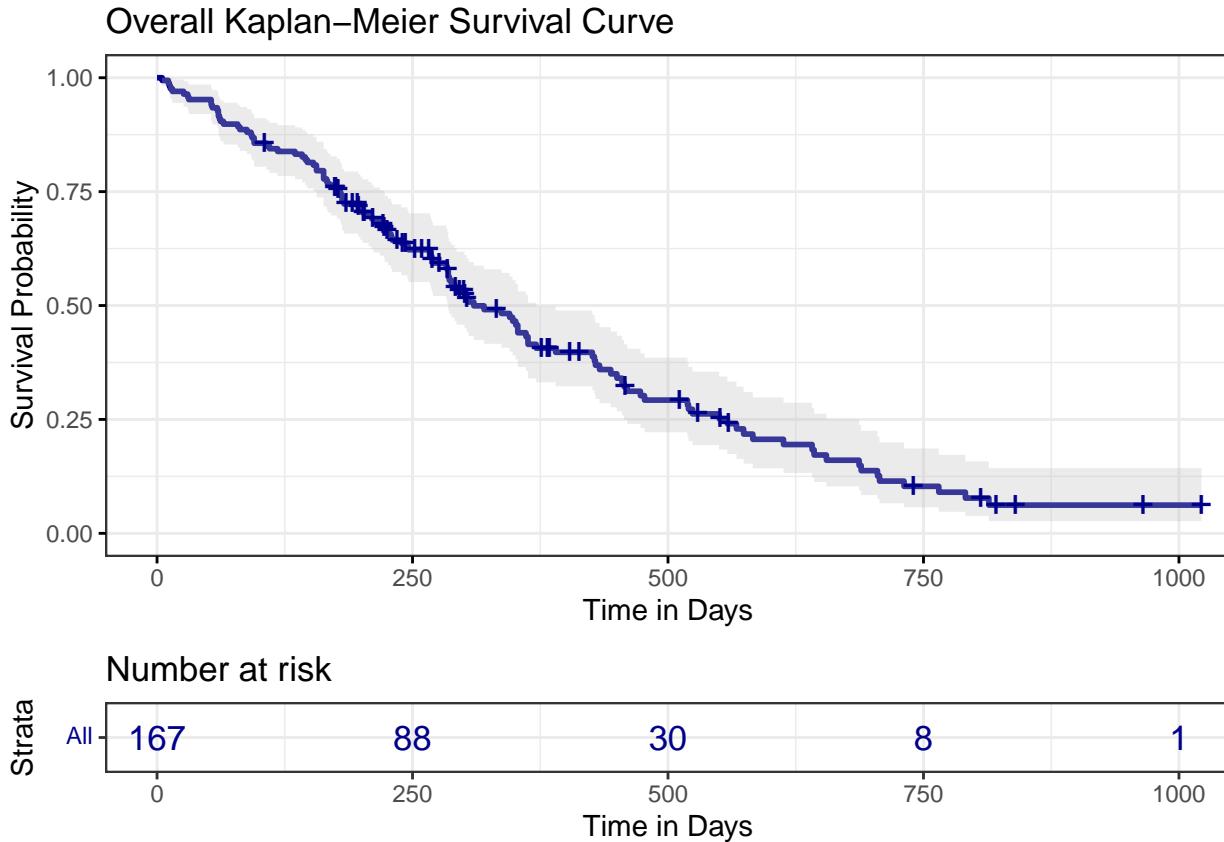
## Call: survfit(formula = surv_object ~ 1, data = lung_cc)
##
##      n  events median 0.95LCL 0.95UCL
## [1,] 167     120     310     285     371

ggsurvplot(
  km_overall_fit,
  data = lung_cc,
  conf.int = TRUE,
  risk.table = TRUE,
```

```
risk.table.col = "strata",
title = "Overall Kaplan-Meier Survival Curve",
xlab = "Time in Days",
ylab = "Survival Probability",
ggtheme = theme_bw(),
palette = "darkblue",
legend = "none"
)

## Warning: Using `size` aesthetic for lines was deprecated in ggplot2 3.4.0.
## i Please use `linewidth` instead.
## i The deprecated feature was likely used in the ggpubr package.
## Please report the issue at <https://github.com/kassambara/ggpubr/issues>.
## This warning is displayed once every 8 hours.
## Call `lifecycle::last_lifecycle_warnings()` to see where this warning was
## generated.

## Ignoring unknown labels:
## * fill : "Strata"
## Ignoring unknown labels:
## * fill : "Strata"
## Ignoring unknown labels:
## * fill : "Strata"
## Ignoring unknown labels:
## * fill : "Strata"
```



Sex

```
# Fit the Kaplan-Meier model to estimate survival curves for each group ('sex')
km_sex_fit <- survfit(surv_object ~ sex, data = lung_cc)

summary(km_sex_fit)
```

```
## Call: survfit(formula = surv_object ~ sex, data = lung_cc)
##
##          sex=Male
##   time n.risk n.event survival std.err lower 95% CI upper 95% CI
##    11     103      1 0.9903 0.00966 0.9715 1.000
##    12     102      1 0.9806 0.01360 0.9543 1.000
##    13     101      1 0.9709 0.01657 0.9389 1.000
##    15     100      1 0.9612 0.01904 0.9246 0.999
##    26      99      1 0.9515 0.02118 0.9108 0.994
##    30      98      1 0.9417 0.02308 0.8976 0.988
##    31      97      1 0.9320 0.02480 0.8847 0.982
##    53      96      2 0.9126 0.02782 0.8597 0.969
##    54      94      1 0.9029 0.02917 0.8475 0.962
##    59      93      1 0.8932 0.03043 0.8355 0.955
##    60      92      1 0.8835 0.03161 0.8237 0.948
##    65      91      1 0.8738 0.03272 0.8119 0.940
##    88      90      1 0.8641 0.03377 0.8004 0.933
##    92      89      1 0.8544 0.03476 0.7889 0.925
##    93      88      1 0.8447 0.03569 0.7775 0.918
##    95      87      1 0.8350 0.03658 0.7663 0.910
##   110     86      1 0.8252 0.03742 0.7551 0.902
##   118     85      1 0.8155 0.03822 0.7440 0.894
##   135     84      1 0.8058 0.03898 0.7329 0.886
##   142     83      1 0.7961 0.03970 0.7220 0.878
##   147     82      1 0.7864 0.04038 0.7111 0.870
##   156     81      2 0.7670 0.04165 0.6895 0.853
##   163     79      3 0.7379 0.04333 0.6576 0.828
##   166     76      1 0.7282 0.04384 0.6471 0.819
##   170     75      1 0.7184 0.04432 0.6366 0.811
##   176     73      1 0.7086 0.04479 0.6260 0.802
##   179     72      1 0.6988 0.04523 0.6155 0.793
##   180     71      1 0.6889 0.04566 0.6050 0.784
##   181     70      2 0.6692 0.04642 0.5842 0.767
##   183     68      1 0.6594 0.04677 0.5738 0.758
##   197     64      1 0.6491 0.04716 0.5629 0.748
##   207     62      1 0.6386 0.04755 0.5519 0.739
##   210     61      1 0.6282 0.04791 0.5409 0.729
##   212     60      1 0.6177 0.04824 0.5300 0.720
##   218     59      1 0.6072 0.04855 0.5191 0.710
##   222     57      1 0.5966 0.04885 0.5081 0.700
##   223     55      1 0.5857 0.04915 0.4969 0.690
##   229     52      1 0.5745 0.04948 0.4852 0.680
##   230     51      1 0.5632 0.04977 0.4736 0.670
##   246     50      1 0.5519 0.05004 0.4621 0.659
##   267     48      1 0.5404 0.05030 0.4503 0.649
##   269     47      1 0.5289 0.05053 0.4386 0.638
##   270     46      1 0.5174 0.05072 0.4270 0.627
```

