

# Sensitivity Analysis: Cox Proportional Hazards Model

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```
library(tidyverse)
library(survival)
library(forestplot)
library(glmnet)
library(ggfortify)
library(kableExtra) # include knitr automatically

source("/work/users/y/u/youkias/BIOS-Material/BIOS992/utils/csv_utils.r")
# * Don't use setwd() for Quarto documents!
# setwd("/work/users/y/u/youkias/BIOS-Material/BIOS992/data")

adjust_type <- ifelse(exists("params"), params$adjust_type, "full") #
↪ options: "minimal", "partial", "full"
```

```

impute_type <- ifelse(exists("params"), params$impute_type, "unimputed") #
  ↪ options: "unimputed", "imputed"
include_statin <- ifelse(exists("params"), params$include_statin, "no") #
  ↪ options: "yes", "no"

```

```

# string of parameters
adjust_type_str <- switch(adjust_type,
  minimal = "minimal",
  partial = "partial",
  full = "full"
)
print(paste0("Model Adjustment Type: ", adjust_type_str))

```

```
[1] "Model Adjustment Type: full"
```

```

impute_type_str <- switch(impute_type,
  unimputed = "unimputed",
  imputed = "imputed"
)
print(paste0("Data Imputation Type: ", impute_type_str))

```

```
[1] "Data Imputation Type: unimputed"
```

## Load Data

```

if (include_statin == "yes") {
  data_train <-
  ↪ read.csv(paste0("/work/users/y/u/youkias/BIOS-Material/BIOS992/data/train_data_",
  ↪ impute_type_str, "_statin.csv"),
    header = TRUE
  )
} else {
  data_train <-
  ↪ read.csv(paste0("/work/users/y/u/youkias/BIOS-Material/BIOS992/data/train_data_",
  ↪ impute_type_str, ".csv"),
    header = TRUE
  )
}

```

```
}
```

```
data_train <- data_train[, -1] # the first column is the index generated by  
↪ sklearn  
(dim(data_train))
```

```
[1] 28127    100
```

```
data <- select_subset(data_train, type = adjust_type)  
(dim(data))
```

```
[1] 28127    89
```

```
colnames(data)
```

[1] "event"	"time"
[3] "age"	"sex"
[5] "ethnicity"	"BMI"
[7] "smoking"	"diabetes"
[9] "systolic_bp"	"hypertension_treatment"
[11] "total_chol"	"hdl_chol"
[13] "education"	"activity"
[15] "max_workload"	"max_heart_rate"
[17] "HRV_MeanNN"	"HRV_SDNN"
[19] "HRV_RMSSD"	"HRV_SDSD"
[21] "HRV_CVNN"	"HRV_CVSD"
[23] "HRV_MedianNN"	"HRV_MadNN"
[25] "HRV_MCVNN"	"HRV_IQRNN"
[27] "HRV_SDRMSSD"	"HRV_Prc20NN"
[29] "HRV_Prc80NN"	"HRV_pNN50"
[31] "HRV_pNN20"	"HRV_MinNN"
[33] "HRV_MaxNN"	"HRV_HTI"
[35] "HRV_TINN"	"HRV_LF"
[37] "HRV_HF"	"HRV_VHF"
[39] "HRV_TP"	"HRV_LFHF"
[41] "HRV_LFn"	"HRV_HFn"
[43] "HRV_LnHF"	"HRV_SD1"
[45] "HRV_SD2"	"HRV_SD1SD2"
[47] "HRV_S"	"HRV_CSI"

[49] "HRV_CVI"	"HRV_CSI_Modified"
[51] "HRV_PIP"	"HRV_IALS"
[53] "HRV_PSS"	"HRV_PAS"
[55] "HRV_GI"	"HRV_SI"
[57] "HRV_AI"	"HRV_PI"
[59] "HRV_C1d"	"HRV_C1a"
[61] "HRV_SD1d"	"HRV_SD1a"
[63] "HRV_C2d"	"HRV_C2a"
[65] "HRV_SD2d"	"HRV_SD2a"
[67] "HRV_Cd"	"HRV_Ca"
[69] "HRV_SDNNd"	"HRV_SDNNa"
[71] "HRV_ApEn"	"HRV_ShanEn"
[73] "HRV_FuzzyEn"	"HRV_MSEn"
[75] "HRV_CMSEn"	"HRV_RCMSEn"
[77] "HRV_CD"	"HRV_HFD"
[79] "HRV_KFD"	"HRV_LZC"
[81] "HRV_DFA_alpha1"	"HRV_MFDFA_alpha1_Width"
[83] "HRV_MFDFA_alpha1_Peak"	"HRV_MFDFA_alpha1_Mean"
[85] "HRV_MFDFA_alpha1_Max"	"HRV_MFDFA_alpha1_Delta"
[87] "HRV_MFDFA_alpha1_Asymmetry"	"HRV_MFDFA_alpha1_Fluctuation"
[89] "HRV_MFDFA_alpha1_Increment"	

```
data <- tibble::as_tibble(data)
```

```
# * There are some imputed ethnicity set to "e". We will exclude them at this
  ↪ time.
```

```
data <- data %>%
  filter(ethnicity != "e")
```

```
# * We also need to manually relevel the categorical variables
```

```
data <- data %>%
  mutate(
    # Set "Never" (0) as baseline for smoking
    smoking = factor(smoking,
      levels = c("0", "1", "2", "-3"),
      labels = c("Never", "Previous", "Current", "Prefer not to
        ↪ answer")
    ),

    # Set "No" (0) as baseline for diabetes
    diabetes = factor(diabetes,
      levels = c("0", "1", "-1", "-3"),
```

```

    labels = c("No", "Yes", "Do not know", "Prefer not to answer")
  ),

  # Ensure other categorical variables are properly factored
  ethnicity = factor(ethnicity,
    levels = c("1", "2", "3", "4", "5", "6"),
    labels = c("White", "Mixed", "Asian/Asian British", "Black/Black
    ↪ British", "Chinese", "Other")
  ),
  education = factor(education,
    levels = c("1", "2", "3", "4", "5", "6", "-7", "-3"),
    labels = c(
      "College/University degree", "A levels/AS levels",
      "0 levels/GCSEs", "CSEs", "NVQ/HND/HNC",
      "Other professional", "None of the above",
      "Prefer not to answer"
    )
  ),
  activity = factor(activity,
    levels = c("0", "1", "2"),
    labels = c("Low", "Moderate", "High")
  ),
  sex = factor(sex,
    levels = c("0", "1"),
    labels = c("Female", "Male")
  ),
  hypertension_treatment = factor(hypertension_treatment,
    levels = c("0", "1"),
    labels = c("No", "Yes")
  )
)

```

```

# * It is very hard to compare the HR as different predictors are on
  ↪ different magnitudes, so we need to normalize them.
time_col <- data$time
event_col <- data$event
data <- data %>%
  select(-c(time, event)) %>%
  mutate(across(where(is.numeric), scale)) %>%
  mutate(
    time = time_col,

```

```

    event = event_col
  )

```

Note now the interpretation of HR is different! For example, if HR=1.16 for the predictor in the univariate model fitted using scaled data, it means that each standard deviation increase is associated with 16% higher risk of event.

