# Analysis of Ten Minute EMS Trauma Scene Time

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# Agenda

- Abstract
- Roadmap of Outcome Variable and Predictors
- Statement of Question
- List of variables
- Exploratory Data Analysis
- Logistic Model Analysis
    - Diagnosis and Compare 2 Logistic Regression Models
- Final Model - Interpretation of Odds Ratio, Plot of Odds
- Overall Conclusion
- Shortcomings of Study and Recommendations for Improvement

# Abstract

This is a retrospective study using Emergency Medical Service (EMS) data from January 1, 2012-October 31, 2016. In emergent trauma care, timely diagnosis is aimed at making life-saving interventions within the so-called “golden hour.” The Central California Emergency Medical Services Agency (CCEMSA) has defined 10 minutes as the gold standard for scene time in trauma calls. Prior to 2014, CCEMSA ambulance calls struggled to exceed a 45% compliance on all trauma calls. In an attempt to improve EMS on scene time a 7 minute pager was implemented on **December 18, 2014** to notify providers 3 minutes prior to the 10 minute time frame. All EMS data (n= 4955) in this study includes Fresno County, Kings County, Madera County and Tulare County.

This study uses methods of injury, patient weight,  response priority (given by dispatch), transportation priority (given by EMS), arrival time of day, and pre/post intervention as response variables. The predictor variable used was whether or not EMS managed to comply with the 10 minute scene time. We would like to know how the pager (intervention) impacts scene time? Does the effect of a pager (intervention) change transportation priority? How can we predict the scene time given the predictors? And which variable (s) has a strong effect of determining if the scene time was over/under the  10 minute time frame? Using logistic regression we concluded that post intervention the odds of compliance increased to 55% with our final model. In addition, the only variables that had significant contributions to our scene time were weight, response priority, intervention, and method of injury while transportation priority was not a contributing factor.

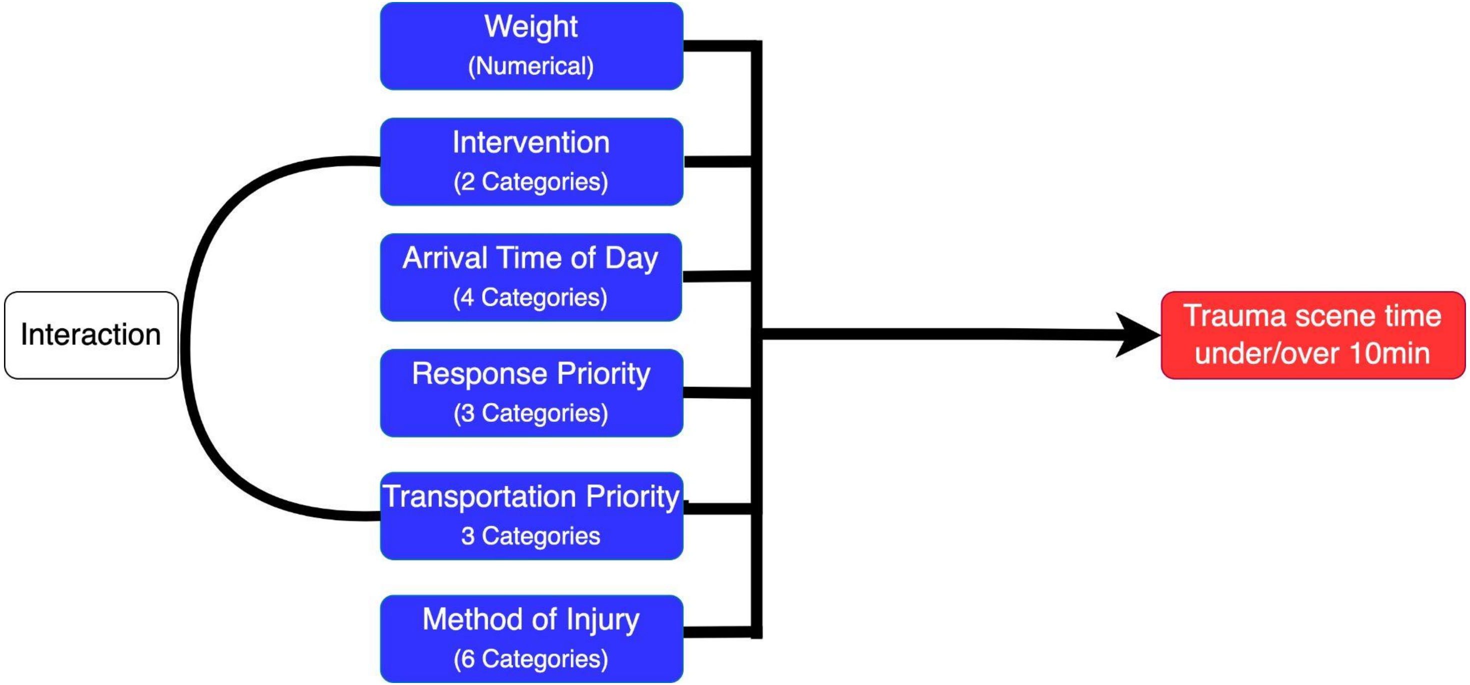
## Stage 1


## Stage 2


Outcome Variable Y:
1: ≤ 10 mins
0: > 10 mins

## Stage 3

# Road Map


Weight
(Numerical)
Intervention
(2 Categories)
Arrival Time of Day
(4 Categories)
Response Priority
(3 Categories)
Transportation Priority
3 Categories
Method of Injury
(6 Categories)
Interaction
Trauma scene time
under/over 10min

# Research Question

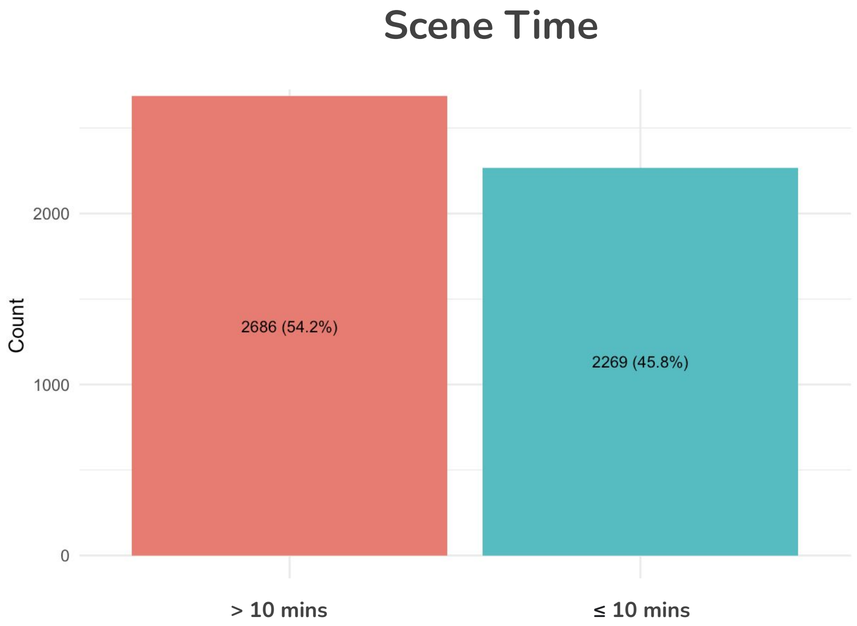
- How does the pager (intervention) impact the trauma scene time?
- How can we predict the scene time given the predictors?
- Which variable(s) has a strong effect of determining whether the trauma scene time is over/under 10 mins?
- Does the effect of a pager (intervention) change with Transportation Priority on scene time?

## Variables

| | Title | Type | Level | Description |
|---|---|---|---|---|
| **Response Variable** | | | | |
| | Scene Time | Binary | 2 | ≤10<br>>10 |
| **Predictor Variable** | | | | |
| | Patient Weight | Numeric | | |
| | Intervetion | Binary | 2 | Pre<br>Post |
| | Arrival Time of Day | Categorical | 4 | Morning (5AM-12PM)<br>Afternoon (12PM-5PM)<br>Evening (5PM-9PM)<br>Night (9PM-5AM) |
| | Response Priority (Given by Dispatch) | Categorical | 3 | High Priority<br>Medium Priority<br>Low Priority |
| | Transportation Priority (Given by EMS) | Categorical | 3 | High Priority<br>Medium Priority<br>Low Priority |
| | Method of Injury | Categorical | 6 | Burn<br>Crash (MVA, MCC, Auto vs Ped)<br>Fall (Structure, Trip, Stumble, Ladder, etc.)<br>GSW (Gunshot Wound)<br>SW (Stab Wound)<br>Other (Assault, Trama, Industrial, etc.) |