```

##   283    45     1  0.5059  0.05088      0.4154    0.616
##   284    44     1  0.4944  0.05101      0.4039    0.605
##   285    42     1  0.4827  0.05113      0.3922    0.594
##   286    41     1  0.4709  0.05122      0.3805    0.583
##   288    40     1  0.4591  0.05128      0.3689    0.571
##   291    39     1  0.4473  0.05129      0.3573    0.560
##   301    36     1  0.4349  0.05135      0.3451    0.548
##   303    34     1  0.4221  0.05141      0.3325    0.536
##   320    32     1  0.4089  0.05147      0.3195    0.523
##   337    31     1  0.3957  0.05147      0.3067    0.511
##   353    30     2  0.3694  0.05131      0.2813    0.485
##   363    28     1  0.3562  0.05114      0.2688    0.472
##   371    27     1  0.3430  0.05092      0.2564    0.459
##   390    26     1  0.3298  0.05064      0.2441    0.446
##   428    23     1  0.3154  0.05043      0.2306    0.432
##   429    22     1  0.3011  0.05014      0.2173    0.417
##   455    21     1  0.2868  0.04976      0.2041    0.403
##   457    20     1  0.2724  0.04929      0.1911    0.388
##   460    18     1  0.2573  0.04882      0.1774    0.373
##   477    17     1  0.2422  0.04824      0.1639    0.358
##   519    16     1  0.2270  0.04754      0.1506    0.342
##   524    15     1  0.2119  0.04672      0.1375    0.326
##   558    14     1  0.1968  0.04577      0.1247    0.310
##   567    13     1  0.1816  0.04468      0.1121    0.294
##   574    12     1  0.1665  0.04344      0.0998    0.278
##   583    11     1  0.1514  0.04205      0.0878    0.261
##   613    10     1  0.1362  0.04048      0.0761    0.244
##   643     9     1  0.1211  0.03870      0.0647    0.227
##   655     8     1  0.1059  0.03671      0.0537    0.209
##   689     7     1  0.0908  0.03444      0.0432    0.191
##   707     6     1  0.0757  0.03185      0.0332    0.173
##   791     5     1  0.0605  0.02886      0.0238    0.154
##   814     3     1  0.0404  0.02533      0.0118    0.138
##
##          sex=Female
##   time n.risk n.event survival std.err lower 95% CI upper 95% CI
##     5     64     1  0.984  0.0155    0.9545  1.000
##    60     63     1  0.969  0.0217    0.9270  1.000
##    61     62     1  0.953  0.0264    0.9027  1.000
##    62     61     1  0.938  0.0303    0.8800  0.999
##    79     60     1  0.922  0.0335    0.8584  0.990
##    81     59     1  0.906  0.0364    0.8376  0.981
##    95     58     1  0.891  0.0390    0.8174  0.970
##   107     56     1  0.875  0.0414    0.7972  0.960
##   145     55     1  0.859  0.0436    0.7774  0.949
##   153     54     1  0.843  0.0456    0.7581  0.937
##   167     53     1  0.827  0.0475    0.7390  0.925
##   199     50     1  0.810  0.0493    0.7194  0.913
##   201     49     1  0.794  0.0510    0.7000  0.900
##   226     45     1  0.776  0.0528    0.6794  0.887
##   239     43     1  0.758  0.0546    0.6584  0.873
##   245     40     1  0.739  0.0564    0.6366  0.859
##   268     37     1  0.719  0.0583    0.6136  0.843
##   285     34     1  0.698  0.0603    0.5894  0.827

```

```

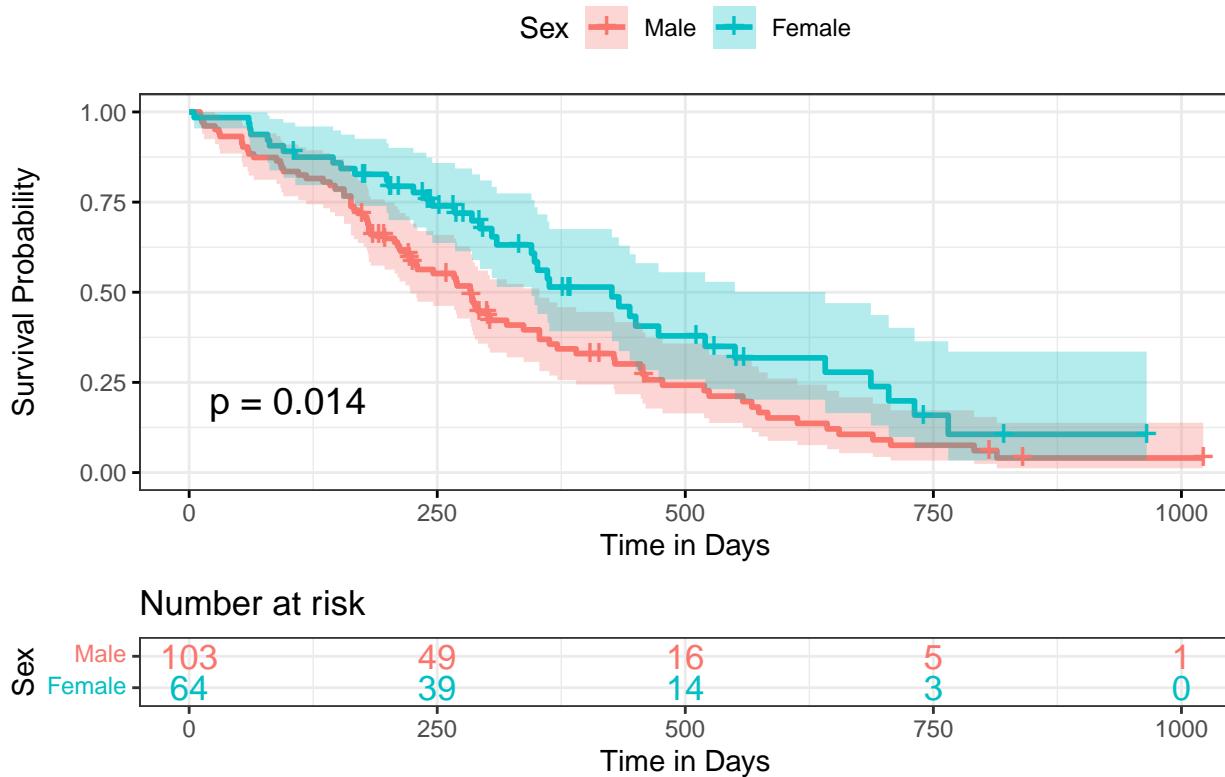
##   293    32     1   0.676   0.0623    0.5647   0.810
##   305    30     1   0.654   0.0641    0.5394   0.792
##   310    29     1   0.631   0.0658    0.5146   0.774
##   345    27     1   0.608   0.0674    0.4892   0.755
##   348    26     1   0.584   0.0687    0.4642   0.736
##   351    25     1   0.561   0.0698    0.4397   0.716
##   361    24     1   0.538   0.0707    0.4155   0.696
##   363    23     1   0.514   0.0714    0.3918   0.675
##   426    19     1   0.487   0.0726    0.3639   0.653
##   433    18     1   0.460   0.0734    0.3366   0.629
##   444    17     1   0.433   0.0739    0.3100   0.605
##   450    16     1   0.406   0.0741    0.2839   0.581
##   473    15     1   0.379   0.0739    0.2585   0.556
##   520    13     1   0.350   0.0738    0.2314   0.529
##   550    11     1   0.318   0.0736    0.2020   0.501
##   641     8     1   0.278   0.0744    0.1648   0.470
##   687     7     1   0.239   0.0736    0.1303   0.437
##   705     6     1   0.199   0.0713    0.0984   0.401
##   731     5     1   0.159   0.0672    0.0695   0.364
##   765     3     1   0.106   0.0623    0.0335   0.335