```

data_complete <- na.omit(data)

```

## Univariate Cox Proportional Hazards Model

```

if (!("time" %in% colnames(data) && "event" %in% colnames(data))) {
  stop("time and event columns are required")
}
predictors <- colnames(data)[!colnames(data) %in% c("time", "event")]

results_univariate <- map_dfr(predictors, function(predictor) {
  formula <- as.formula(paste("Surv(time, event) ~", predictor))
  # cox_model_single <- coxph(Surv(time, event) ~ get(predictor), data =
  ↪ data) # equivalent way
  cox_model_single <- coxph(formula, data = data)

  coef <- coef(cox_model_single) # log hazard ratio
  se <- sqrt(diag(vcov(cox_model_single)))

  hr <- exp(coef)
  lower_ci <- exp(coef - 1.96 * se)
  upper_ci <- exp(coef + 1.96 * se)
  p_value <-
  ↪ summary(cox_model_single)$coefficients[1:dim(summary(cox_model_single)$coefficients)[1],
  ↪ 5]

  if (determine_type(predictor) == "categorical") {
    # exclude -1, -3, -7 in names
    return(
      data.frame(
        predictor = names(coef),
        hr = hr,

```

```

        lower_ci = lower_ci,
        upper_ci = upper_ci,
        p_value = p_value
    )
} else {
    return(
        data.frame(
            predictor = predictor,
            hr = hr,
            lower_ci = lower_ci,
            upper_ci = upper_ci,
            p_value = p_value
        )
    )
}
})
results_univariate$hr <- round(results_univariate$hr, 2)
results_univariate$lower_ci <- round(results_univariate$lower_ci, 2)
results_univariate$upper_ci <- round(results_univariate$upper_ci, 2)
results_univariate$ci <- paste0("(", results_univariate$lower_ci, ",",
  ↪ results_univariate$upper_ci, ")")
results_univariate$p_value <- round(results_univariate$p_value, 3)
results_univariate <- results_univariate %>% arrange(desc(hr)) # sort
  ↪ descendingly by HR

```

```

# Create forest plot
results_univariate %>%
  forestplot(
    labeltext = c(predictor, hr, ci, p_value),
    mean = hr,
    lower = lower_ci,
    upper = upper_ci,
    xlab = "Hazard Ratio",
    title = "Univariate Cox Models",
    xlog = TRUE, # * Make sure the CI are not symmetric and need to be
  ↪ transformed
    boxsize = 0.2,
    xticks = c(0.2, 0.4, 0.8, 1.2, 1.6, 2.0, 2.4, 2.8, 3.2),
    clip = c(0.2, 3.2),
    zero = 1
  )

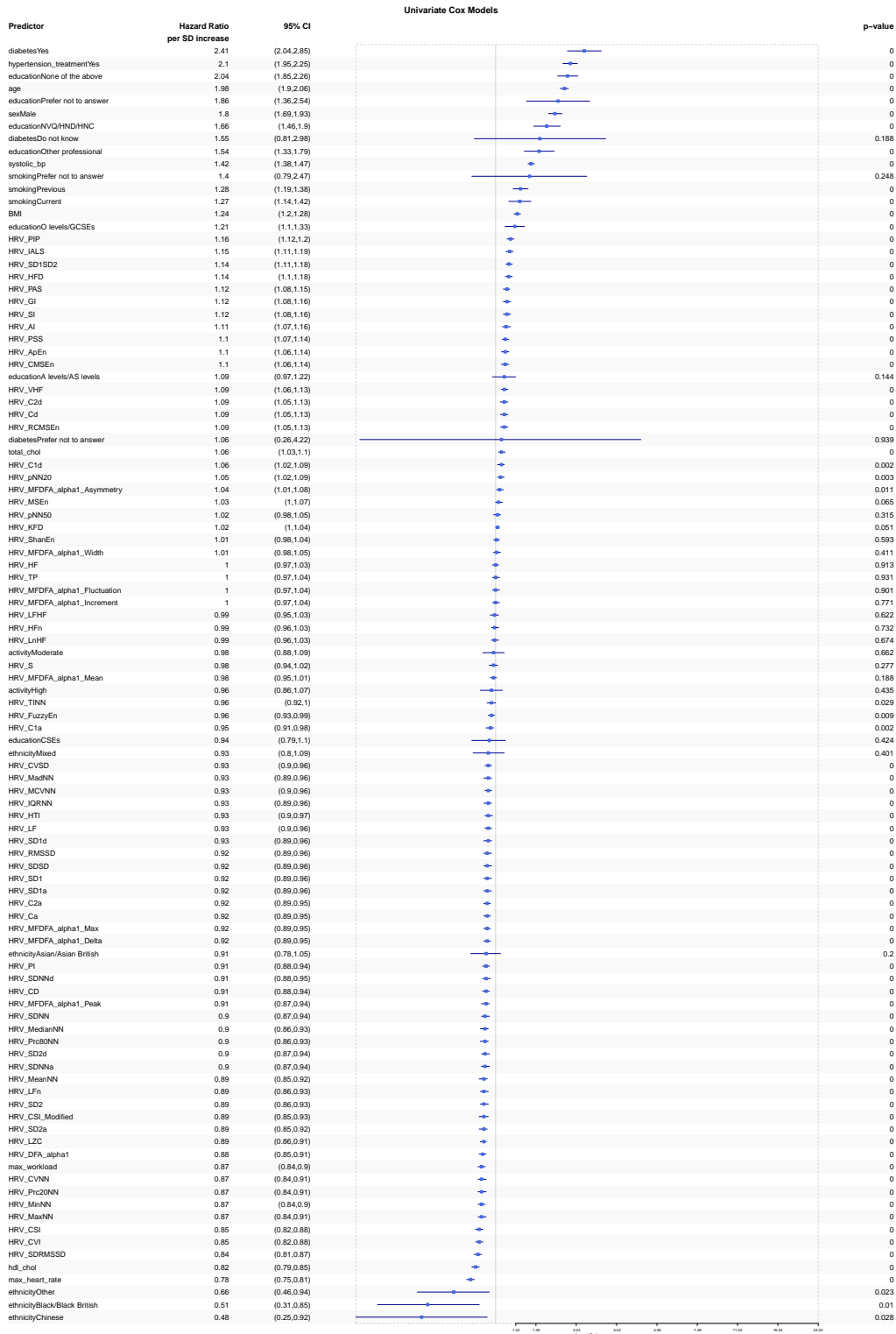
```

```

) %>%
fp_set_style(
  box = "royalblue",
  line = "darkblue",
  summary = "royalblue"
) %>%
fp_add_header(
  predictor = c("Predictor", ""),
  hr = c("Hazard Ratio", "per SD increase"),
  ci = c("95% CI", ""),
  p_value = c("p-value", "")
) %>%
fp_decorate_graph(
  box = gpar(lty = 2, col = "lightgray"),
  graph.pos = 4
) %>% # change the position of forest plot
fp_set_zebra_style("#f9f9f9")

```





## Multivariate Cox Proportional Hazards Model