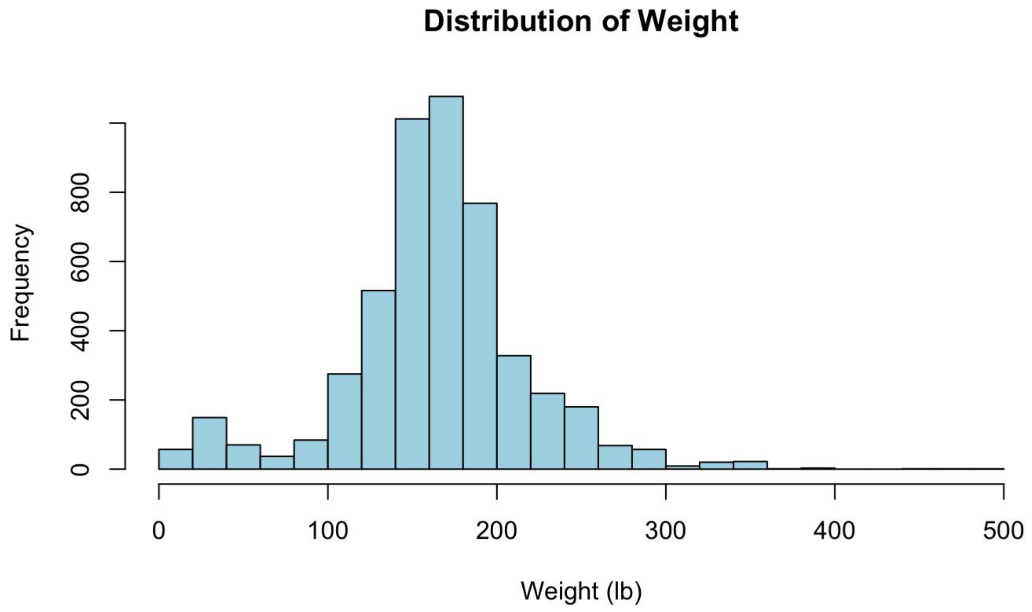
# Exploratory Data Analysis (EDA)

# Bar Plots for Response Variable (Y)




- This is our bar plots of Response Variable Under and Over 10 mins of Trauma Scene Time
- It shows that 54.2% of observations are over 10 minutes and 45.8% are under 10 minutes which are basically almost balanced.

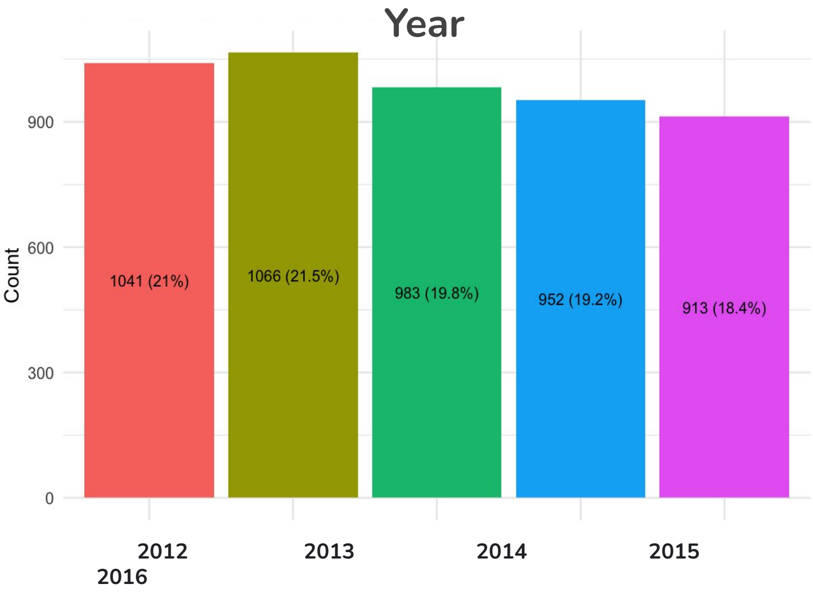
# Histogram of Numeric Predictor - Weight

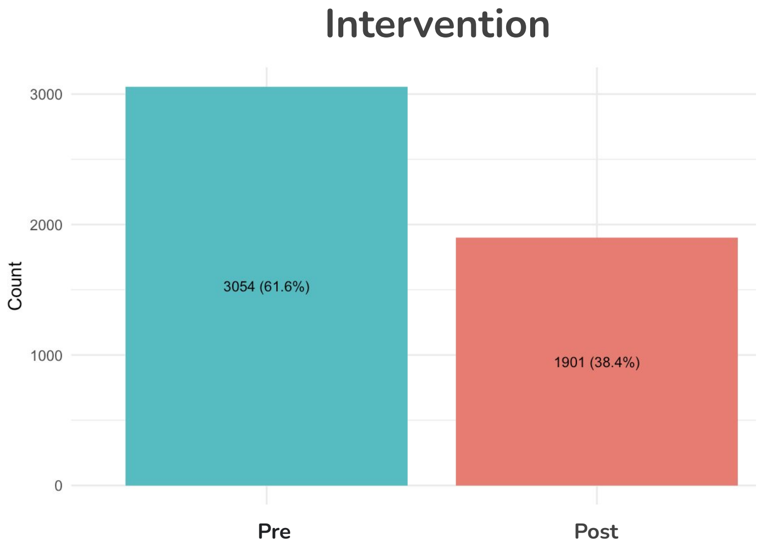



- This histogram shows the distribution of the Weight which is almost normally distributed
- Below the chart shows the minimum weight is 6 lb, maximum weight is 490 lb.

| Minimum | First Quantile | Median | Mean | Third Quantile | Maximum |
|---|---|---|---|---|---|
| 6 | 145 | 170 | 169 | 200 | 490 |

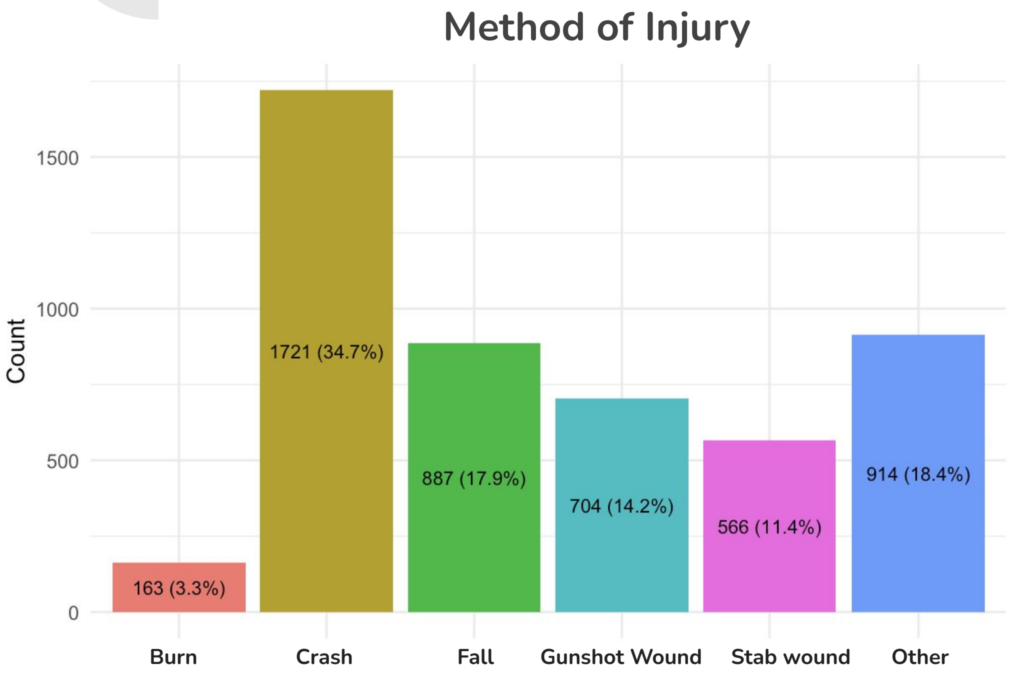
# Bar Plots - Years into Intervention



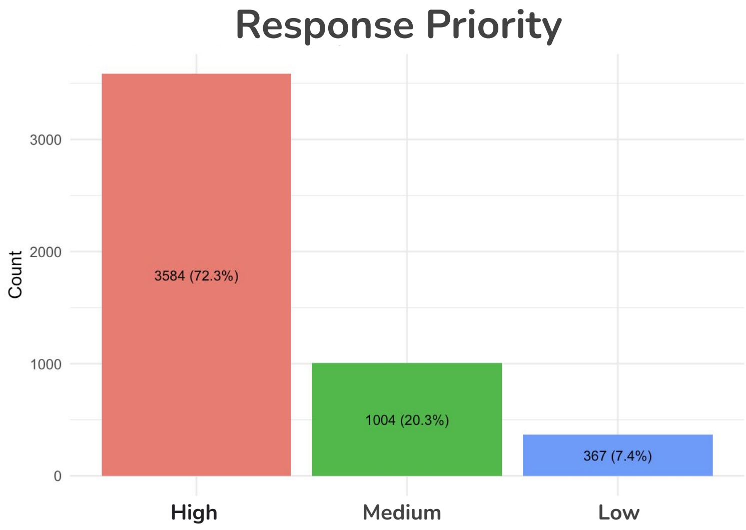



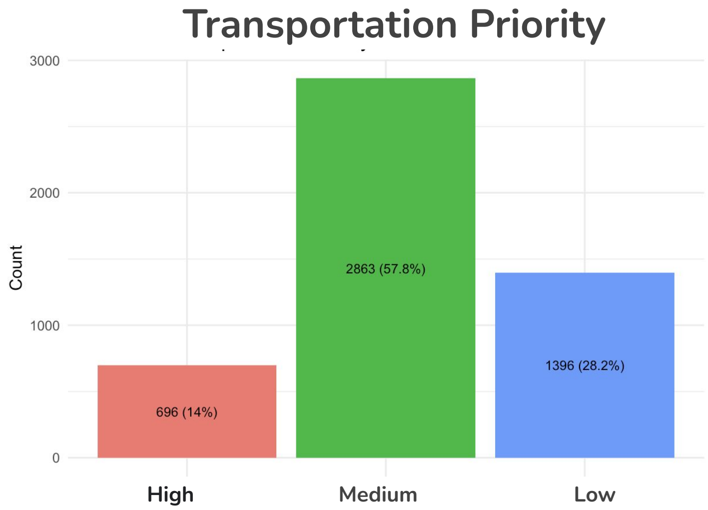

We recategorized the variable Year to Intervention based on the pager was implemented on **December 18, 2014**
Our pre intervention data contains 61.6% (3054) of the data in comparison to post intervention 38.4% (1901).