# --- Visualize the Estimated Survival Probabilities ---

# Generate the Kaplan-Meier plot using ggsurvplot
ggsurvplot(
  km_sex_fit,
  data = lung_cc,
  pval = TRUE,                               # The p-value from the log-rank test will be displayed
  conf.int = TRUE,                            # Display confidence intervals for the curves
  risk.table = TRUE,                          # Add a table showing the number of subjects at risk
  risk.table.col = "strata",      # Color the risk table to match the curves
  legend.labs = c("Male", "Female"),
  legend.title = "Sex",
  xlab = "Time in Days",
  ylab = "Survival Probability",
  title = "Kaplan-Meier Survival Curves by Sex",
  ggtheme = theme_bw()                      # Apply a clean theme
)

```

Kaplan–Meier Survival Curves by Sex



```
# With rho = 0 this is the log-rank or Mantel-Haenszel test, and with rho = 1 it is equivalent to the P
log_rank_sex <- survdiff(surv_object ~ sex, data = lung_cc, rho = 0)
print(log_rank_sex)
```

```
## Call:
## survdiff(formula = surv_object ~ sex, data = lung_cc, rho = 0)
##
##          N Observed Expected (O-E)^2/E (O-E)^2/V
## sex=Male   103      82    68.7     2.57     6.05
## sex=Female  64      38    51.3     3.44     6.05
##
##  Chisq= 6 on 1 degrees of freedom, p= 0.01
wilcoxon_sex <- survdiff(surv_object ~ sex, data = lung_cc, rho = 1)
print(wilcoxon_sex)
```

```
## Call:
## survdiff(formula = surv_object ~ sex, data = lung_cc, rho = 1)
##
##          N Observed Expected (O-E)^2/E (O-E)^2/V
## sex=Male   103      51.0    41.8     2.01     6.76
## sex=Female  64      21.1    30.3     2.77     6.76
##
##  Chisq= 6.8 on 1 degrees of freedom, p= 0.009
```

The p-value is even smaller than the log-rank p-value. This not only confirms the result of the log-rank test but also suggests that the survival advantage for females is particularly pronounced at the beginning and middle of the follow-up period.

```

# Fleming-Harrington test statistic
fit_sex <- ten(surv_object ~ sex, data = lung_cc)
comp(fit_sex)

##                                Q      Var      Z pNorm
## 1      -13.2826    29.2085 -2.4577    5
## n     -1424.0000 303810.1223 -2.5835    4
## sqrtN   -133.2089  2591.7008 -2.6166    1
## S1      -9.0659   12.2163 -2.5938    2
## S2      -8.9740   11.9825 -2.5925    3
## FH_p=1_q=1   -2.1759    1.0197 -2.1548    6
## maxAbsZ      Var      Q pSupBr
## 1      1.3806e+01 2.9209e+01 2.5545    5
## n      1.4410e+03 3.0381e+05 2.6143    4
## sqrtN   1.3534e+02 2.5917e+03 2.6585    1
## S1      9.1529e+00 1.2216e+01 2.6187    2
## S2      9.0560e+00 1.1982e+01 2.6162    3
## FH_p=1_q=1 2.2505e+00 1.0197e+00 2.2287    6

lrt_mat <- attr(fit_sex, "lrt")
data.frame(
  test = c("Log-Rank", "Wilcoxon", "Tarone", "Peto", "Modified-Peto", "FH(1, 1)"),
  Z_squared = lrt_mat[, "Z"]^2
)

##          test      Z
## 1 Log-Rank 6.040270
## 2 Wilcoxon 6.674485
## 3 Tarone  6.846710
## 4 Peto    6.727883
## 5 Modified-Peto 6.720914
## 6 FH(1, 1) 4.643096

```

The final summary table (`Z_squared`) shows that regardless of the specific test used, the result is always highly significant (all Z^2 values correspond to p-values well below 0.05).

ECOG performance status (unstratified)

```

# --- Fit the Kaplan-Meier model for ph_ecog ---
km_ecog_fit <- survfit(surv_object ~ ph_ecog, data = lung_cc)

summary(km_ecog_fit)

## Call: survfit(formula = surv_object ~ ph_ecog, data = lung_cc)
##
##          ph_ecog=0
##  time n.risk n.event survival std.err lower 95% CI upper 95% CI
##    5     47      1    0.979  0.0210    0.9383    1.000
##   15     46      1    0.957  0.0294    0.9014    1.000
##   31     45      1    0.936  0.0357    0.8688    1.000
##   53     44      1    0.915  0.0407    0.8385    0.998
##   81     43      1    0.894  0.0450    0.8097    0.986
##  147     42      1    0.872  0.0487    0.7820    0.973
##  176     40      1    0.851  0.0521    0.7543    0.959
##  246     34      1    0.826  0.0563    0.7223    0.944

```