```
cox_model_full <- coxph(Surv(time, event) ~ ., data = data)
summary(cox_model_full)
```

```
cox_model_full_complete <- coxph(Surv(time, event) ~ ., data = data_complete)
summary(cox_model_full_complete)
```

## PH Assumption Assessment

```
cox.zph(cox_model_full)
```

	chisq	df	p
age	2.66e-01	1	0.60618
sex	6.93e+00	1	0.00848
ethnicity	2.22e+00	5	0.81765
BMI	5.50e-02	1	0.81457
smoking	3.37e+00	3	0.33740
diabetes	4.14e+00	3	0.24646
systolic_bp	4.69e-01	1	0.49347
hypertension_treatment	1.14e+01	1	0.00073
total_chol	1.18e+00	1	0.27710
hdl_chol	5.43e+00	1	0.01980
education	2.37e+00	7	0.93622
activity	1.74e+00	2	0.41794
max_workload	3.06e+00	1	0.08017
max_heart_rate	2.94e+00	1	0.08641
HRV_MeanNN	5.04e+00	1	0.02475
HRV_SDNN	3.01e+00	1	0.08268
HRV_RMSSD	3.28e+00	1	0.07025
HRV_SDSD	3.31e+00	1	0.06896
HRV_CVNN	1.30e+00	1	0.25512
HRV_CVSD	1.39e+00	1	0.23887
HRV_MedianNN	6.72e+00	1	0.00953
HRV_MadNN	3.38e+00	1	0.06608
HRV_MCVNN	1.13e-01	1	0.73656
HRV_IQRNN	3.91e+00	1	0.04796

HRV_SDRMSSD	1.40e-01	1	0.70822
HRV_Prc20NN	2.04e+00	1	0.15357
HRV_Prc80NN	5.40e+00	1	0.02015
HRV_pNN50	1.41e-01	1	0.70695
HRV_pNN20	1.55e+00	1	0.21270
HRV_MinNN	9.02e-01	1	0.34233
HRV_MaxNN	2.00e+00	1	0.15730
HRV_HTI	8.59e-01	1	0.35395
HRV_TINN	1.91e+00	1	0.16651
HRV_LF	1.59e+00	1	0.20714
HRV_HF	2.34e-02	1	0.87843
HRV_VHF	1.57e-01	1	0.69194
HRV_LFHF	2.24e+00	1	0.13460
HRV_LFn	1.49e+00	1	0.22222
HRV_HFn	1.49e+00	1	0.22202
HRV_LnHF	1.78e-01	1	0.67305
HRV_SD2	3.03e+00	1	0.08164
HRV_SD1SD2	4.66e-02	1	0.82916
HRV_S	2.38e+00	1	0.12251
HRV_CSI	2.42e-02	1	0.87644
HRV_CVI	2.29e+00	1	0.12985
HRV_CSI_Modified	2.13e+00	1	0.14419
HRV_PIP	5.69e-01	1	0.45052
HRV_IALS	2.98e-01	1	0.58500
HRV_PSS	5.59e-01	1	0.45484
HRV_PAS	1.70e+00	1	0.19165
HRV_GI	1.69e+00	1	0.19373
HRV_SI	2.31e+00	1	0.12882
HRV_AI	1.03e+00	1	0.31130
HRV_PI	2.65e-01	1	0.60664
HRV_C1d	3.50e-01	1	0.55392
HRV_SD1d	3.44e+00	1	0.06361
HRV_SD1a	3.17e+00	1	0.07516
HRV_C2d	2.96e-01	1	0.58615
HRV_SD2d	2.50e+00	1	0.11379
HRV_SD2a	3.32e+00	1	0.06860
HRV_Cd	6.29e-01	1	0.42789
HRV_SDNNd	3.06e+00	1	0.08027
HRV_SDNNa	3.44e+00	1	0.06371
HRV_ApEn	3.01e+00	1	0.08288
HRV_ShanEn	5.80e-01	1	0.44644
HRV_FuzzyEn	6.57e-01	1	0.41778
HRV_MSEn	4.54e-01	1	0.50032

HRV_CMSEn	3.19e+00	1	0.07390
HRV_RCMSEn	1.87e+00	1	0.17105
HRV_CD	5.79e-04	1	0.98081
HRV_HFD	1.13e-01	1	0.73644
HRV_KFD	8.23e-01	1	0.36421
HRV_LZC	3.40e-06	1	0.99853
HRV_DFA_alpha1	1.86e-02	1	0.89149
HRV_MFDFA_alpha1_Width	3.97e-03	1	0.94978
HRV_MFDFA_alpha1_Peak	7.05e-01	1	0.40126
HRV_MFDFA_alpha1_Mean	1.54e-02	1	0.90124
HRV_MFDFA_alpha1_Max	2.80e-02	1	0.86715
HRV_MFDFA_alpha1_Delta	4.98e-02	1	0.82347
HRV_MFDFA_alpha1_Asymmetry	1.94e-02	1	0.88926
HRV_MFDFA_alpha1_Fluctuation	4.39e-03	1	0.94720
HRV_MFDFA_alpha1_Increment	7.86e-04	1	0.97764
GLOBAL	1.26e+02	97	0.02429