# Bar Plot - MOI




- This bar plots shows that the 6 Methods of Injury
- The highest amount of injury is caused by crash which is 34.7%
- The lowest amount of  injury is caused by burn which is 3.3%
- The amount of other injuries are nearly the same

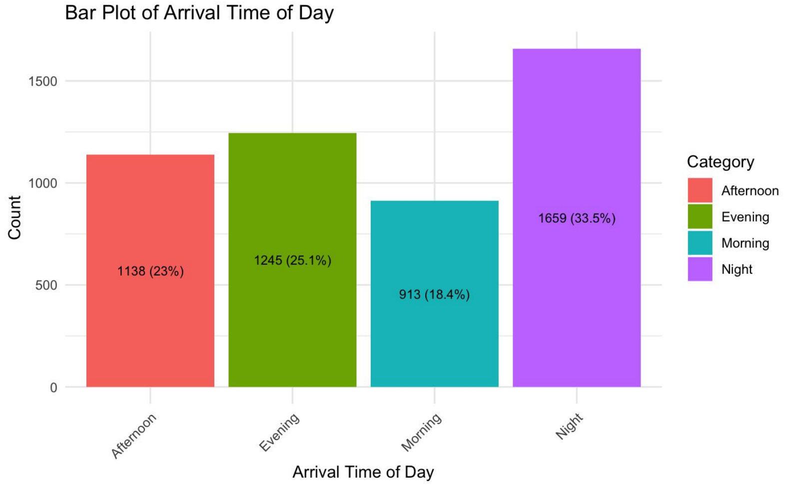


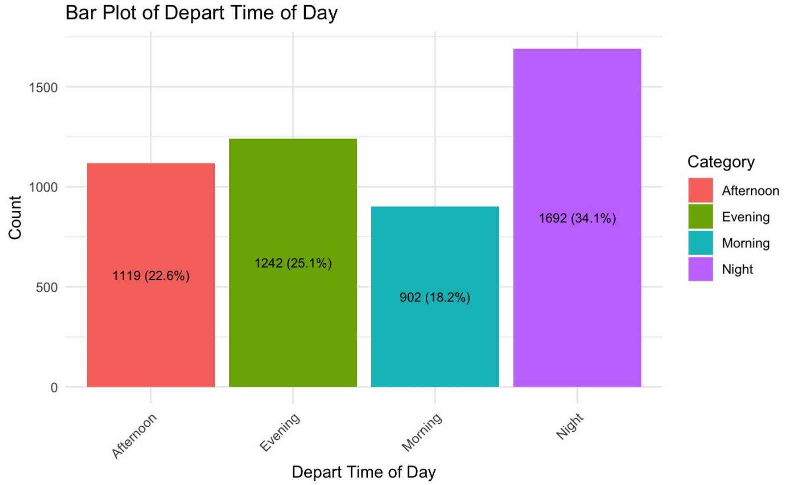




# Bar Plots - Response and Transportation Priority

- The above bar plot shows that the most of the response is high priority which is 72.3%
- The below bar plot shows that the most of the transportation priority which is 57.8%
- We thought that priority of transportation and response count distribution will be consistent, but it shows that proportion of highest response priority is much higher than proportion of highest transportation priority

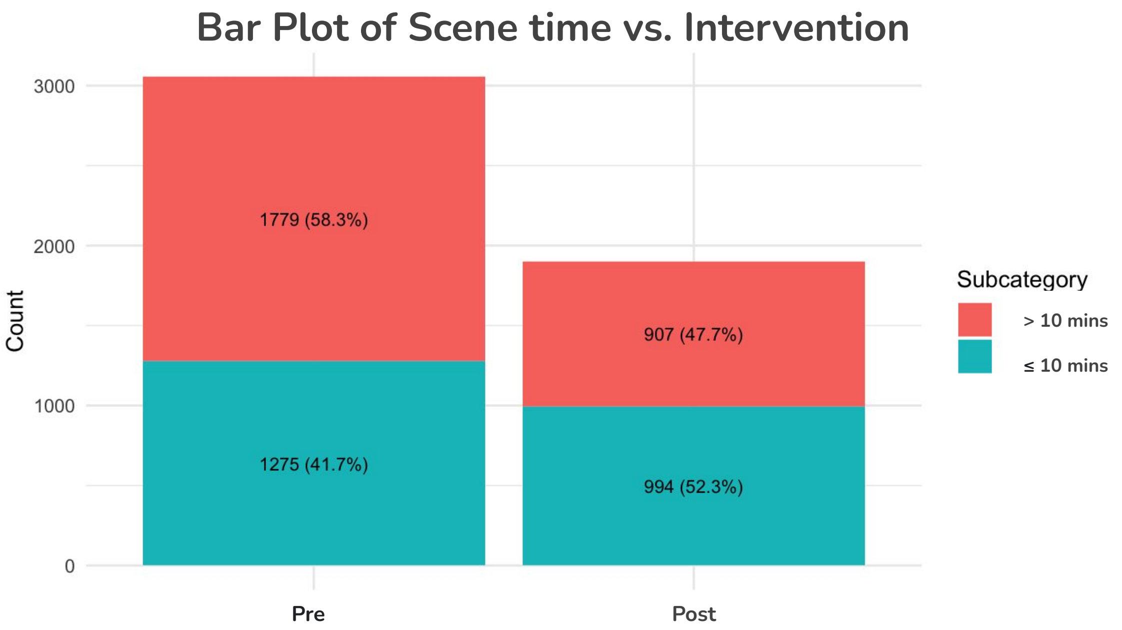
# Bar Plots - Arrival and Depart Time of Day



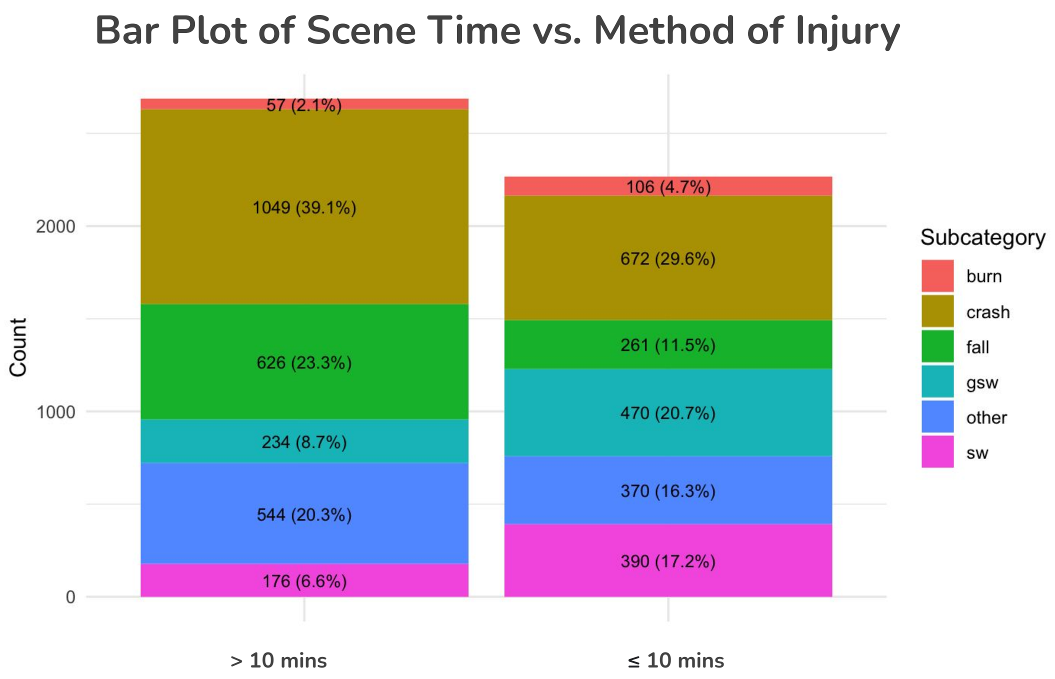

- The amount of arrival and departure counts for injury events in the part of the day are nearly the same, so the arrival time is used in the model.
- The highest arrival counts is happening in the night which is 33.5%
- The lowest a arrival counts is happening in the morning which is 18.4%