```

##   267    30     1   0.798   0.0607   0.6874   0.926
##   285    26     1   0.767   0.0657   0.6487   0.908
##   286    25     1   0.737   0.0699   0.6116   0.887
##   303    22     1   0.703   0.0743   0.5716   0.865
##   320    21     1   0.670   0.0779   0.5331   0.841
##   337    19     1   0.634   0.0814   0.4933   0.816
##   348    18     1   0.599   0.0842   0.4549   0.789
##   353    17     2   0.529   0.0878   0.3818   0.732
##   371    15     1   0.493   0.0887   0.3468   0.702
##   428    12     1   0.452   0.0904   0.3057   0.669
##   433    11     1   0.411   0.0910   0.2664   0.635
##   455    10     1   0.370   0.0907   0.2289   0.598
##   558     9     1   0.329   0.0895   0.1930   0.561
##   574     7     1   0.282   0.0882   0.1527   0.520
##   643     6     1   0.235   0.0851   0.1155   0.478
##   655     5     1   0.188   0.0800   0.0816   0.433
##   705     4     1   0.141   0.0725   0.0515   0.386
##   791     3     1   0.094   0.0617   0.0260   0.340
##
##          ph_ecog=1
##   time n.risk n.event survival std.err lower 95% CI upper 95% CI
##   59      81      1   0.9877  0.0123   0.9639   1.000
##   60      80      2   0.9630  0.0210   0.9227   1.000
##   62      78      1   0.9506  0.0241   0.9046   0.999
##   79      77      1   0.9383  0.0267   0.8873   0.992
##   88      76      1   0.9259  0.0291   0.8706   0.985
##   92      75      1   0.9136  0.0312   0.8544   0.977
##   95      74      1   0.9012  0.0331   0.8385   0.969
##   110     73      1   0.8889  0.0349   0.8230   0.960
##   135     72      1   0.8765  0.0366   0.8078   0.951
##   142     71      1   0.8642  0.0381   0.7927   0.942
##   145     70      1   0.8519  0.0395   0.7779   0.933
##   156     69      1   0.8395  0.0408   0.7633   0.923
##   163     68      2   0.8148  0.0432   0.7345   0.904
##   167     66      1   0.8025  0.0442   0.7203   0.894
##   170     65      1   0.7901  0.0452   0.7062   0.884
##   179     62      1   0.7774  0.0463   0.6918   0.874
##   181     61      2   0.7519  0.0481   0.6632   0.852
##   197     57      1   0.7387  0.0491   0.6485   0.841
##   207     54      1   0.7250  0.0500   0.6333   0.830
##   210     53      1   0.7113  0.0509   0.6182   0.818
##   218     52      1   0.6977  0.0517   0.6033   0.807
##   223     49      1   0.6834  0.0526   0.5877   0.795
##   226     47      1   0.6689  0.0535   0.5719   0.782
##   229     46      1   0.6543  0.0542   0.5562   0.770
##   230     45      1   0.6398  0.0550   0.5407   0.757
##   245     43      1   0.6249  0.0557   0.5248   0.744
##   268     42      1   0.6100  0.0563   0.5091   0.731
##   269     41      1   0.5952  0.0568   0.4936   0.718
##   270     40      1   0.5803  0.0573   0.4781   0.704
##   283     39      1   0.5654  0.0578   0.4628   0.691
##   284     38      1   0.5505  0.0581   0.4476   0.677
##   293     37      1   0.5356  0.0584   0.4325   0.663
##   301     35      1   0.5203  0.0587   0.4171   0.649

```

```

##   305    32     1  0.5041  0.0591    0.4006    0.634
##   345    31     1  0.4878  0.0594    0.3843    0.619
##   363    30     2  0.4553  0.0597    0.3521    0.589
##   390    27     1  0.4384  0.0598    0.3355    0.573
##   426    24     1  0.4202  0.0601    0.3175    0.556
##   429    23     1  0.4019  0.0602    0.2997    0.539
##   450    22     1  0.3836  0.0601    0.2821    0.522
##   457    21     1  0.3654  0.0600    0.2648    0.504
##   460    19     1  0.3461  0.0598    0.2467    0.486
##   473    18     1  0.3269  0.0595    0.2288    0.467
##   477    17     1  0.3077  0.0590    0.2112    0.448
##   519    16     1  0.2884  0.0584    0.1940    0.429
##   520    15     1  0.2692  0.0576    0.1770    0.409
##   550    13     1  0.2485  0.0568    0.1588    0.389
##   567    12     1  0.2278  0.0557    0.1411    0.368
##   583    11     1  0.2071  0.0543    0.1238    0.346
##   613    10     1  0.1864  0.0527    0.1071    0.324
##   641     9     1  0.1657  0.0507    0.0909    0.302
##   687     8     1  0.1450  0.0484    0.0753    0.279
##   689     7     1  0.1243  0.0457    0.0604    0.256
##   731     6     1  0.1035  0.0425    0.0463    0.232
##   765     4     1  0.0777  0.0390    0.0290    0.208
##
##          ph_ecog=2
##   time n.risk n.event survival std.err lower 95% CI upper 95% CI
##   11      38     1  0.9737  0.0260    0.9241  1.000
##   12      37     1  0.9474  0.0362    0.8790  1.000
##   13      36     1  0.9211  0.0437    0.8392  1.000
##   26      35     1  0.8947  0.0498    0.8023  0.998
##   30      34     1  0.8684  0.0548    0.7673  0.983
##   53      33     1  0.8421  0.0592    0.7338  0.966
##   54      32     1  0.8158  0.0629    0.7014  0.949
##   61      31     1  0.7895  0.0661    0.6699  0.930
##   65      30     1  0.7632  0.0690    0.6393  0.911
##   93      29     1  0.7368  0.0714    0.6093  0.891
##   95      28     1  0.7105  0.0736    0.5800  0.870
##  107     26     1  0.6832  0.0756    0.5499  0.849
##  153     25     1  0.6559  0.0774    0.5204  0.827
##  156     24     1  0.6285  0.0789    0.4915  0.804
##  163     23     1  0.6012  0.0800    0.4632  0.780
##  166     22     1  0.5739  0.0809    0.4353  0.757
##  180     21     1  0.5466  0.0815    0.4080  0.732
##  183     20     1  0.5192  0.0819    0.3811  0.707
##  199     19     1  0.4919  0.0820    0.3547  0.682
##  201     18     1  0.4646  0.0819    0.3288  0.656
##  212     16     1  0.4355  0.0818    0.3014  0.629
##  222     15     1  0.4065  0.0813    0.2747  0.602
##  239     14     1  0.3775  0.0805    0.2485  0.573
##  285     13     1  0.3484  0.0794    0.2229  0.545
##  288     12     1  0.3194  0.0779    0.1980  0.515
##  291     11     1  0.2904  0.0760    0.1738  0.485
##  310      9     1  0.2581  0.0741    0.1470  0.453
##  351      8     1  0.2258  0.0715    0.1214  0.420
##  361      7     1  0.1936  0.0682    0.0970  0.386

```