```
cox.zph(cox_model_full_complete)
```

	chisq	df	p
age	2.66e-01	1	0.60618
sex	6.93e+00	1	0.00848
ethnicity	2.22e+00	5	0.81765
BMI	5.50e-02	1	0.81457
smoking	3.37e+00	3	0.33740
diabetes	4.14e+00	3	0.24646
systolic_bp	4.69e-01	1	0.49347
hypertension_treatment	1.14e+01	1	0.00073
total_chol	1.18e+00	1	0.27710
hdl_chol	5.43e+00	1	0.01980
education	2.37e+00	7	0.93622
activity	1.74e+00	2	0.41794
max_workload	3.06e+00	1	0.08017
max_heart_rate	2.94e+00	1	0.08641
HRV_MeanNN	5.04e+00	1	0.02475
HRV_SDNN	3.01e+00	1	0.08268
HRV_RMSSD	3.28e+00	1	0.07025
HRV_SDS	3.31e+00	1	0.06896
HRV_CVNN	1.30e+00	1	0.25512
HRV_CVSD	1.39e+00	1	0.23887
HRV_MedianNN	6.72e+00	1	0.00953
HRV_MadNN	3.38e+00	1	0.06608

HRV_MCVNN	1.13e-01	1	0.73656
HRV_IQRNN	3.91e+00	1	0.04796
HRV_SDRMSSD	1.40e-01	1	0.70822
HRV_Prc20NN	2.04e+00	1	0.15357
HRV_Prc80NN	5.40e+00	1	0.02015
HRV_pNN50	1.41e-01	1	0.70695
HRV_pNN20	1.55e+00	1	0.21270
HRV_MinNN	9.02e-01	1	0.34233
HRV_MaxNN	2.00e+00	1	0.15730
HRV_HTI	8.59e-01	1	0.35395
HRV_TINN	1.91e+00	1	0.16651
HRV_LF	1.59e+00	1	0.20714
HRV_HF	2.34e-02	1	0.87843
HRV_VHF	1.57e-01	1	0.69194
HRV_LFHF	2.24e+00	1	0.13460
HRV_LFn	1.49e+00	1	0.22222
HRV_HFn	1.49e+00	1	0.22202
HRV_LnHF	1.78e-01	1	0.67305
HRV_SD2	3.03e+00	1	0.08164
HRV_SD1SD2	4.66e-02	1	0.82916
HRV_S	2.38e+00	1	0.12251
HRV_CSI	2.42e-02	1	0.87644
HRV_CVI	2.29e+00	1	0.12985
HRV_CSI_Modified	2.13e+00	1	0.14419
HRV_PIP	5.69e-01	1	0.45052
HRV_IALS	2.98e-01	1	0.58500
HRV_PSS	5.59e-01	1	0.45484
HRV_PAS	1.70e+00	1	0.19165
HRV_GI	1.69e+00	1	0.19373
HRV_SI	2.31e+00	1	0.12882
HRV_AI	1.03e+00	1	0.31130
HRV_PI	2.65e-01	1	0.60664
HRV_C1d	3.50e-01	1	0.55392
HRV_SD1d	3.44e+00	1	0.06361
HRV_SD1a	3.17e+00	1	0.07516
HRV_C2d	2.96e-01	1	0.58615
HRV_SD2d	2.50e+00	1	0.11379
HRV_SD2a	3.32e+00	1	0.06860
HRV_Cd	6.29e-01	1	0.42789
HRV_SDNNd	3.06e+00	1	0.08027
HRV_SDNNa	3.44e+00	1	0.06371
HRV_ApEn	3.01e+00	1	0.08288
HRV_ShanEn	5.80e-01	1	0.44644

HRV_FuzzyEn	6.57e-01	1	0.41778
HRV_MSEn	4.54e-01	1	0.50032
HRV_CMSEn	3.19e+00	1	0.07390
HRV_RCMSEn	1.87e+00	1	0.17105
HRV_CD	5.79e-04	1	0.98081
HRV_HFD	1.13e-01	1	0.73644
HRV_KFD	8.23e-01	1	0.36421
HRV_LZC	3.40e-06	1	0.99853
HRV_DFA_alpha1	1.86e-02	1	0.89149
HRV_MFDFA_alpha1_Width	3.97e-03	1	0.94978
HRV_MFDFA_alpha1_Peak	7.05e-01	1	0.40126
HRV_MFDFA_alpha1_Mean	1.54e-02	1	0.90124
HRV_MFDFA_alpha1_Max	2.80e-02	1	0.86715
HRV_MFDFA_alpha1_Delta	4.98e-02	1	0.82347
HRV_MFDFA_alpha1_Asymmetry	1.94e-02	1	0.88926
HRV_MFDFA_alpha1_Fluctuation	4.39e-03	1	0.94720
HRV_MFDFA_alpha1_Increment	7.86e-04	1	0.97764
GLOBAL	1.26e+02	97	0.02429

The proportional hazards assumption was tested using Schoenfeld residuals. None of the variables violated the PH assumption (all  $p > 0.05$ ), indicating that the Cox proportional hazards model was appropriate for our analysis.

## Variable Selection

### LASSO

```
# * LASSO doesn't allow missing values
set.seed(1234)
# x <- as.matrix(data_complete %>% select(-c(time, event)))
# * We need to explicitly use model.matrix for categorical variables
x <- model.matrix(~ . - 1 - time - event, data = data_complete)
y <- Surv(data_complete$time, data_complete$event)
cox_model_lasso.cv <- cv.glmnet(
  x,
  y,
  family = "cox",
  alpha = 1, # 1 for LASSO, 0 for Ridge
  nfolds = 10
)
```

```
# plot(cox_model_lasso.cv) # Plot partial likelihood deviance vs log(lambda)
print(cox_model_lasso.cv$lambda.min)
```

```
[1] 0.007299261
```

```
print(cox_model_lasso.cv$lambda.1se)
```

```
[1] 0.01536424
```

As mentioned in the paper, we will use the value of hyperparameter `lambda.1se` that gave the most shrunk model but still was within one standard error from the value that gave the lowest error. This is shown to produce consistently better performance than `lambda.min`.

```
cox_model_lasso <- glmnet(
  x,
  y,
  family = "cox",
  alpha = 1,
  lambda = cox_model_lasso.cv$lambda.1se
)
cox_model_lasso.coef <- coef(cox_model_lasso)
print(cox_model_lasso.coef)
selected_vars <- rownames(cox_model_lasso.coef)[which(cox_model_lasso.coef !=
  ↪ 0)]
print(selected_vars)
```

```
# * To visualize the LASSO path, we should not supply lambda
cox_model_lasso_fullpath <- glmnet(
  x,
  y,
  family = "cox",
  alpha = 1
)
```

```
# plot(cox_model_lasso_fullpath, xvar = "lambda", label = TRUE)
autoplot(cox_model_lasso_fullpath, xvar = "lambda", label = TRUE, label.size
  ↪ = 15) +
  theme_bw() +
  theme(legend.position = "bottom") # better way of visualizing the LASSO
  ↪ path
```





## Stepwise Selection based on BIC

```
# * Stepwise selection doesn't allow missing values
cox_model_step <- MASS::stepAIC(cox_model_full_complete,
  direction = "both",
  k = log(nrow(data)), # Use BIC instead of AIC
  trace = FALSE
)
```

```
summary(cox_model_step)
```

Call:

