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**Support:**

**1. Coefficients:**

* **coef (support = -1.1936):** This is the estimated regression coefficient for the support variable. A negative coefficient means that as support increases, the hazard of the event occurring decreases. The negative sign suggests that higher levels of support are associated with a **lower risk of the event happening**. Specifically, for each one-unit increase in the support variable, the risk of the event decreases by the value of the coefficient.
* **exp(coef) (exp(-1.1936) = 0.3031):** This is the hazard ratio (HR), which represents the relative hazard of the event for each one-unit increase in the support variable. The HR of 0.3031 means that for each unit increase in support, the hazard of the event occurring decreases by approximately **69.69%**. This is a substantial protective effect: as support increases, the likelihood of the event occurring decreases significantly.

**2. Standard Error of the Coefficient:**

* **se(coef) = 0.2004:** This is the standard error of the coefficient estimate. It measures how precisely the coefficient has been estimated. Since the coefficient is large relative to its standard error, it indicates that the estimate is fairly precise.

**3. Z-statistic and p-value:**

* **z = -5.955:** This is the z-statistic, which is the coefficient divided by its standard error. A large absolute value for the z-statistic suggests that the coefficient is significantly different from zero, meaning that support has a meaningful effect on the hazard.
* **Pr(>|z|) = 2.6e-09 (very small p-value):** This p-value is extremely small, much less than the commonly used significance threshold of 0.05. This indicates that the null hypothesis (that the effect of support is zero) is rejected. **Thus, support is statistically significant** in predicting the event. The relationship between support and the hazard of the event occurring is not due to random chance.

**4. Confidence Intervals:**

* **lower .95 = 0.2047 and upper .95 = 0.449:** These are the 95% confidence intervals for the hazard ratio. Since the confidence interval does not include 1 (the threshold for no effect), this further supports the conclusion that support significantly affects the risk of the event. The confidence interval (0.2047 to 0.449) indicates that the true hazard ratio for the effect of support is likely to fall within this range, reinforcing that higher support is associated with a reduced risk of the event.

**5. Concordance:**

* **Concordance = 0.852 (se = 0.023):** The concordance index (C-index) measures how well the model discriminates between individuals with higher or lower risk of the event. A C-index of 0.852 suggests that the model does an excellent job of distinguishing between individuals at higher vs. lower risk of the event. This is a strong C-index, indicating that the model has good predictive power.

**6. Likelihood Ratio, Wald, and Score Tests:**

* **Likelihood ratio test = 70.66 on 1 df, p = < 2e-16:** The likelihood ratio test compares the likelihood of the full model (including support) to a reduced model (without support). The large test statistic (70.66) and very small p-value (< 2e-16) strongly suggest that support is a statistically significant predictor of the event.
* **Wald test = 35.46 on 1 df, p = 3e-09:** The Wald test evaluates the significance of the support coefficient. The large test statistic (35.46) and small p-value (3e-09) confirm that support is highly significant.
* **Score (logrank) test = 54.57 on 1 df, p = 2e-13:** The score test (also known as the logrank test) evaluates whether the support variable is a significant predictor of survival. Again, the large test statistic (54.57) and small p-value (2e-13) suggest that support is a strong and significant predictor of the event.

**Summary of Results:**

* **Effect of Support:** The negative coefficient (-1.1936) and the hazard ratio (0.3031) suggest that higher support is associated with a significantly **lower risk of the event**. Specifically, for each unit increase in support, the risk of the event occurring decreases by about 69.69%.
* **Statistical Significance:** The very small p-value (2.6e-09) confirms that support is a **statistically significant** predictor of the event. The confidence interval for the hazard ratio (0.2047 to 0.449) further supports this finding, showing that the protective effect of support is likely to be real and not due to random chance.
* **Model Fit:** The concordance index of 0.852 indicates that the model does a great job of distinguishing between individuals at high and low risk for the event.
* **Tests:** The likelihood ratio, Wald, and Score tests all provide strong evidence that support is a **highly significant** predictor of the event.