```

##   444      6      1  0.1613  0.0640      0.0741    0.351
##   524      4      1  0.1210  0.0594      0.0462    0.317
##   707      2      1  0.0605  0.0521      0.0112    0.327
##   814      1      1  0.0000     NaN        NA        NA
##
##          ph_ecog=3
##      time      n.risk      n.event      survival      std.err lower 95% CI
##      118          1           1           0             NaN        NA
## upper 95% CI
##      NA

ggsurvplot(
  km_ecog_fit,
  data = lung_cc,

  # --- Add Key Statistical Information ---
  pval = TRUE,                      # Display the log-rank test p-value
  conf.int = FALSE,                  # Show 95% confidence intervals

  # --- Add Contextual Information ---
  risk.table = TRUE,                 # Include a table showing the number of patients at risk
  risk.table.y.text.col = TRUE,       # Color the risk table text to match curves
  risk.table.y.text = FALSE,         # Remove y-axis tick labels from the risk table

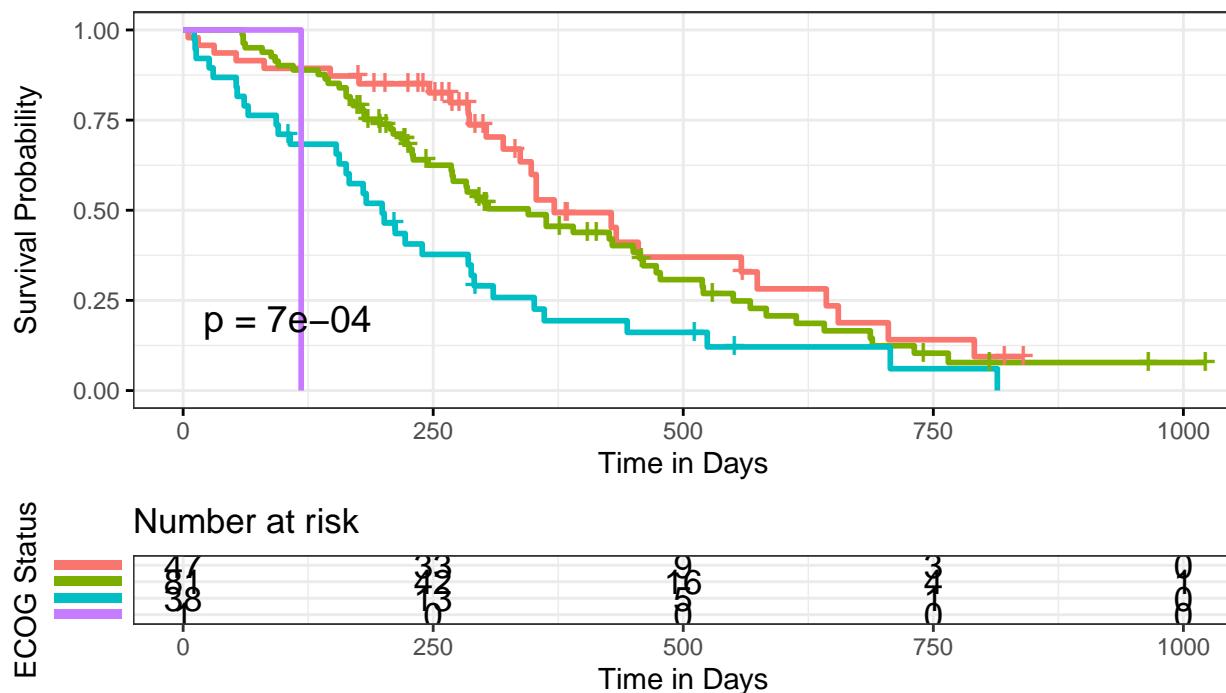
  # --- Customize Aesthetics and Labels ---
  title = "Kaplan-Meier Survival Curves by ECOG Performance Status",
  xlab = "Time in Days",
  ylab = "Survival Probability",
  legend.title = "ECOG Status",
  # Provide clear, descriptive labels for each group in the legend
  legend.labs = c(
    "0 (Asymptomatic)",
    "1 (Symptomatic, Ambulatory)",
    "2 (In bed <50% of day)",
    "3 (In bed >50% of day)"
  ),
  ggtheme = theme_bw()              # Use a clean black and white theme
)

## Ignoring unknown labels:
## * colour : "ECOG Status"

```

Kaplan–Meier Survival Curves by ECOG Performance Status

ECOG Status + 0 (Asymptomatic) + 1 (Symptomatic, Ambulatory) + 2 (In bed <50% of day) + 3 (In bed >= 50% of day)



```
# --- Perform the test ---
log_rank_ecog <- survdiff(surv_object ~ ph_ecog, data = lung_cc, rho = 0)
print(log_rank_ecog)
```

```
## Call:
## survdiff(formula = surv_object ~ ph_ecog, data = lung_cc, rho = 0)
##
##          N Observed Expected (0-E)^2/E (0-E)^2/V
## ph_ecog=0 47      27    38.054     3.211     4.737
## ph_ecog=1 81      59    62.376     0.183     0.383
## ph_ecog=2 38      33    19.394     9.546    11.483
## ph_ecog=3  1       1     0.176     3.864     3.895
##
##  Chisq= 17  on 3 degrees of freedom, p= 7e-04
wilcoxon_ecog <- survdiff(surv_object ~ ph_ecog, data = lung_cc, rho = 1)
print(wilcoxon_ecog)
```

```
## Call:
## survdiff(formula = surv_object ~ ph_ecog, data = lung_cc, rho = 1)
##
##          N Observed Expected (0-E)^2/E (0-E)^2/V
## ph_ecog=0 47     14.231   22.518     3.050     6.299
## ph_ecog=1 81     33.801   37.054     0.286     0.826
## ph_ecog=2 38     23.250   12.392     9.513    15.668
## ph_ecog=3  1      0.844    0.162     2.878     3.144
##
##  Chisq= 20.8  on 3 degrees of freedom, p= 1e-04
```

The fact that the Wilcoxon test yields a smaller p-value than the log-rank test suggests that the survival differences between the groups are particularly pronounced early in the follow-up period.

ECOG performance status (stratified by sex)

```
log_rank_ecog_bysex <- survdiff(surv_object ~ ph_ecog + strata(sex), data = lung_cc, rho = 0)
print(log_rank_ecog_bysex)

## Call:
## survdiff(formula = surv_object ~ ph_ecog + strata(sex), data = lung_cc,
##           rho = 0)
##
##          N Observed Expected (O-E)^2/E (O-E)^2/V
## ph_ecog=0 47      27    38.330     3.349     5.003
## ph_ecog=1 81      59    62.336     0.178     0.381
## ph_ecog=2 38      33    19.131     10.053    12.287
## ph_ecog=3  1       1     0.203     3.136     3.173
##
##  Chisq= 17.1  on 3 degrees of freedom, p= 7e-04
wilcoxon_ecog_bysex <- survdiff(surv_object ~ ph_ecog + strata(sex), data = lung_cc, rho = 1)
print(wilcoxon_ecog_bysex)