```
coxph(formula = Surv(time, event) ~ age + sex + ethnicity + BMI +
  smoking + diabetes + systolic_bp + hypertension_treatment +
  total_chol + hdl_chol + education + activity + max_workload +
  max_heart_rate + HRV_MeanNN + HRV_SDNN + HRV_RMSSD + HRV_SDSD +
  HRV_CVNN + HRV_CVSD + HRV_MedianNN + HRV_MadNN + HRV_MCVNN +
  HRV_IQRNN + HRV_SDRMSSD + HRV_Prc20NN + HRV_Prc80NN + HRV_pNN50 +
  HRV_pNN20 + HRV_MinNN + HRV_MaxNN + HRV_HTI + HRV_TINN +
  HRV_LF + HRV_HF + HRV_TP + HRV_LFHF + HRV_LFn + HRV_HFn +
  HRV_LnHF + HRV_SD1 + HRV_SD2 + HRV_SD1SD2 + HRV_S + HRV_CSI +
  HRV_CVI + HRV_CSI_Modified + HRV_PIP + HRV_IALS + HRV_PSS +
  HRV_PAS + HRV_GI + HRV_PI + HRV_C1d + HRV_Cd + HRV_MSEn +
  HRV_CMSEn + HRV_RCMSEn + HRV_CD + HRV_HFD + HRV_KFD + HRV_LZC +
  HRV_DFA_alpha1 + HRV_MFDFA_alpha1_Width + HRV_MFDFA_alpha1_Peak +
  HRV_MFDFA_alpha1_Mean + HRV_MFDFA_alpha1_Max + HRV_MFDFA_alpha1_Delta +
  HRV_MFDFA_alpha1_Asymmetry + HRV_MFDFA_alpha1_Fluctuation +
  HRV_MFDFA_alpha1_Increment, data = data_complete)
```

n= 19577, number of events= 2389

	coef	exp(coef)	se(coef)	z	Pr(> z )
age	5.861e-01	1.797e+00	2.952e-02	19.857	< 2e-16
sexMale	5.807e-01	1.787e+00	7.001e-02	8.294	< 2e-16
ethnicityMixed	7.598e-02	1.079e+00	9.744e-02	0.780	0.435535
ethnicityAsian/Asian British	1.575e-01	1.171e+00	9.237e-02	1.705	0.088232
ethnicityBlack/Black British	-1.608e-01	8.514e-01	2.916e-01	-0.552	0.581192
ethnicityChinese	-2.680e-01	7.649e-01	4.108e-01	-0.652	0.514081
ethnicityOther	-6.822e-02	9.341e-01	2.157e-01	-0.316	0.751817
BMI	1.402e-01	1.151e+00	2.367e-02	5.923	3.15e-09

smokingPrevious	7.236e-02	1.075e+00	4.425e-02	1.635	0.101979
smokingCurrent	3.037e-01	1.355e+00	7.310e-02	4.155	3.25e-05
smokingPrefer not to answer	-4.663e-02	9.544e-01	4.118e-01	-0.113	0.909826
diabetesYes	3.111e-01	1.365e+00	1.110e-01	2.804	0.005049
diabetesDo not know	7.142e-02	1.074e+00	4.498e-01	0.159	0.873826
diabetesPrefer not to answer	4.548e+00	9.444e+01	1.017e+00	4.473	7.72e-06
systolic_bp	3.863e-02	1.039e+00	2.428e-02	1.591	0.111572
hypertension_treatmentYes	3.431e-01	1.409e+00	4.874e-02	7.039	1.93e-12
total_chol	4.060e-02	1.041e+00	2.236e-02	1.815	0.069482
hdl_chol	-9.409e-02	9.102e-01	2.720e-02	-3.459	0.000543
educationA levels/AS levels	1.034e-01	1.109e+00	6.931e-02	1.493	0.135539
educationO levels/GCSEs	4.498e-02	1.046e+00	5.905e-02	0.762	0.446242
educationCSEs	1.485e-01	1.160e+00	1.062e-01	1.398	0.162208
educationNVQ/HND/HNC	1.515e-01	1.164e+00	8.229e-02	1.841	0.065624
educationOther professional	1.638e-01	1.178e+00	9.074e-02	1.805	0.071106
educationNone of the above	1.882e-01	1.207e+00	6.596e-02	2.853	0.004334
educationPrefer not to answer	1.013e-01	1.107e+00	2.618e-01	0.387	0.698824
activityModerate	1.502e-02	1.015e+00	6.166e-02	0.244	0.807579
activityHigh	-6.190e-02	9.400e-01	6.215e-02	-0.996	0.319258
max_workload	-9.637e-02	9.081e-01	3.574e-02	-2.697	0.007002
max_heart_rate	-3.739e-02	9.633e-01	2.873e-02	-1.302	0.193082
HRV_MeanNN	-3.274e-01	7.208e-01	6.490e-01	-0.505	0.613892
HRV_SDNN	4.413e-01	1.555e+00	1.251e+00	0.353	0.724220
HRV_RMSSD	1.434e+01	1.694e+06	1.420e+01	1.010	0.312453
HRV_SSD	-1.479e+01	3.767e-07	1.382e+01	-1.070	0.284428
HRV_CVNN	-3.884e-01	6.782e-01	4.208e-01	-0.923	0.356016
HRV_CVSD	1.983e-01	1.219e+00	3.377e-01	0.587	0.557003
HRV_MedianNN	-3.754e-02	9.632e-01	2.144e-01	-0.175	0.860989
HRV_MadNN	2.104e-01	1.234e+00	2.546e-01	0.826	0.408621
HRV_MCVNN	-1.526e-01	8.585e-01	1.197e-01	-1.274	0.202553
HRV_IQRNN	-2.739e-02	9.730e-01	1.280e-01	-0.214	0.830566