# Bar Plot - Scene Time VS. Intervention



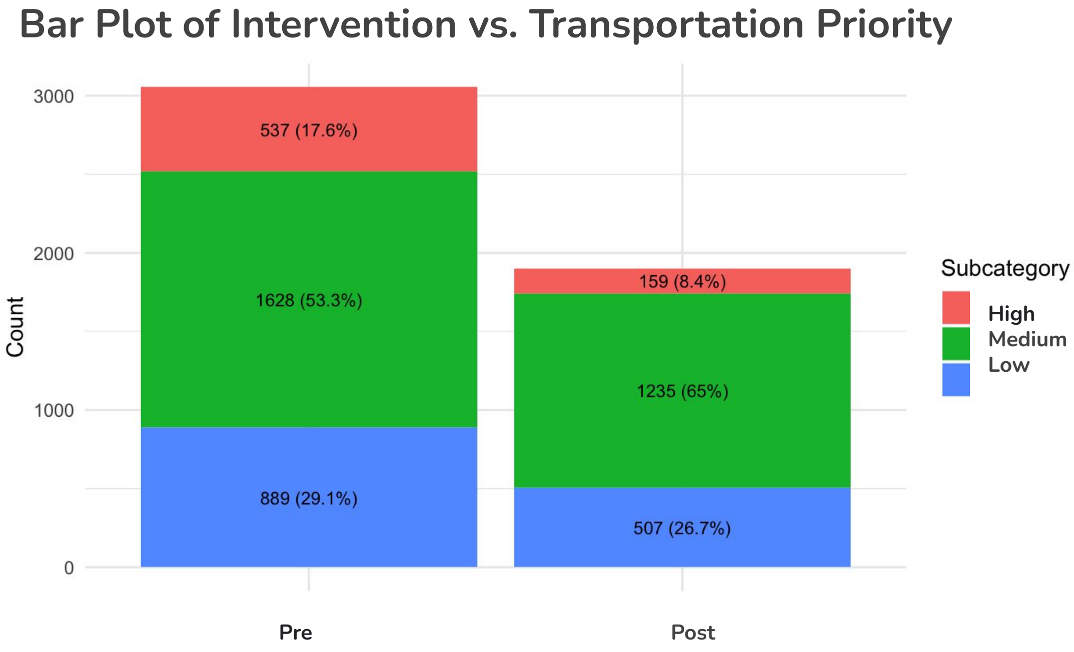

- Bar plots reflect the proportions of the under or over mins in before and after the intervention.
- Before the intervention, the time under 10 minutes improved.

# Bar Plot - Scene Time VS. MOI



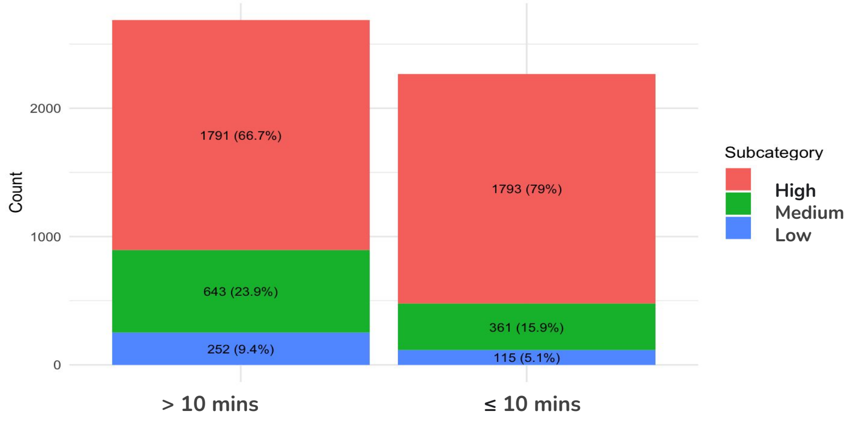

- These bar plots show how Method of Injury is sectioned off with trauma calls that managed to adhere to the 10 minute or less scene time vs those over the 10 minute time frame.
- Regardless of time, crash is the most common.

# Bar Plot - Intervention VS. Transportation Priority

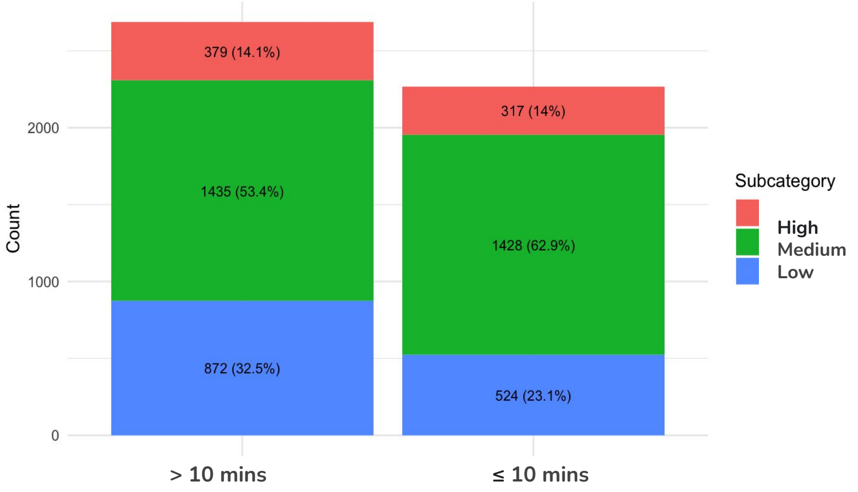



- We want to explore the relationship between the before and after Intervention in different level of the Transportation Priority
- It was surprise that we find the proportion of the highest priority of Transportation is decrease after the Intervention.

## Bar Plot of Scene Time vs. Response Priority



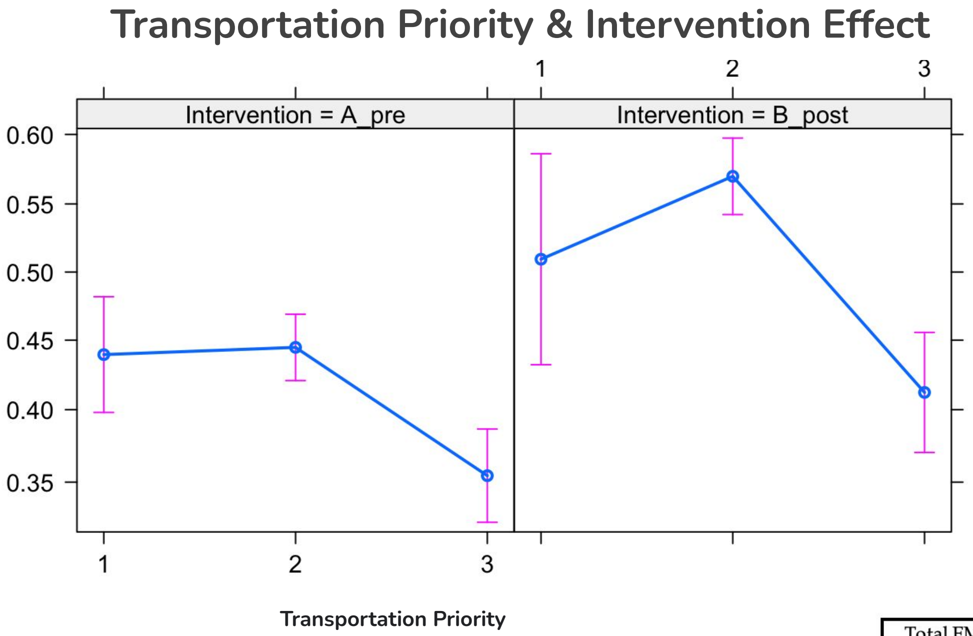

## Bar Plot of Scene Time vs. Transportation Priority



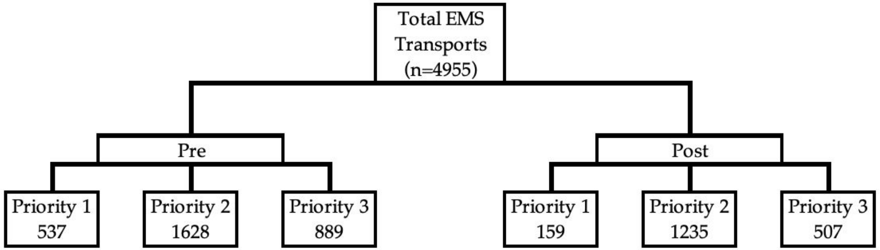

- The first bar plots show transportation priority given by EMS after accessing the scene. The second graph shows Response priority given by dispatch.
- Transportation priority mostly was rated medium priority in comparison to Response time was mostly rated as high priority.