## Call:
## survdiff(formula = surv_object ~ ph_ecog + strata(sex), data = lung_cc,
##           rho = 1)
##
##          N Observed Expected (O-E)^2/E (O-E)^2/V
## ph_ecog=0 47    13.478   22.324     3.505     7.26
## ph_ecog=1 81    34.002   37.497     0.326     0.96
## ph_ecog=2 38    23.686   11.987    11.419    18.70
## ph_ecog=3  1     0.825    0.184     2.226     2.47
##
##  Chisq= 23.4  on 3 degrees of freedom, p= 3e-05
```

Log-rank: The result is virtually identical to the unstratified test. The Chi-square statistic and the p-value have barely changed. It means that the strong predictive power of ECOG status is independent of the patient's sex. The effect is not being confounded by sex.

Wilcoxon: After stratifying by sex, the Chi-square value increased (from 20.8 to 23.4) and the p-value became even smaller. This suggests that after controlling for the baseline survival differences between sexes, the effect of ECOG status on early deaths becomes even more pronounced and clear.

Final summary for stratified analysis: ECOG is an Independent Predictor: The effect of ECOG performance status on survival is not explained away by the patient's sex. It is a strong, independent prognostic factor. Sex is not acting as a major confounder in the relationship between ECOG status and survival. Whether a patient is male or female, having a worse ECOG score (e.g., a score of 2 vs. 0) is strongly associated with a significantly poorer survival outcome. The effect holds true within both groups.

Univariate Cox Regression (Single-variable screening)

```
# List of all predictor variables to test
predictors <- c("age", "sex", "ph_ecog", "ph_karno", "pat_karno", "meal_cal", "wt_loss")

# Create an empty list to store results
univariate_results <- list()
```

```

# Loop through each predictor and fit a univariate Cox model
for (var in predictors) {
  formula <- as.formula(paste("Surv(time, event) ~", var))
  cox_model <- coxph(formula, data = lung_cc)

  # Extract coefficients, HR, CI, and p-value
  summary_model <- summary(cox_model)

  univariate_results[[var]] <- data.frame(
    Variable = var,
    HR = summary_model$conf.int[1, "exp(coef)"],
    Lower_CI = summary_model$conf.int[1, "lower .95"],
    Upper_CI = summary_model$conf.int[1, "upper .95"],
    P_value = summary_model$coefficients[1, "Pr(>|z|)"]
  )
}

# Combine all results into one table
univariate_table <- do.call(rbind, univariate_results)
rownames(univariate_table) <- NULL

# Display the table
print(univariate_table)

##      Variable        HR   Lower_CI   Upper_CI     P_value
## 1       age 1.0200874 0.9988278 1.0417995 0.064195884
## 2       sex 0.6192558 0.4212238 0.9103896 0.014790685
## 3   ph_ecog 4.8252501 1.2331287 18.8812725 0.023758640
## 4   ph_karno 0.9878729 0.9749832 1.0009329 0.068635439
## 5  pat_karno 0.9812708 0.9694664 0.9932189 0.002199523
## 6   meal_cal 0.9998804 0.9994063 1.0003547 0.620970110
## 7   wt_loss 1.0001532 0.9871172 1.0133615 0.981737216

# Create a more detailed summary table using gtsummary
tbl_univariate <-
 tbl_uvregression(
  lung_cc %>% select(time, event, age, sex, ph_ecog, ph_karno, pat_karno, meal_cal, wt_loss),
  method = coxph,
  y = Surv(time, event),
  exponentiate = TRUE,
  pvalue_fun = ~style_pvalue(.x, digits = 3)
) %>%
bold_p(t = 0.05) %>%
bold_labels()

tbl_univariate

```

In univariable Cox models, female sex was associated with a substantially lower hazard of death compared with males (HR 0.62, 95% CI 0.42–0.91, p=0.015). Worse ECOG performance status showed a significant linear trend toward higher mortality risk (p for linear trend = 0.024). Higher patient-rated Karnofsky score was strongly protective (HR 0.98 per point, 95% CI 0.97–0.99, p=0.002). Age and physician-rated Karnofsky score exhibited borderline associations with survival, whereas meal calories and weight loss were not significantly associated with overall survival in univariable analyses

Characteristic	N	HR	95% CI	p-value
age	167	1.02	1.00, 1.04	0.064
sex	167	—	—	
Male		—	—	
Female		0.62	0.42, 0.91	0.015
ph_ecog	167	—	—	
ph_ecog.L		4.83	1.23, 18.9	0.024
ph_ecog.Q		1.63	0.58, 4.57	0.356
ph_ecog.C		1.08	0.64, 1.85	0.765
ph_karno	167	0.99	0.97, 1.00	0.069
pat_karno	167	0.98	0.97, 0.99	0.002
meal_cal	167	1.00	1.00, 1.00	0.621
wt_loss	167	1.00	0.99, 1.01	0.982

Abbreviations: CI = Confidence Interval, HR = Hazard Ratio

Variable Selection

```
significant_vars <- univariate_table %>%
  filter(P_value < 0.10) %>%
  pull(Variable)

print("Variables selected for multivariable model (p < 0.10):")

## [1] "Variables selected for multivariable model (p < 0.10):"
print(significant_vars)

## [1] "age"       "sex"       "ph_ecog"   "ph_karno"  "pat_karno"
```

Covariates with $p < 0.10$ in univariable Cox models were considered as candidates for the multivariable model. Given the strong clinical relevance, age and sex were retained a priori. Because physician- and patient-rated Karnofsky scores are highly correlated, we included only the patient-rated score (pat_karno), which showed a stronger univariable association ($p=0.002$), in the primary model.

Multivariable Cox Regression (Initial Model)

```
cox_multi_model <- coxph(Surv(time, event) ~ age + sex + ph_ecog + pat_karno,
                           data = lung_cc)

summary(cox_multi_model)

## Call:
## coxph(formula = Surv(time, event) ~ age + sex + ph_ecog + pat_karno,
##       data = lung_cc)
##
##    n= 167, number of events= 120
##
##              coef exp(coef)  se(coef)      z Pr(>|z|)
## age      0.006488  1.006509  0.011276  0.575  0.5650
## sexFemale -0.483159  0.616832  0.198121 -2.439  0.0147 *
## ph_ecog.L  1.325682  3.764752  0.711628  1.863  0.0625 .
```