HRV_SDRMSSD	3.496e-01	1.419e+00	2.816e-01	1.241	0.214467
HRV_Prc20NN	-1.499e-01	8.608e-01	1.087e-01	-1.380	0.167725
HRV_Prc80NN	-9.533e-02	9.091e-01	1.995e-01	-0.478	0.632817
HRV_pNN50	4.890e-02	1.050e+00	4.150e-02	1.178	0.238651
HRV_pNN20	-8.245e-02	9.209e-01	5.237e-02	-1.574	0.115380
HRV_MinNN	5.338e-02	1.055e+00	3.980e-02	1.341	0.179797
HRV_MaxNN	-1.761e-01	8.386e-01	1.859e-01	-0.947	0.343538
HRV_HTI	1.305e-01	1.139e+00	3.749e-02	3.480	0.000501
HRV_TINN	5.706e-02	1.059e+00	4.097e-02	1.393	0.163682
HRV_LF	-7.462e-02	9.281e-01	6.416e-02	-1.163	0.244851
HRV_HF	-6.530e-02	9.368e-01	1.428e-01	-0.457	0.647555
HRV_TP	7.072e-02	1.073e+00	1.687e-01	0.419	0.675053

HRV_LFHF	-2.764e-01	7.585e-01	2.072e-01	-1.334	0.182289
HRV_LFn	1.841e-01	1.202e+00	9.215e-02	1.998	0.045738
HRV_HFn	4.285e-02	1.044e+00	6.931e-02	0.618	0.536384
HRV_LnHF	6.735e-02	1.070e+00	9.797e-02	0.688	0.491751
HRV_SD1	NA	NA	0.000e+00	NA	NA
HRV_SD2	4.632e-01	1.589e+00	8.422e-01	0.550	0.582345
HRV_SD1SD2	9.770e-02	1.103e+00	1.050e-01	0.930	0.352338
HRV_S	1.631e-01	1.177e+00	4.368e-01	0.374	0.708757
HRV_CSI	-1.375e-01	8.715e-01	2.928e-01	-0.470	0.638577
HRV_CVI	2.846e-01	1.329e+00	3.482e-01	0.818	0.413598
HRV_CSI_Modified	-1.545e-01	8.568e-01	3.617e-01	-0.427	0.669261
HRV_PIP	3.169e-01	1.373e+00	3.694e-01	0.858	0.390989
HRV_IALS	-1.771e-01	8.377e-01	3.459e-01	-0.512	0.608663
HRV_PSS	-2.206e-02	9.782e-01	4.386e-02	-0.503	0.615002
HRV_PAS	-1.499e-02	9.851e-01	3.487e-02	-0.430	0.667333
HRV_GI	1.542e-01	1.167e+00	6.457e-02	2.388	0.016922
HRV_PI	-6.698e-03	9.933e-01	3.431e-02	-0.195	0.845211
HRV_C1d	-5.709e-02	9.445e-01	5.303e-02	-1.077	0.281673
HRV_Cd	3.131e-02	1.032e+00	4.398e-02	0.712	0.476536
HRV_MSEn	-5.214e-03	9.948e-01	3.538e-02	-0.147	0.882822
HRV_CMSEn	4.081e-02	1.042e+00	8.227e-02	0.496	0.619850
HRV_RCMSEn	-1.187e-02	9.882e-01	7.948e-02	-0.149	0.881305
HRV_CD	-2.824e-02	9.722e-01	3.967e-02	-0.712	0.476579
HRV_HFD	8.009e-02	1.083e+00	5.314e-02	1.507	0.131811
HRV_KFD	1.246e-02	1.013e+00	9.643e-03	1.292	0.196207
HRV_LZC	-3.662e-03	9.963e-01	3.549e-02	-0.103	0.917835
HRV_DFA_alpha1	-9.290e-02	9.113e-01	8.978e-02	-1.035	0.300776
HRV_MFDFA_alpha1_Width	-4.519e-02	9.558e-01	1.937e-01	-0.233	0.815563
HRV_MFDFA_alpha1_Peak	-1.569e-02	9.844e-01	5.952e-02	-0.264	0.792121
HRV_MFDFA_alpha1_Mean	1.268e-01	1.135e+00	1.958e-01	0.648	0.517093
HRV_MFDFA_alpha1_Max	6.365e-02	1.066e+00	1.198e-01	0.531	0.595162
HRV_MFDFA_alpha1_Delta	-5.828e-02	9.434e-01	1.235e-01	-0.472	0.636991
HRV_MFDFA_alpha1_Asymmetry	-2.123e-02	9.790e-01	3.818e-02	-0.556	0.578234
HRV_MFDFA_alpha1_Fluctuation	-3.179e-03	9.968e-01	2.017e-01	-0.016	0.987424
HRV_MFDFA_alpha1_Increment	-4.321e-02	9.577e-01	2.575e-01	-0.168	0.866733
age	***				
sexMale	***				
ethnicityMixed					
ethnicityAsian/Asian British	.				
ethnicityBlack/Black British					
ethnicityChinese					
ethnicityOther					

BMI	***
smokingPrevious	
smokingCurrent	***
smokingPrefer not to answer	
diabetesYes	**
diabetesDo not know	
diabetesPrefer not to answer	***
systolic_bp	
hypertension_treatmentYes	***
total_chol	.
hdl_chol	***
educationA levels/AS levels	
educationO levels/GCSEs	
educationCSEs	
educationNVQ/HND/HNC	.
educationOther professional	.
educationNone of the above	**
educationPrefer not to answer	
activityModerate	
activityHigh	
max_workload	**
max_heart_rate	
HRV_MeanNN	
HRV_SDNN	
HRV_RMSSD	
HRV_SDSD	
HRV_CVNN	
HRV_CVSD	
HRV_MedianNN	
HRV_MadNN	
HRV_MCVNN	
HRV_IQRNN	
HRV_SDRMSSD	
HRV_Prc20NN	
HRV_Prc80NN	
HRV_pNN50	
HRV_pNN20	
HRV_MinNN	
HRV_MaxNN	
HRV_HTI	***
HRV_TINN	
HRV_LF	
HRV_HF	