Scene Time Under 10 minutes

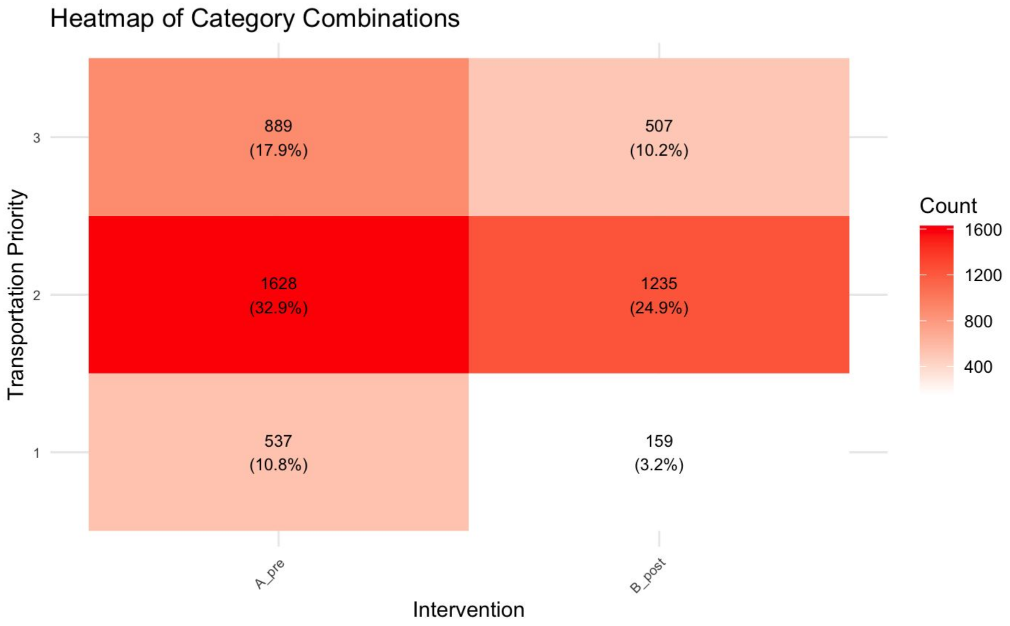
# Interaction Effect Plot




- This Interaction Effect Plots shows that the Interaction effect between Transportation and Intervention.
- We can see before the intervention, the proportion of within 10 min trauma scene time overall low than after intervention in 3 level of the transportation priority.

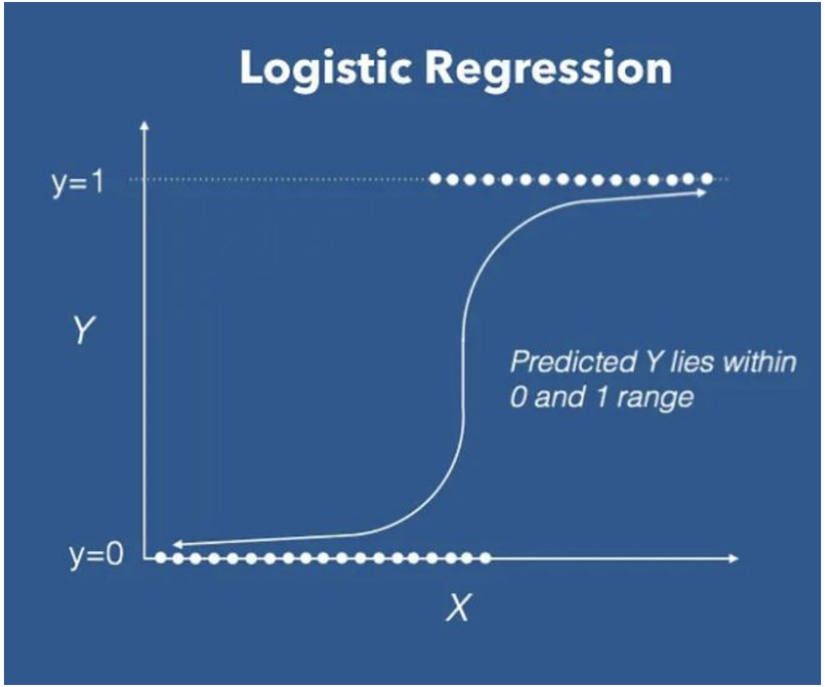


# Heatmap - Transportation Priority VS. Intervention




- This Heatmap shows that the highest proportion of Transportation priority is second priority before the Intervention

# Modeling


Logistic Regression
y=1
Y
Predicted Y lies within
0 and 1 range
y=0
X

# Blockwise Variable Selection for Model 1

| Variables | | | |
|---|---|---|---|
| Intercept | 0.104 | 1.110*** | 1.248*** |
| Weight | -0.003*** | -0.004*** | -0.004*** |
| Intervention | | | |
| Post | 0.435*** | 0.447*** | 0.440*** |
| MOI | | | |
| Crash | | -1.002*** | -1.157*** |
| Fall | | -1.481*** | -1.399*** |
| gsw | | 0.228 | 0.052 |
| Other | | -0.936*** | -0.794*** |
| sw | | 0.349 . | 0.241 |
| Arrival Time of Day | | | |
| Evening | | 0.044 | 0.015 |
| Morning | | -0.154 | -0.172 . |
| Night | | -0.230** | -0.270** |
| Response Priority | | | |
| 2 | | | -0.382*** |
| 3 | | | -0.630*** |
| Transportation Priority | | | |
| 2 | | | 0.161 . |
| 3 | | | -0.148 |
| Deviance | 6757.2 | 6302.3 | 6245.1 |
| AIC | 6763.2 | 6324.3 | 6275.1 |

'***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

- Blocks were decided by Importance and relationship with the other variables.
- The change in Residual deviance is high when adding MOI and Arrival Time of Day. Adding Response Priority and Transportation Priority also results in a decrease of Residual deviance and AIC.
- We conclude to use all six variables for our model.

# Model 1

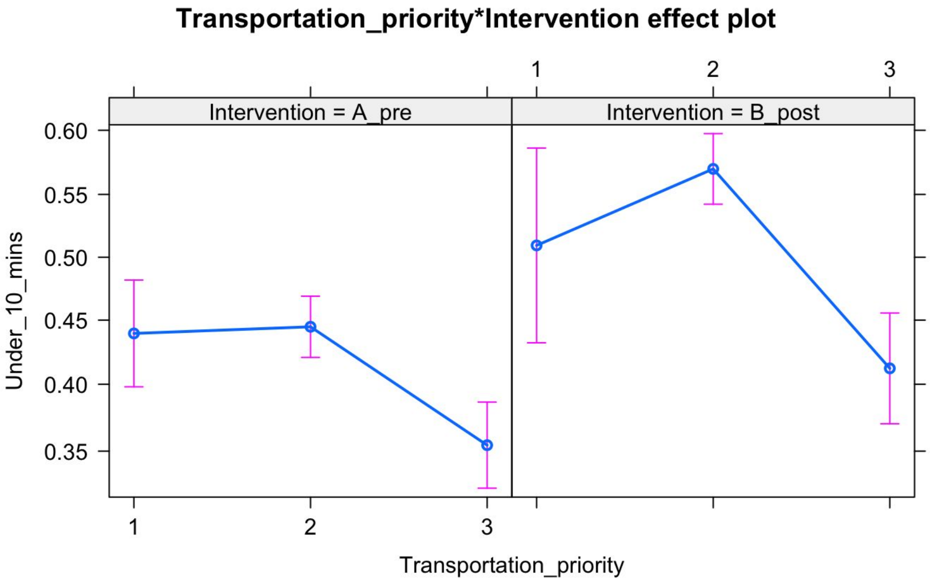
$$P_{Under10mins} = \frac{1}{1+e^{-S_1}}$$

Where,

$$\begin{aligned} S_1 = \beta X = 1.248 &- 0.0038 \times \text{Weight} - 0.382 \times \text{RP2} \\ &- 0.630 \times \text{RP3} + 0.161 \times \text{TP2} \\ &- 0.148 \times \text{TP3} + 0.440 \times \text{Intervention post} \\ &- 1.157 \times \text{Crash} - 1.399 \times \text{Fall} + 0.052 \times \text{GSW} \\ &- 0.794 \times \text{Other} + 0.241 \times \text{SW} \\ &+ 0.015 \times \text{Evening} - 0.172 \times \text{Morning} \\ &- 0.269 \times \text{Night} \end{aligned}$$

| Predictor | Log-Odds | p.value |
|---|---|---|
| (Intercept) *** | 1.248 | 3.947242e-09 |
| Weight *** | -0.0038 | 2.635558e-11 |
| Response_priority2 *** | -0.382 | 3.743418e-05 |
| Response_priority3 *** | -0.630 | 1.766480e-06 |
| Transportation_priority2 (.) | 0.161 | 7.597574e-02 |
| Transportation_priority3 | -0.148 | 1.452418e-01 |
| Intervention_post *** | 0.440 | 3.401391e-12 |
| crash *** | -1.157 | 8.438418e-11 |
| fall *** | -1.399 | 5.066319e-14 |
| gsw | 0.052 | 7.839559e-01 |
| other *** | -0.794 | 1.748787e-05 |
| sw | 0.241 | 2.154638e-01 |
| Evening | 0.015 | 8.607977e-01 |
| Morning (.) | -0.172 | 7.034613e-02 |
| Night ** | -0.269 | 1.443084e-03 |