**Satisfaction**

**1. Coefficients:**

* **coef (satisfaction = -0.04133): This is the estimated regression coefficient for the satisfaction variable. The negative value of the coefficient suggests that as satisfaction increases, the hazard (rate of the event occurring) decreases, although the effect is quite small. In other words, higher satisfaction might be associated with a slightly lower risk of the event occurring, but the effect is not statistically significant based on the p-value.**
* **exp(coef) (exp(-0.04133) = 0.95952): This is the hazard ratio (HR) for satisfaction. A hazard ratio of 0.95952 means that for each one-unit increase in satisfaction, the hazard of the event occurring is multiplied by 0.9595. This is a slight decrease in the hazard of the event (about a 4.05% lower risk), but the effect is minimal and not statistically significant.**

**2. Standard Error of the Coefficient:**

* **se(coef) = 0.11677: This is the standard error of the estimated coefficient. It indicates how precise the coefficient estimate is. In this case, the standard error is larger than the coefficient itself, suggesting that the estimate is not highly precise.**

**3. Z-statistic and p-value:**

* **z = -0.354: The z-statistic is the ratio of the coefficient to its standard error. Since the z-statistic is very close to zero, it suggests that the coefficient is not significantly different from zero, meaning there is little evidence that satisfaction has a substantial effect on the event.**
* **Pr(>|z|) = 0.723 (p-value): This p-value is much larger than the common threshold for significance (0.05), indicating that the effect of satisfaction on the event is not statistically significant. This means we fail to reject the null hypothesis that satisfaction has no effect on the event.**

**4. Confidence Intervals:**

* **lower .95 = 0.7632 and upper .95 = 1.206: These are the 95% confidence intervals for the hazard ratio. Since the confidence interval includes 1 (the threshold for no effect), it further supports the conclusion that satisfaction does not have a statistically significant effect on the hazard of the event. The confidence interval range (0.7632 to 1.206) suggests that the true hazard ratio could be anywhere from a 24% reduction in risk to a 20% increase in risk, making the effect uncertain.**

**5. Concordance:**

* **Concordance = 0.55 (se = 0.051): The concordance index (C-index) measures the discriminatory power of the model, i.e., how well the model differentiates between those who will experience the event sooner versus later. A C-index of 0.55 is close to 0.5, which indicates that the model has no better than random discrimination. This suggests that satisfaction as a predictor does not improve the model's ability to predict the event compared to random guessing.**

**6. Likelihood Ratio, Wald, and Score Tests:**

* **Likelihood ratio test = 0.13 on 1 df, p = 0.7: This test compares the likelihood of the full model (including satisfaction) to a reduced model (excluding satisfaction). The small test statistic (0.13) and the p-value of 0.7 indicate that satisfaction is not a significant predictor of the event.**
* **Wald test = 0.13 on 1 df, p = 0.7: The Wald test also indicates that satisfaction is not significant in predicting the event. The p-value (0.7) is much greater than 0.05, confirming that satisfaction has no substantial effect.**
* **Score (logrank) test = 0.13 on 1 df, p = 0.7: The score (logrank) test similarly shows that satisfaction is not a significant predictor. Again, the p-value (0.7) indicates that the effect of satisfaction is not statistically significant.**

**Summary of Results:**

* **Effect of Satisfaction: The coefficient (-0.04133) and hazard ratio (0.9595) suggest a very slight decrease in the risk of the event with higher satisfaction. However, the effect is not statistically significant, as indicated by the p-value (0.723) and the confidence interval (0.7632 to 1.206) that includes 1.**
* **Statistical Significance: The very high p-value (0.723) confirms that satisfaction is not a significant predictor of the event. The model provides little evidence to support the hypothesis that satisfaction affects the hazard of the event.**
* **Model Fit: The concordance index of 0.55 suggests that the model does not provide good predictive discrimination and is essentially no better than random guessing in predicting who will experience the event.**
* **Tests: The likelihood ratio, Wald, and Score tests all show that satisfaction is not a statistically significant predictor.**

**Conclusion:**

**In this analysis, satisfaction does not have a statistically significant effect on the risk of the event. The results suggest that there is no meaningful association between satisfaction and the event in this dataset. The model fit is poor, and the p-values for the tests indicate that satisfaction is not a reliable predictor in this case.**

**Cox Model:**

**Cox Proportional Hazards Model Overview**

**The Cox Proportional Hazards Model is a statistical technique used to model the relationship between the survival time (the time until an event occurs) and one or more predictor variables (covariates). It is commonly used in survival analysis, particularly when you're interested in understanding how variables like age, treatment, or lifestyle factors affect the time to an event (such as death, disease progression, etc.).**