```

HRV_TP
HRV_LFHF
HRV_LFn
HRV_HFn
HRV_LnHF
HRV_SD1
HRV_SD2
HRV_SD1SD2
HRV_S
HRV_CSI
HRV_CVI
HRV_CSI_Modified
HRV_PIP
HRV_IALS
HRV_PSS
HRV_PAS
HRV_GI
HRV_PI
HRV_C1d
HRV_Cd
HRV_MSEn
HRV_CMSEn
HRV_RCMSEn
HRV_CD
HRV_HFD
HRV_KFD
HRV_LZC
HRV_DFA_alpha1
HRV_MFDFA_alpha1_Width
HRV_MFDFA_alpha1_Peak
HRV_MFDFA_alpha1_Mean
HRV_MFDFA_alpha1_Max
HRV_MFDFA_alpha1_Delta
HRV_MFDFA_alpha1_Asymmetry
HRV_MFDFA_alpha1_Fluctuation
HRV_MFDFA_alpha1_Increment

```

\*

\*

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

	exp(coef)	exp(-coef)	lower .95	upper .95
age	1.797e+00	5.565e-01	1.696e+00	1.904e+00
sexMale	1.787e+00	5.595e-01	1.558e+00	2.050e+00
ethnicityMixed	1.079e+00	9.268e-01	8.914e-01	1.306e+00

ethnicityAsian/Asian British	1.171e+00	8.543e-01	9.767e-01	1.403e+00
ethnicityBlack/Black British	8.514e-01	1.174e+00	4.808e-01	1.508e+00
ethnicityChinese	7.649e-01	1.307e+00	3.419e-01	1.711e+00
ethnicityOther	9.341e-01	1.071e+00	6.120e-01	1.426e+00
BMI	1.151e+00	8.692e-01	1.098e+00	1.205e+00
smokingPrevious	1.075e+00	9.302e-01	9.857e-01	1.172e+00
smokingCurrent	1.355e+00	7.381e-01	1.174e+00	1.564e+00
smokingPrefer not to answer	9.544e-01	1.048e+00	4.259e-01	2.139e+00
diabetesYes	1.365e+00	7.326e-01	1.098e+00	1.697e+00
diabetesDo not know	1.074e+00	9.311e-01	4.448e-01	2.593e+00
diabetesPrefer not to answer	9.444e+01	1.059e-02	1.287e+01	6.929e+02
systolic_bp	1.039e+00	9.621e-01	9.911e-01	1.090e+00
hypertension_treatmentYes	1.409e+00	7.096e-01	1.281e+00	1.551e+00
total_chol	1.041e+00	9.602e-01	9.968e-01	1.088e+00
hdl_chol	9.102e-01	1.099e+00	8.629e-01	9.601e-01
educationA levels/AS levels	1.109e+00	9.017e-01	9.681e-01	1.270e+00
educationO levels/GCSEs	1.046e+00	9.560e-01	9.317e-01	1.174e+00
educationCSEs	1.160e+00	8.620e-01	9.420e-01	1.429e+00
educationNVQ/HND/HNC	1.164e+00	8.594e-01	9.903e-01	1.367e+00
educationOther professional	1.178e+00	8.489e-01	9.860e-01	1.407e+00
educationNone of the above	1.207e+00	8.285e-01	1.061e+00	1.374e+00
educationPrefer not to answer	1.107e+00	9.037e-01	6.624e-01	1.849e+00
activityModerate	1.015e+00	9.851e-01	8.996e-01	1.146e+00
activityHigh	9.400e-01	1.064e+00	8.322e-01	1.062e+00
max_workload	9.081e-01	1.101e+00	8.467e-01	9.740e-01
max_heart_rate	9.633e-01	1.038e+00	9.106e-01	1.019e+00
HRV_MeanNN	7.208e-01	1.387e+00	2.020e-01	2.572e+00
HRV_SDNN	1.555e+00	6.432e-01	1.340e-01	1.804e+01
HRV_RMSSD	1.694e+06	5.904e-07	1.388e-06	2.067e+18
HRV_SDSD	3.767e-07	2.655e+06	6.508e-19	2.180e+05
HRV_CVNN	6.782e-01	1.475e+00	2.973e-01	1.547e+00
HRV_CVSD	1.219e+00	8.201e-01	6.290e-01	2.364e+00
HRV_MedianNN	9.632e-01	1.038e+00	6.327e-01	1.466e+00
HRV_MadNN	1.234e+00	8.103e-01	7.493e-01	2.033e+00
HRV_MCVNN	8.585e-01	1.165e+00	6.789e-01	1.086e+00
HRV_IQRNN	9.730e-01	1.028e+00	7.571e-01	1.250e+00
HRV_SDRMSSD	1.419e+00	7.050e-01	8.168e-01	2.464e+00
HRV_Prc20NN	8.608e-01	1.162e+00	6.957e-01	1.065e+00
HRV_Prc80NN	9.091e-01	1.100e+00	6.148e-01	1.344e+00
HRV_pNN50	1.050e+00	9.523e-01	9.681e-01	1.139e+00
HRV_pNN20	9.209e-01	1.086e+00	8.310e-01	1.020e+00
HRV_MinNN	1.055e+00	9.480e-01	9.757e-01	1.140e+00
HRV_MaxNN	8.386e-01	1.193e+00	5.825e-01	1.207e+00

HRV_HTI	1.139e+00	8.777e-01	1.059e+00	1.226e+00
HRV_TINN	1.059e+00	9.445e-01	9.770e-01	1.147e+00
HRV_LF	9.281e-01	1.077e+00	8.184e-01	1.052e+00
HRV_HF	9.368e-01	1.067e+00	7.080e-01	1.239e+00
HRV_TP	1.073e+00	9.317e-01	7.711e-01	1.494e+00
HRV_LFHF	7.585e-01	1.318e+00	5.054e-01	1.139e+00
HRV_LFn	1.202e+00	8.319e-01	1.003e+00	1.440e+00
HRV_HFn	1.044e+00	9.581e-01	9.112e-01	1.196e+00
HRV_LnHF	1.070e+00	9.349e-01	8.828e-01	1.296e+00
HRV_SD1	NA	NA	NA	NA
HRV_SD2	1.589e+00	6.293e-01	3.050e-01	8.280e+00
HRV_SD1SD2	1.103e+00	9.069e-01	8.975e-01	1.355e+00
HRV_S	1.177e+00	8.495e-01	5.001e-01	2.771e+00
HRV_CSI	8.715e-01	1.147e+00	4.909e-01	1.547e+00
HRV_CVI	1.329e+00	7.523e-01	6.718e-01	2.630e+00
HRV_CSI_Modified	8.568e-01	1.167e+00	4.217e-01	1.741e+00
HRV_PIP	1.373e+00	7.284e-01	6.656e-01	2.832e+00
HRV_IALS	8.377e-01	1.194e+00	4.253e-01	1.650e+00
HRV_PSS	9.782e-01	1.022e+00	8.976e-01	1.066e+00
HRV_PAS	9.851e-01	1.015e+00	9.200e-01	1.055e+00
HRV_GI	1.167e+00	8.571e-01	1.028e+00	1.324e+00
HRV_PI	9.933e-01	1.007e+00	9.287e-01	1.062e+00
HRV_C1d	9.445e-01	1.059e+00	8.513e-01	1.048e+00
HRV_Cd	1.032e+00	9.692e-01	9.466e-01	1.125e+00
HRV_MSEn	9.948e-01	1.005e+00	9.282e-01	1.066e+00
HRV_CMSEn	1.042e+00	9.600e-01	8.865e-01	1.224e+00
HRV_RCMSEn	9.882e-01	1.012e+00	8.457e-01	1.155e+00
HRV_CD	9.722e-01	1.029e+00	8.994e-01	1.051e+00
HRV_HFD	1.083e+00	9.230e-01	9.762e-01	1.202e+00
HRV_KFD	1.013e+00	9.876e-01	9.936e-01	1.032e+00
HRV_LZC	9.963e-01	1.004e+00	9.294e-01	1.068e+00
HRV_DFA_alpha1	9.113e-01	1.097e+00	7.642e-01	1.087e+00
HRV_MFDFA_alpha1_Width	9.558e-01	1.046e+00	6.538e-01	1.397e+00
HRV_MFDFA_alpha1_Peak	9.844e-01	1.016e+00	8.760e-01	1.106e+00
HRV_MFDFA_alpha1_Mean	1.135e+00	8.809e-01	7.735e-01	1.666e+00
HRV_MFDFA_alpha1_Max	1.066e+00	9.383e-01	8.427e-01	1.348e+00
HRV_MFDFA_alpha1_Delta	9.434e-01	1.060e+00	7.406e-01	1.202e+00
HRV_MFDFA_alpha1_Asymmetry	9.790e-01	1.021e+00	9.084e-01	1.055e+00
HRV_MFDFA_alpha1_Fluctuation	9.968e-01	1.003e+00	6.713e-01	1.480e+00
HRV_MFDFA_alpha1_Increment	9.577e-01	1.044e+00	5.782e-01	1.586e+00

Concordance= 0.72 (se = 0.005 )

Likelihood ratio test= 1514 on 85 df, p=<2e-16

```
Wald test                = 1411  on 85 df,    p=<2e-16
Score (logrank) test = 1665  on 85 df,    p=<2e-16
```

## Summary of Variable Selection

We will compare the selection of variables from all models we have built.

```
# Obtain the selected variables from all models
variable_names_all <- colnames(data) %>%
  setdiff(c("time", "event"))

variable_names_univariate <- results_univariate %>%
  filter(p_value < 0.05) %>%
  pull(predictor)

variable_names_multivariate <- summary(cox_model_full_complete)$coefficients
  ↪ %>%
  as.data.frame() %>%
  rownames_to_column(var = "predictor") %>% # transpose, "predictor" will
  ↪ now be the column name
  filter(`Pr(>|z|)` < 0.05) %>%
  pull(predictor)

variable_names_lasso <-
  ↪ rownames(cox_model_lasso.coef)[which(cox_model_lasso.coef != 0)]

variable_names_step <- summary(cox_model_step)$coefficients %>%
  as.data.frame() %>%
  filter(`Pr(>|z|)` < 0.05) %>%
  rownames()
```

```
# * We need to handle the categorical variables for correct displaying
get_base_variable_name <- function(variable_name) {
  if
    ↪ (grepl("^(sex|ethnicity|education|smoking|diabetes|activity|hypertension_treatment)[
    ↪ variable_name)) {
    return(sub("([a-z_]+)[A-Z].*", "\\1", variable_name))
  }
  return(variable_name)
}
```