# Interaction Effect Plot: Transportation Priority and Intervention



# Model 2

$$P_{Under10mins} = \frac{1}{1+e^{-S_2}}$$

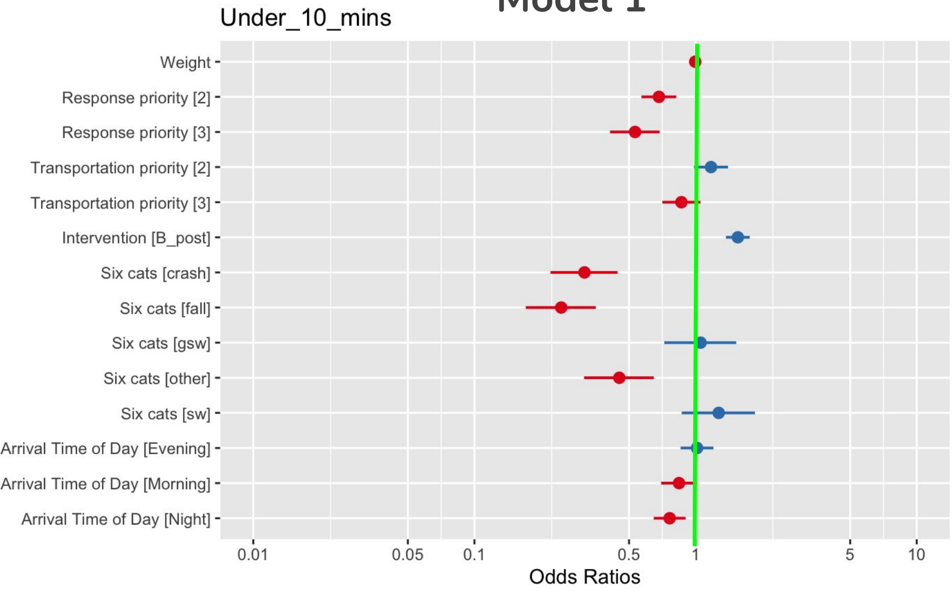
Where,

$$\begin{aligned} \mathrm{S}_2 = \beta X = 1.283 &- 0.0038 \times \text{Weight} - 0.383 \times \text{RP2} \\ &- 0.621 \times \text{RP3} + 0.076 \times \text{TP2} \\ &- 0.126 \times \text{TP3} - 1.146 \times \text{Crash} \\ &- 1.395 \times \text{Fall} + 0.060 \times \text{GSW} - 0.788 \times \text{Other} \\ &+ 0.253 \times \text{SW} + 0.268 \times \text{Intervention post} \\ &+ 0.018 \times \text{Evening} - 0.171 \times \text{Morning} \\ &- 0.268 \times \text{Night} + 0.276 \times \text{TP2*Intervention post} \\ &+ 0.0088 \times \text{TP3*Intervention post} \end{aligned}$$

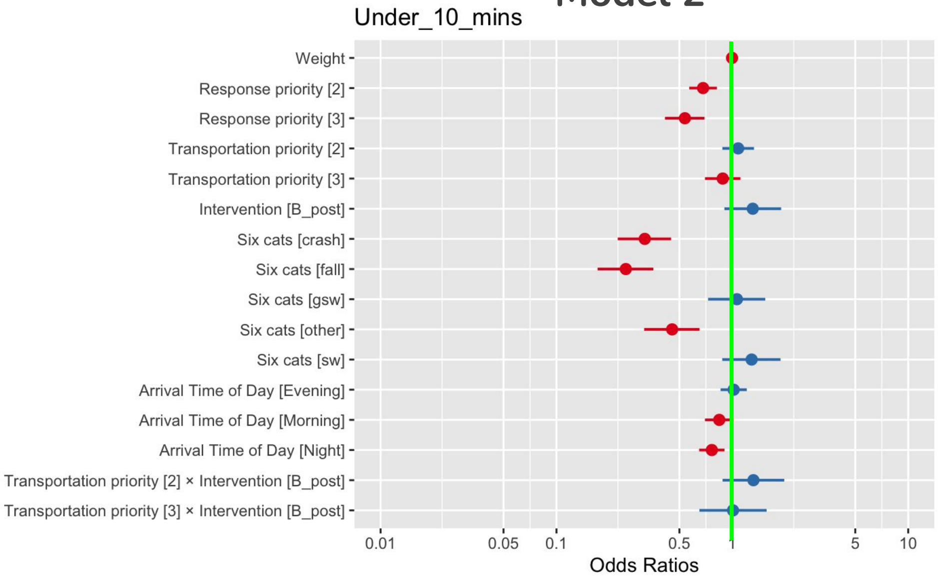
| Predictors | Log-Odds | p-value |
|---|---|---|
| (Intercept)*** | 1.283 | 2.854464e-09 |
| Weight*** | -0.0038 | 1.961397e-11 |
| Response_priority2*** | -0.383 | 3.464769e-05 |
| Response_priority3*** | -0.621 | 2.582540e-06 |
| Transportation_priority2 | 0.076 | 4.705701e-01 |
| Transportation_priority3 | -0.126 | 2.874378e-01 |
| Intervention_post | 0.268 | 1.578875e-01 |
| crash*** | -1.146 | 1.211255e-10 |
| fall*** | -1.395 | 5.947980e-14 |
| gsw | 0.060 | 7.531209e-01 |
| other*** | -0.788 | 1.999022e-05 |
| sw | 0.253 | 1.939487e-01 |
| Evening | 0.018 | 8.395518e-01 |
| Morning(.) | -0.171 | 7.211363e-02 |
| Night** | -0.268 | 1.536192e-03 |
| Transportation_priority2:InterventionB_post | 0.276 | 1.794463e-01 |
| Transportation_priority3:InterventionB_post | 0.0088 | 9.687646e-01 |

# Confidence Intervals for Odds Ratios: Model1,Model2

## Model 1



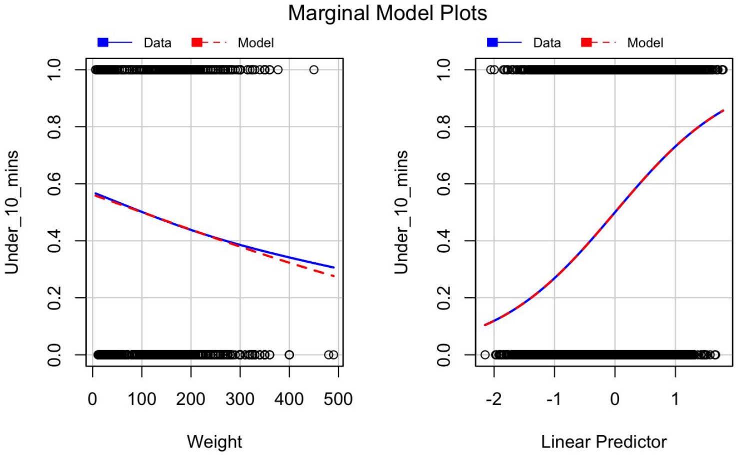

## Model 2



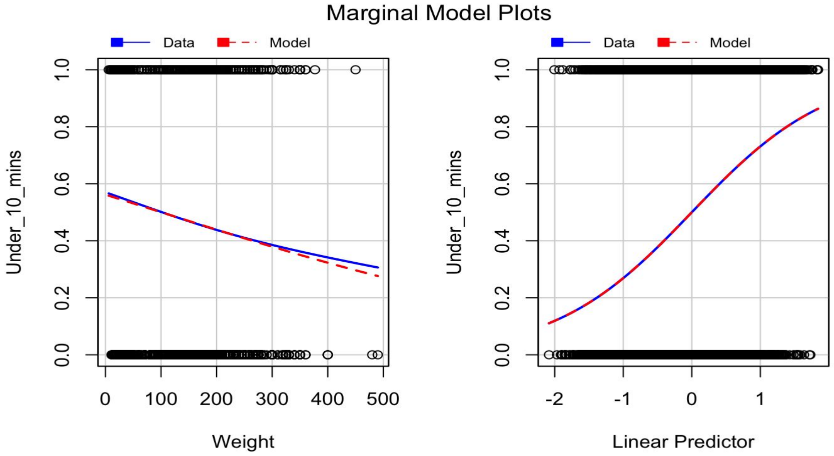

Variables located to the left of the green line (odds ratio 1) have a negative effect on the outcome, right have a positive effect, and variables on top of the line are neutral.

# Marginal Model Plots (MMP)

## Model 1




## Model 2




In both Model 1 and Model 2, the Model for weight is overlapping the data. The plot against the linear predictor also follows the trend and forms a S-shaped curve, indicating that this is a good sign of model fit.