* **Hazard function (λ(t)): This is the risk of an event happening at time t, given that the individual has survived up to that point. The hazard function models the instantaneous risk of an event occurring.**
* **Hazard ratio (HR): The Cox model estimates the effect of each covariate on the hazard function. The hazard ratio for a variable (like support or satisfaction) quantifies how that variable changes the hazard of the event occurring. For example, a hazard ratio of 0.5 means the event is 50% less likely to happen for each unit increase in the predictor.**

**In a Cox model, time to event is modeled as a function of both the baseline hazard (which is the hazard of the event occurring without any predictors) and the covariates (predictors such as social support, satisfaction, etc.). The model doesn't directly estimate the survival time, but instead, it estimates the hazard function for different levels of the covariates.**

**Interpretation of the Cox Model Results**

**1. Hazard Ratio (exp(coef)):**

**The hazard ratio (HR) is the most important outcome from a Cox model. It tells you how much the hazard (risk) of the event changes for each one-unit increase in the predictor variable (covariate).**

* **HR < 1: This means the predictor reduces the risk of the event occurring. For example, a hazard ratio of 0.8 means that for each unit increase in the predictor, the event is 20% less likely to occur.**
* **HR > 1: This means the predictor increases the risk of the event. A hazard ratio of 1.2 means that for each unit increase in the predictor, the event is 20% more likely to occur.**

**2. Survival Proportion:**

**The survival proportion refers to the probability that an individual will survive (i.e., not experience the event) up to a certain time. It’s essentially the complement of the hazard function (the risk of the event occurring).**

**In the context of the Cox model, the survival function gives us the probability that a subject survives beyond a particular time. Here's how it's interpreted:**

* **Survival probability at time t is the probability that the subject has not experienced the event up to that time, given the values of the covariates. For example, if the survival probability is 0.8 at time t, this means that 80% of individuals in the dataset will have survived beyond that point in time.**

**3. What Does "Survival Proportion" Mean in Your Results?**

* **When you predict survival probability in a Cox model, you're estimating the proportion of individuals who will survive (i.e., not experience the event) at any given time, based on the values of the predictor variables.**
* **For example, if your support variable has a significant negative effect on the hazard (as in your earlier models), this means that higher levels of support will increase the survival proportion, or the likelihood of survival at any given time.**

**Example:**

**Let’s say you have the following information from your Cox model:**

* **support variable has a hazard ratio of 0.524 (indicating that higher support reduces the risk of the event by about 47.6%).**
* **satisfaction variable has a hazard ratio of 0.959 (indicating a very slight reduction in risk, but it is not statistically significant).**

**The survival proportion would be calculated based on these variables and would tell you, for example, the likelihood that a person with high support (a higher value of the support variable) survives for 30 days without the event occurring. The higher the support, the higher the survival proportion (i.e., the probability that the event will not occur in the next 30 days).**

**How to Interpret Survival Proportions in Context:**

* **Cumulative Survival Probability: If you're looking at a survival curve for two groups (e.g., high support vs. low support), the survival proportion tells you the likelihood of surviving at different time points. For instance, if the curve shows that at 30 days, the survival probability for the high support group is 0.85, it means 85% of individuals with high support will have survived up to 30 days without the event.**
* **Effect of Covariates: If a variable like support has a significant effect (e.g., HR = 0.524), it means that increasing support is associated with higher survival proportions at each time point because it reduces the hazard. This would be reflected in the survival curves for individuals with high support vs. low support.**

**Summary:**

* **The Cox model estimates how covariates (such as support, satisfaction) affect the hazard (risk) of the event occurring.**
* **The hazard ratio (exp(coef)) quantifies how much the hazard changes with a one-unit change in the covariate.**
* **The survival proportion (or survival probability) tells you the likelihood that an individual will survive (not experience the event) at a particular time point.**
* **A higher survival proportion means a greater chance of not experiencing the event, and higher support or satisfaction can lead to a higher survival proportion if those variables reduce the risk of the event.**

**In summary, the survival proportion helps you understand how likely someone is to survive beyond a specific time, based on the values of the predictors in the Cox model.**

**Kaplan-Meier curve**