```

## ph_ecog.Q  0.417938  1.518827  0.531404  0.786  0.4316
## ph_ecog.C  0.119441  1.126866  0.285060  0.419  0.6752
## pat_karno -0.006584  0.993438  0.008366 -0.787  0.4313
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##           exp(coef) exp(-coef) lower .95 upper .95
## age          1.0065    0.9935   0.9845   1.0290
## sexFemale    0.6168    1.6212   0.4183   0.9095
## ph_ecog.L    3.7648    0.2656   0.9332  15.1871
## ph_ecog.Q    1.5188    0.6584   0.5360   4.3037
## ph_ecog.C    1.1269    0.8874   0.6445   1.9702
## pat_karno    0.9934    1.0066   0.9773   1.0099
##
## Concordance= 0.653  (se = 0.031 )
## Likelihood ratio test= 21.4  on 6 df,  p=0.002
## Wald test          = 22.47  on 6 df,  p=0.001
## Score (logrank) test = 24.29  on 6 df,  p=5e-04

```

In the initial multivariable Cox model including age, sex, ECOG performance status, and patient-rated Karnofsky score, the overall model was statistically significant (likelihood ratio test $p = 0.002$), with a concordance index of 0.65, indicating moderate discriminative ability. After adjustment for the other covariates, female patients had a substantially lower hazard of death compared with males (HR 0.62, 95% CI 0.42–0.91, $p = 0.015$). ECOG performance status showed a borderline linear trend toward higher mortality (HR 3.76 for a one-step worsening in ECOG, 95% CI 0.93–15.19, $p = 0.063$). In contrast, age and patient-rated Karnofsky score were not significantly associated with survival in this multivariable model (all $p > 0.40$).

Tied Events Handling + Model Simplification

```

cox_multi_efron <- coxph(
  Surv(time, event) ~ age + sex + ph_ecog + pat_karno,
  data = lung_cc,
  ties = "efron"
)

cox_multi_breslow <- coxph(
  Surv(time, event) ~ age + sex + ph_ecog + pat_karno,
  data = lung_cc,
  ties = "breslow"
)

summary(cox_multi_efron)

## Call:
## coxph(formula = Surv(time, event) ~ age + sex + ph_ecog + pat_karno,
##       data = lung_cc, ties = "efron")
##
## n= 167, number of events= 120
##
##           coef exp(coef)  se(coef)      z Pr(>|z|)
## age      0.006488  1.006509  0.011276  0.575  0.5650
## sexFemale -0.483159  0.616832  0.198121 -2.439  0.0147 *
## ph_ecog.L  1.325682  3.764752  0.711628  1.863  0.0625 .
## ph_ecog.Q  0.417938  1.518827  0.531404  0.786  0.4316

```

```

## ph_ecog.C  0.119441  1.126866  0.285060  0.419   0.6752
## pat_karno -0.006584  0.993438  0.008366 -0.787   0.4313
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##          exp(coef) exp(-coef) lower .95 upper .95
## age         1.0065    0.9935    0.9845    1.0290
## sexFemale   0.6168    1.6212    0.4183    0.9095
## ph_ecog.L   3.7648    0.2656    0.9332   15.1871
## ph_ecog.Q   1.5188    0.6584    0.5360    4.3037
## ph_ecog.C   1.1269    0.8874    0.6445    1.9702
## pat_karno   0.9934    1.0066    0.9773    1.0099
##
## Concordance= 0.653  (se = 0.031 )
## Likelihood ratio test= 21.4  on 6 df,  p=0.002
## Wald test           = 22.47  on 6 df,  p=0.001
## Score (logrank) test = 24.29  on 6 df,  p=5e-04
summary(cox_multi_breslow)

## Call:
## coxph(formula = Surv(time, event) ~ age + sex + ph_ecog + pat_karno,
##       data = lung_cc, ties = "breslow")
##
## n= 167, number of events= 120
##
##          coef exp(coef)  se(coef)      z Pr(>|z|)
## age      0.006475  1.006496  0.011274  0.574   0.5657
## sexFemale -0.482427  0.617284  0.198125 -2.435   0.0149 *
## ph_ecog.L  1.326123  3.766413  0.711627  1.864   0.0624 .
## ph_ecog.Q  0.418666  1.519933  0.531395  0.788   0.4308
## ph_ecog.C  0.119903  1.127388  0.285042  0.421   0.6740
## pat_karno -0.006594  0.993427  0.008361 -0.789   0.4303
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##          exp(coef) exp(-coef) lower .95 upper .95
## age         1.0065    0.9935    0.9845    1.0290
## sexFemale   0.6173    1.6200    0.4186    0.9102
## ph_ecog.L   3.7664    0.2655    0.9337   15.1938
## ph_ecog.Q   1.5199    0.6579    0.5364    4.3067
## ph_ecog.C   1.1274    0.8870    0.6448    1.9711
## pat_karno   0.9934    1.0066    0.9773    1.0098
##
## Concordance= 0.653  (se = 0.031 )
## Likelihood ratio test= 21.37  on 6 df,  p=0.002
## Wald test           = 22.45  on 6 df,  p=0.001
## Score (logrank) test = 24.26  on 6 df,  p=5e-04

```

To assess the impact of tied event times, we refit the multivariable Cox model using both the Efron and Breslow methods for handling ties. The estimated hazard ratios, confidence intervals, and p-values were nearly identical across the two approaches, and the concordance index remained 0.65 in both models. These findings suggest that ties had minimal influence on the results, and we therefore used the Efron method in all subsequent analyses.

Model Simplification

```
# Remove non-significant variables (age, pat_karno)
# Test 3 simplified models

# Model A: Sex only (most parsimonious)
cox_model_A <- coxph(Surv(time, event) ~ sex, data = lung_cc)

# Model B: Sex + ph_ecog (categorical)
cox_model_B <- coxph(Surv(time, event) ~ sex + ph_ecog, data = lung_cc)

# Model C: Sex + ph_ecog (as numeric/ordinal)
lung_cc <- lung_cc %>%
  mutate(ph_ecog_num = as.numeric(as.character(ph_ecog)))

cox_model_C <- coxph(Surv(time, event) ~ sex + ph_ecog_num, data = lung_cc)

# Display all models
cat("=====\\n")

## =====
cat("Model A: Sex Only\\n")

## Model A: Sex Only
cat("=====\\n")

## =====
summary(cox_model_A)

## Call:
## coxph(formula = Surv(time, event) ~ sex, data = lung_cc)
##
##    n= 167, number of events= 120
##
##              coef exp(coef) se(coef)      z Pr(>|z|)
## sexFemale -0.4792    0.6193   0.1966 -2.437   0.0148 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##          exp(coef) exp(-coef) lower .95 upper .95
## sexFemale    0.6193     1.615    0.4212    0.9104
##
## Concordance= 0.567  (se = 0.025 )
## Likelihood ratio test= 6.25  on 1 df,  p=0.01
## Wald test           = 5.94  on 1 df,  p=0.01
## Score (logrank) test = 6.05  on 1 df,  p=0.01
cat("\\n=====\\n")

##
## =====
cat("Model B: Sex + ECOG (Categorical)\\n")

## Model B: Sex + ECOG (Categorical)
```

```

cat("=====\\n")
## =====
summary(cox_model_B)