# Multicollinearity

## GVIF table

| | Model 1 | Model 2 |
|---|---|---|
| Weight | 1.046 | 1.047 |
| Response_priority | 1.563 | 1.566 |
| Transportation_priority | 1.074 | 2.311 |
| Intervention | 1.035 | 9.247 |
| MOI | 1.686 | 1.691 |
| Arrival_Time_of_Day | 1.088 | 1.089 |
| Transportation_priority :Intervention | N/A | 16.494 |

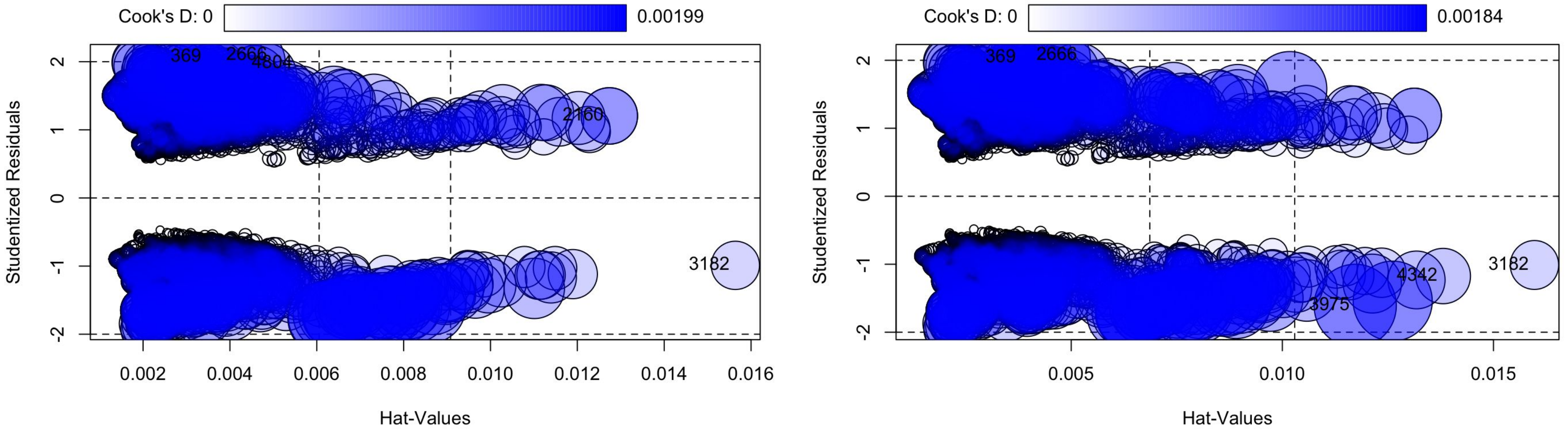
- All GVIFs in  model 1 are good, model 1 does not have multicollinear problem
- Model 2 has two unacceptably high GVIFs, model 2 is facing a multicollinear problem.
- Transportation_priority and Intervention have significant increasing in GVIF but Transportation_priority's is still in a good range.

# Model 2 -Multicollinearity

| | GVIF | Df | GVIF-adj |
|---|---:|---:|---:|
| Weight | 1.047 | 1 | 1.023 |
| Response_priority | 1.566 | 2 | 1.119 |
| Transportation_priority | 2.311 | 2 | 1.233 |
| MOI | 1.691 | 5 | 1.054 |
| Intervention | 9.247 | 1 | 3.041 |
| Arrival_Time_of_Day | 1.089 | 3 | 1.014 |
| Transportation_priority:Intervention | 16.494 | 2 | 2.015 |

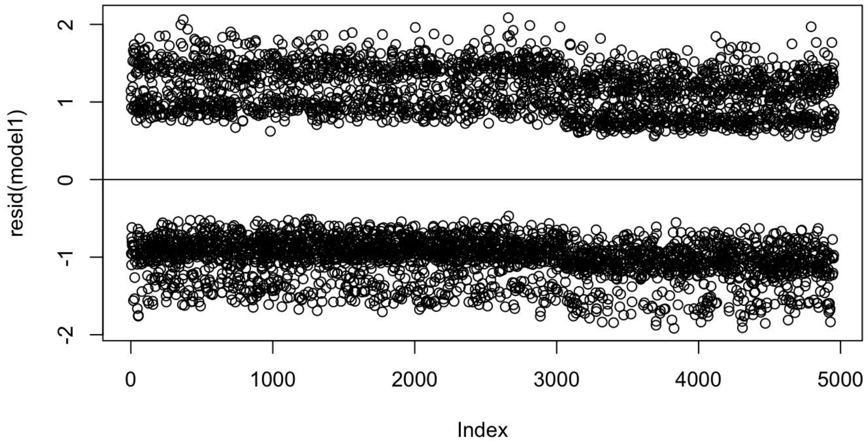
- The GVIF of Transportation_priority:Intervention is extremely large
- Compare to model one, Transportation_priority and Intervention have significant increase in GVIF

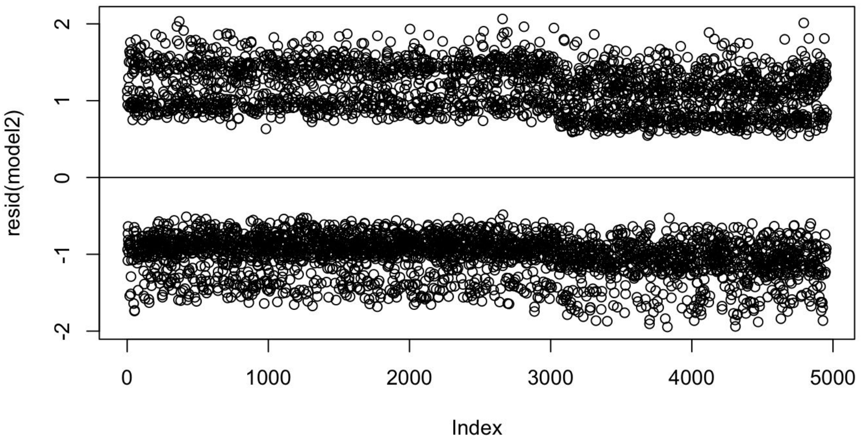
# Model 1 & Model 2 - Influential Plots




- The model 1 and model 2's Influential plots are pretty similar
- Influential plots showing studentized residuals against hat-values, each bubbles shows each observation with the size of the bubble often relating to the weight of the observation.
- The potentially influential observations:"369," "266," "2160," and "3182," but since our sample size is large, it will have small influence on the model performance.

# Model 1, Model 2 - Residual Plots




- Model 1 and Model 2’s residual plots are similar
- Random distribution
- No clear trend or patterns
- Consistent Variance
- No significant outliers in range from -2 to 2

# Model 1 & Model 2 Fit: Pearson's Chi-square Test Results

H0: The logistics linear model is a good fit for the data

Ha: The logistics linear model is not a good fit for the data

| | |
|---|---|
| Model 1 - Pearson's Chi-Square | 4962.948 |
| Model 1 - Critical Value at 95% CI | 5104.625 |

| | |
|---|---|
| Model 2 - Pearson's Chi-Square | 4962.513 |
| Model 2 - Critical Value at 95% CI | 5102.591 |

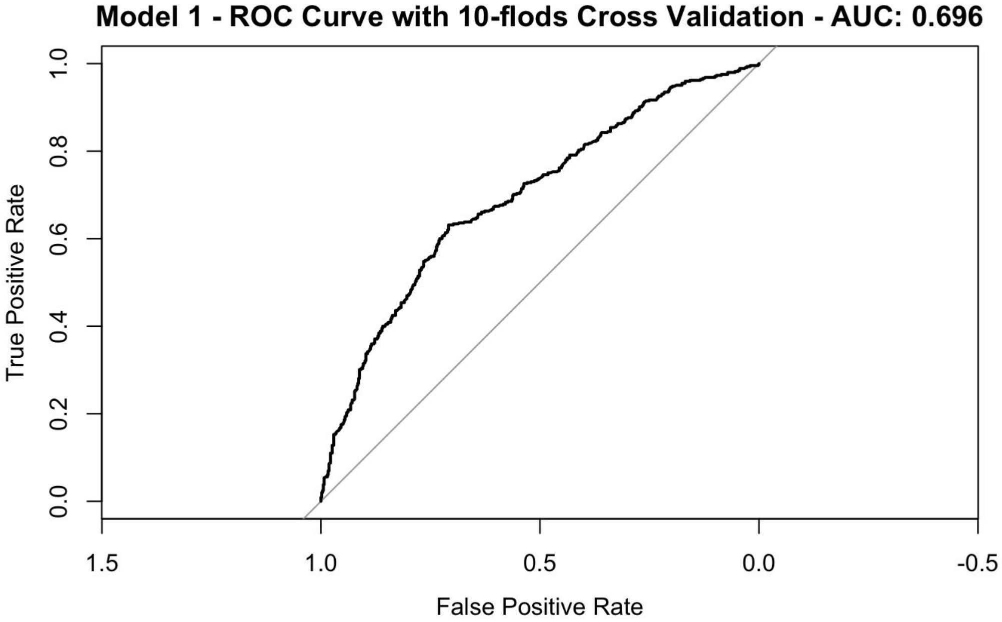
**Conclusion:** Since both model's pearson's chi-square values are less than the critical values, we would like to not reject the null hypothesis and conclude that the logistics linear models for **(model1) and (model2) are both good fits for the data**.