```

variable_selection_matrix <- matrix(
  0,
  nrow = length(variable_names_all),
  ncol = 4 # univariate, multivariate, lasso, stepwise
)
colnames(variable_selection_matrix) <- c("univariate", "multivariate",
  ↪ "lasso", "stepwise")
rownames(variable_selection_matrix) <- variable_names_all

for (variable in variable_names_all) {
  if (determine_type(variable) == "categorical") {
    if (variable %in% sapply(variable_names_univariate,
      ↪ get_base_variable_name)) {
      variable_selection_matrix[variable, "univariate"] <- 1
    }
    if (variable %in% sapply(variable_names_multivariate,
      ↪ get_base_variable_name)) {
      variable_selection_matrix[variable, "multivariate"] <- 1
    }
    if (variable %in% sapply(variable_names_lasso,
      ↪ get_base_variable_name)) {
      variable_selection_matrix[variable, "lasso"] <- 1
    }
    if (variable %in% sapply(variable_names_step,
      ↪ get_base_variable_name)) {
      variable_selection_matrix[variable, "stepwise"] <- 1
    }
  } else {
    if (variable %in% variable_names_univariate) {
      variable_selection_matrix[variable, "univariate"] <- 1
    }
    if (variable %in% variable_names_multivariate) {
      variable_selection_matrix[variable, "multivariate"] <- 1
    }
    if (variable %in% variable_names_lasso) {
      variable_selection_matrix[variable, "lasso"] <- 1
    }
    if (variable %in% variable_names_step) {
      variable_selection_matrix[variable, "stepwise"] <- 1
    }
  }
}
}

```

```

symbol_selected <- "*"

selection_table <- data.frame(
  Variable = variable_names_all,
  Univariate = ifelse(variable_selection_matrix[, "univariate"] == 1,
    ↪ symbol_selected, ""),
  Multivariate = ifelse(variable_selection_matrix[, "multivariate"] == 1,
    ↪ symbol_selected, ""),
  LASSO = ifelse(variable_selection_matrix[, "lasso"] == 1,
    ↪ symbol_selected, ""),
  Stepwise = ifelse(variable_selection_matrix[, "stepwise"] == 1,
    ↪ symbol_selected, "")
) %>%
  mutate(Num_Selected = rowSums(variable_selection_matrix)) %>%
  arrange(desc(Num_Selected), Variable) %>%
  as.data.frame() %>%
  remove_rownames()

variable_categories <- sapply(variable_names_all, determine_category)
category_colors <- c(
  "covariate" = "#FFB6C1", #
  "time"      = "#1E90FF", #
  "frequency" = "#32CD32", #
  "poincare"  = "#FF4500", #
  "entropy"   = "#FF8C00", #
  "fractal"   = "#FFD700", #
  "unknown"   = "#000000" #
)
category_colors_names <- c(
  "covariate" = "pink", #
  "time"      = "blue", #
  "frequency" = "green", #
  "poincare"  = "red", #
  "entropy"   = "orange", #
  "fractal"   = "gold" #
)
category_legend <- sapply(names(category_colors_names), function(cat) {
  sprintf(
    "%s: %s",
    tools::toTitleCase(cat),
    tools::toTitleCase(category_colors_names[cat])
  )
})

```

```

}) %>%
  paste(collapse = "; ")

selection_table %>%
  kbl(
    caption = "Variable Selection by Different Models",
    align = c("|l", "c", "c", "c", "c", "c|"),
    col.names = c("Variable", "Univariate", "Multivariate", "LASSO",
      ↪ "Stepwise", "Selected Times"),
    longtable = TRUE
  ) %>%
  kable_styling(
    bootstrap_options = c("striped", "hover", "condensed", "responsive"),
    position = "center",
    font_size = 9,
    latex_options = c("repeat_header", "striped", "HOLD_position")
  ) %>%
  # Add color for different categories of variables
  column_spec(1,
    color =
      ↪ category_colors[variable_categories[selection_table$Variable]],
    bold = TRUE
  ) %>%
  # Add a header colname for four columns: Univariate, Multivariate, LASSO,
  ↪ Stepwise
  add_header_above(c(
    " " = 1,
    "Selection Methods" = 4,
    " " = 1
  )) %>%
  footnote(
    general = sprintf("%s", category_legend),
    general_title = "Note:"
  )

```

Warning: 'xfun::attr()' is deprecated.  
 Use 'xfun::attr2()' instead.  
 See help("Deprecated")

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Table 1: Variable Selection by Different Models

Variable	Selection Methods				Selected Times
	Univariate	Multivariate	LASSO	Stepwise	
BMI	*	*	*	*	4
age	*	*	*	*	4
hdl_chol	*	*	*	*	4
hypertension_treatment	*	*	*	*	4
sex	*	*	*	*	4
HRV_HTI	*	*		*	3
diabetes	*	*		*	3
education	*	*		*	3
max_workload	*	*		*	3
smoking	*	*		*	3
HRV_ApEn	*	*			2
HRV_GI	*			*	2
HRV_LFn	*			*	2
systolic_bp	*		*		2
HRV_AI	*				1
HRV_C1a	*				1
HRV_C1d	*				1
HRV_C2a	*				1
HRV_C2d	*				1
HRV_CD	*				1
HRV_CMSEn	*				1
HRV_CSI	*				1
HRV_CSI_Modified	*				1
HRV_CVI	*				1
HRV_CVNN	*				1
HRV_CVSD	*				1
HRV_Ca	*				1
HRV_Cd	*				1
HRV_DFA_alpha1	*				1
HRV_FuzzyEn	*				1
HRV_HFD	*				1
HRV_IALS	*				1
HRV_IQRNN	*				1
HRV_LF	*				1
HRV_LZC	*				1
HRV_MCVNN	*				1
HRV_MFDFA_alpha1_Asymmetry	*				1
HRV_MFDFA_alpha1_Delta	*				1
HRV_MFDFA_alpha1_Max	*				1
HRV_MFDFA_alpha1_Peak	*				1
HRV_MadNN	*				1
HRV_MaxNN	*				1

Table 1: Variable Selection by Different Models (*continued*)

Variable	Univariate	Multivariate	LASSO	Stepwise	Selected Times
HRV_MeanNN	*				1
HRV_MedianNN	*				1
HRV_MinNN	*				1
HRV_PAS	*				1
HRV_PI	*				1
HRV_PIP	*				1
HRV_PSS	*				1
HRV_Prc20NN	*				1
HRV_Prc80NN	*				1
HRV_RCMSEn	*				1
HRV_RMSSD	*				1
HRV_SD1	*				1
HRV_SD1SD2	*				1
HRV_SD1a	*				1
HRV_SD1d	*				1
HRV_SD2	*				1
HRV_SD2a	*				1
HRV_SD2d	*				1
HRV_SDNN	*				1
HRV_SDNNa	*				1
HRV_SDNNd	*				1
HRV_SDRMSSD	*				1
HRV_SDSD	*				1
HRV_SI	*				1
HRV_ShanEn		*			1
HRV_TINN	*				1
HRV_VHF	*				1
HRV_pNN20	*				1
ethnicity	*				1
max_heart_rate	*				1
total_chol	*				1
HRV_HF					0
HRV_HF <sub>n</sub>					0
HRV_KFD					0
HRV_LFHF					0
HRV_LnHF					0
HRV_MFDFA_alpha1_Fluctuation					0
HRV_MFDFA_alpha1_Increment					0
HRV_MFDFA_alpha1_Mean					0
HRV_MFDFA_alpha1_Width					0
HRV_MSEn					0
HRV_S					0
HRV_TP					0
HRV_pNN50					0
activity					0

Note:

Covariate: Pink; Time: Blue; Frequency: Green; Poincare: Red; Entropy: Orange; Fractal: Gold