## Call:
## coxph(formula = Surv(time, event) ~ sex + ph_ecog, data = lung_cc)
##
##    n= 167, number of events= 120
##
##          coef exp(coef) se(coef)      z Pr(>|z|)
## sexFemale -0.49977  0.60667  0.19741 -2.532  0.0114 *
## ph_ecog.L  1.47356  4.36475  0.69684  2.115  0.0345 *
## ph_ecog.Q  0.37911  1.46098  0.52802  0.718  0.4728
## ph_ecog.C  0.04551  1.04657  0.27299  0.167  0.8676
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##          exp(coef) exp(-coef) lower .95 upper .95
## sexFemale    0.6067     1.6483    0.4120    0.8933
## ph_ecog.L    4.3647     0.2291   11.138   17.1045
## ph_ecog.Q    1.4610     0.6845    0.5190    4.1124
## ph_ecog.C    1.0466     0.9555    0.6129    1.7870
##
## Concordance= 0.646  (se = 0.03 )
## Likelihood ratio test= 20.39  on 4 df,  p=4e-04
## Wald test           = 21.86  on 4 df,  p=2e-04
## Score (logrank) test = 23.52  on 4 df,  p=1e-04
cat("\\n=====\\n")

##
## =====
cat("Model C: Sex + ECOG (Numeric)\\n")

## Model C: Sex + ECOG (Numeric)
cat("=====\\n")

##
## =====
summary(cox_model_C)

## Call:
## coxph(formula = Surv(time, event) ~ sex + ph_ecog_num, data = lung_cc)
##
##    n= 167, number of events= 120
##
##          coef exp(coef) se(coef)      z Pr(>|z|)
## sexFemale   -0.5101    0.6004   0.1969 -2.591 0.009579 **
## ph_ecog_num  0.4825    1.6201   0.1323  3.647 0.000266 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##          exp(coef) exp(-coef) lower .95 upper .95
## sexFemale    0.6004     1.6655    0.4082    0.8832

```

```

## ph_ecog_num      1.6201      0.6172      1.2501      2.0998
##
## Concordance= 0.641  (se = 0.031 )
## Likelihood ratio test= 19.48 on 2 df,  p=6e-05
## Wald test          = 19.35 on 2 df,  p=6e-05
## Score (logrank) test = 19.62 on 2 df,  p=5e-05

# Model comparison
cat("\n=====\n")

##
## =====
cat("MODEL COMPARISON SUMMARY\n")

## MODEL COMPARISON SUMMARY
cat("=====\\n")

##
## =====

# Extract metrics
aic_A <- AIC(cox_model_A)
aic_B <- AIC(cox_model_B)
aic_C <- AIC(cox_model_C)

c_A <- summary(cox_model_A)$concordance[1]
c_B <- summary(cox_model_B)$concordance[1]
c_C <- summary(cox_model_C)$concordance[1]

cat("\nModel A (sex only):\n")

##
## Model A (sex only):
cat("  AIC =", round(aic_A, 2), "\\n")

##   AIC = 1011.99
cat("  C-index =", round(c_A, 3), "\\n")

##   C-index = 0.567
cat("\nModel B (sex + ph_ecog categorical):\n")

##
## Model B (sex + ph_ecog categorical):
cat("  AIC =", round(aic_B, 2), "\\n")

##   AIC = 1003.84
cat("  C-index =", round(c_B, 3), "\\n")

##   C-index = 0.646
cat("\nModel C (sex + ph_ecog numeric):\n")

##
## Model C (sex + ph_ecog numeric):

```

```

cat("  AIC =", round(aic_C, 2), "\n")
##   AIC = 1000.75
cat("  C-index =", round(c_C, 3), "\n")
##   C-index = 0.641
cat("\nNote: Lower AIC = Better fit\n")

##
## Note: Lower AIC = Better fit
cat("      Higher C-index = Better discrimination\n")

##      Higher C-index = Better discrimination
# Likelihood Ratio Tests
cat("\n=====\\n")

##
## =====
cat("LIKELIHOOD RATIO TESTS\\n")

## LIKELIHOOD RATIO TESTS
cat("=====\\n")

##
## =====
cat("\n--- Test 1: Model A vs Model B ---\\n")

##
## --- Test 1: Model A vs Model B ---
cat("(Does adding ph_ecog categorical improve the model?)\\n")

## (Does adding ph_ecog categorical improve the model?)
lrt_AB <- anova(cox_model_A, cox_model_B, test = "Chisq")
print(lrt_AB)

## Analysis of Deviance Table
## Cox model: response is Surv(time, event)
## Model 1: ~ sex
## Model 2: ~ sex + ph_ecog
##    loglik  Chisq Df Pr(>|Chi|)
## 1 -504.99
## 2 -497.92 14.144  3   0.002715 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
cat("\n--- Test 2: Model A vs Model C ---\\n")

##
## --- Test 2: Model A vs Model C ---
cat("(Does adding ph_ecog numeric improve the model?)\\n")

## (Does adding ph_ecog numeric improve the model?)

```

```

lrt_AC <- anova(cox_model_A, cox_model_C, test = "Chisq")
print(lrt_AC)

## Analysis of Deviance Table
## Cox model: response is Surv(time, event)
## Model 1: ~ sex
## Model 2: ~ sex + ph_ecog_num
##   loglik  Chisq Df Pr(>|Chi|)
## 1 -504.99
## 2 -498.38 13.235  1  0.0002747 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
cat("\n--- Test 3: Model B vs Model C ---\n")

## 
## --- Test 3: Model B vs Model C ---
cat("(Is categorical or numeric ph_ecog better?)\n")

## (Is categorical or numeric ph_ecog better?)

lrt_BC <- anova(cox_model_C, cox_model_B, test = "Chisq")
print(lrt_BC)

## Analysis of Deviance Table
## Cox model: response is Surv(time, event)
## Model 1: ~ sex + ph_ecog_num
## Model 2: ~ sex + ph_ecog
##   loglik  Chisq Df Pr(>|Chi|)
## 1 -498.38
## 2 -497.92 0.9089  2      0.6348

```

Starting from a multivariable model including age, sex, ECOG performance status, and patient-rated Karnofsky score, we removed age ($p=0.565$) and patient-rated Karnofsky score ($p=0.431$) as they were not statistically significant after adjustment for other covariates. We then compared three reduced Cox models: (A) sex only, (B) sex plus ECOG treated as a categorical factor, and (C) sex plus ECOG treated as a numeric ordinal variable (0–3).

Adding ECOG status substantially improved model fit compared with the sex-only model. For model B, the likelihood ratio test versus model A yielded $\chi^2=14.14$ on 3 df ($p=0.003$), with concordance increasing from 0.567 to 0.646. For model C, the likelihood ratio test versus model A yielded $\chi^2=13.24$ on 1 df ($p<0.001$), with concordance of 0.641. Models B and C demonstrated similar performance (AIC=1003.84 vs 1000.75; C-index=0.646 vs 0.641), with no significant difference between them ($\chi^2=0.91$ on 2 df, $p=0.635$).

We selected model C (sex + ECOG as a numeric ordinal variable) as the final Cox model based on the principle of parsimony: it achieved similar predictive performance with fewer parameters (2 vs 4) and offered a simpler, more interpretable linear effect for ECOG performance status.