# Model 1 Measure of Accuracy with 10-folds Cross Validation

Model 1 Accuracy Rate: **64.78%**

| | Prediction | |
|---|---|---|
| True | 0 | 1 |
| 0 | 484 | 287 |
| 1 | 62 | 158 |

0: Over 10 mins
1: Under 10 mins

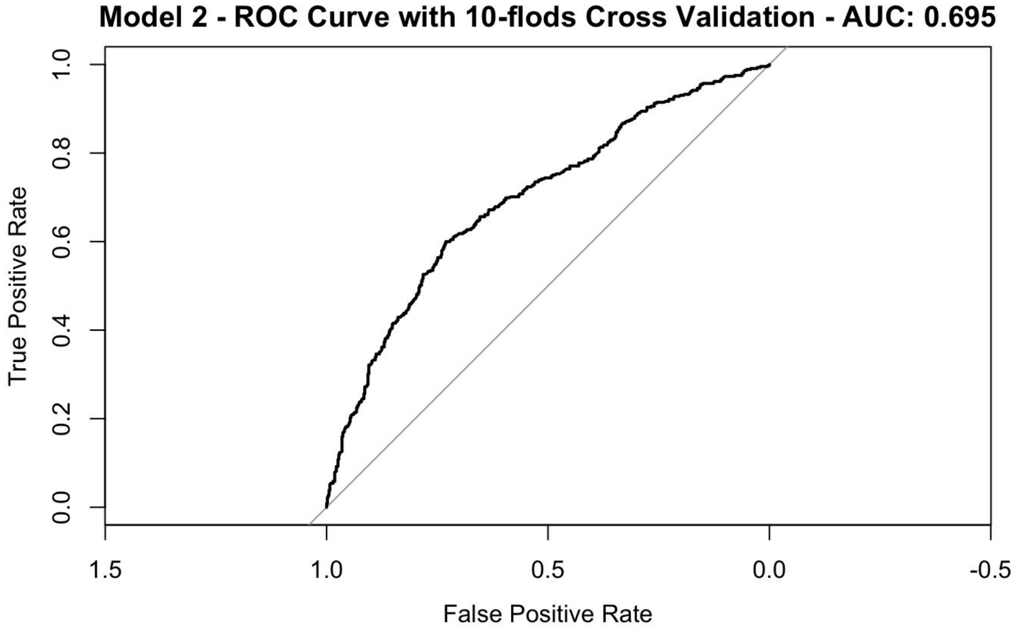


# Model 2 Measure of Accuracy with 10-folds Cross Validation

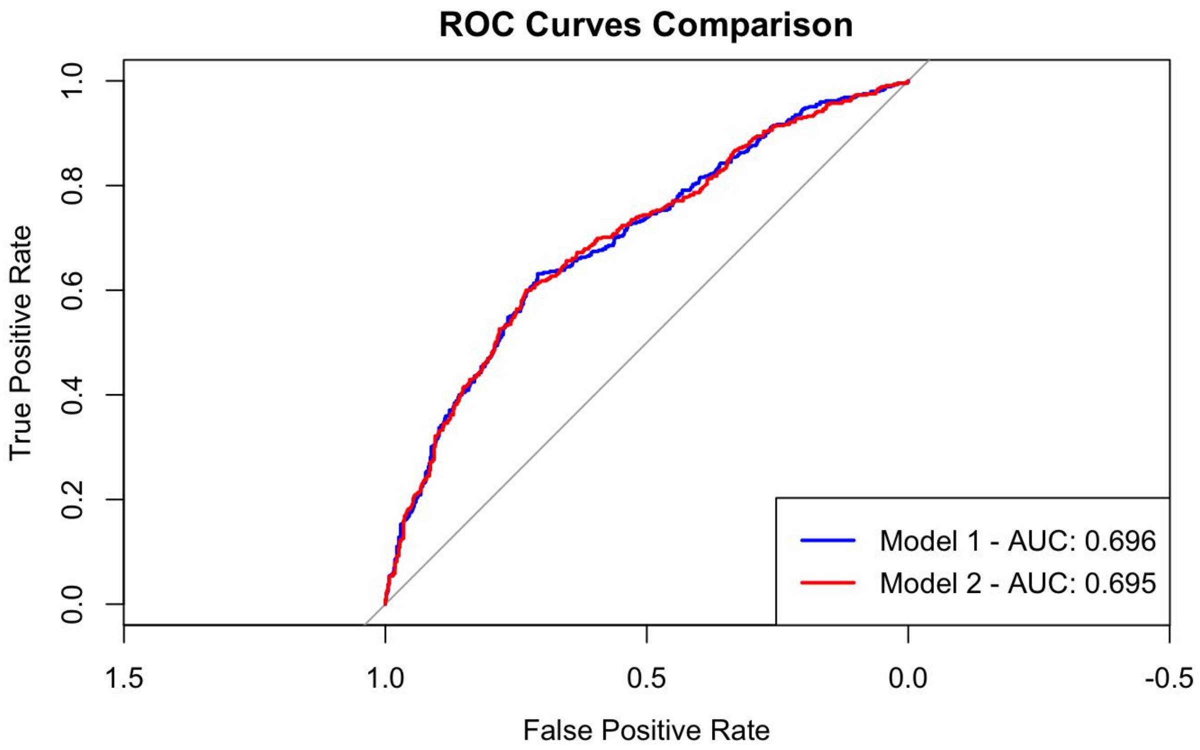
Model 2 Accuracy Rate: **64.28%**

| | Prediction | |
|---|---|---|
| True | 0 | 1 |
| 0 | 483 | 291 |
| 1 | 63 | 154 |

0: Over 10 mins
1: Under 10 mins



# Model 1 and Model 2 ROC Curves Comparison



# Model 1, Model 2 Comparison

| Model | Predictors | AUC | Accuracy | AIC | Residual Deviance | Pearson Chi-square |
|---|---|---|---|---|---|---|
| Model 1 (Without Interaction) | 6 Predictors: Weight,Intervention, MOI, TP, RP, Arrival Time of Day | 69.6% | 64.78% | 6275.1 | 6245.1 | Good Fit for the Data |
| Model 2 (With Interaction) | 7 Predictors: Weight,Intervention, MOI, TP, RP, Arrival Time of Day, TP*Intervention | 69.5% | 64.28% | 6274.8 | 6240.8 | Good Fit for the Data |

# Final Model

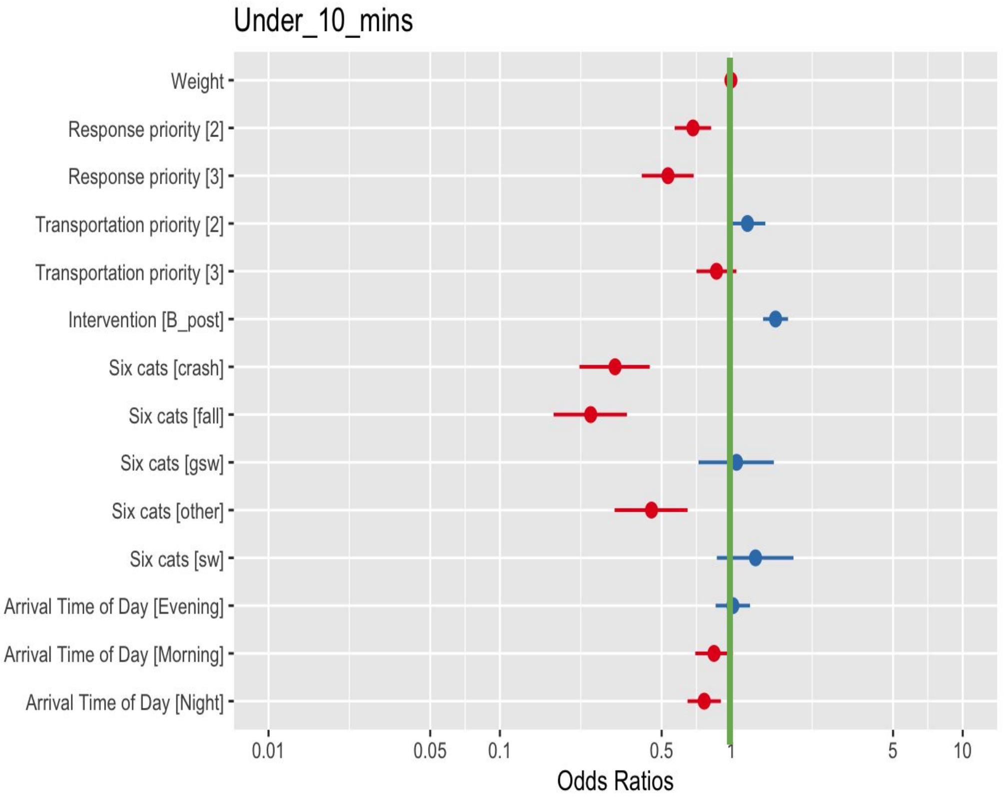
$$P_{Under10mins} = \frac{1}{1 + e^{-S_1}}$$

Where,

$$\begin{aligned} S_1 = \beta X = 1.248 &- 0.0038 \times \text{Weight} - 0.382 \times \text{RP2} \\ &- 0.630 \times \text{RP3} + 0.161 \times \text{TP2} \\ &- 0.148 \times \text{TP3} + 0.440 \times \text{Intervention post} \\ &- 1.157 \times \text{Crash} - 1.399 \times \text{Fall} + 0.052 \times \text{GSW} \\ &- 0.794 \times \text{Other} + 0.241 \times \text{SW} \\ &+ 0.015 \times \text{Evening} - 0.172 \times \text{Morning} \\ &- 0.269 \times \text{Night} \end{aligned}$$

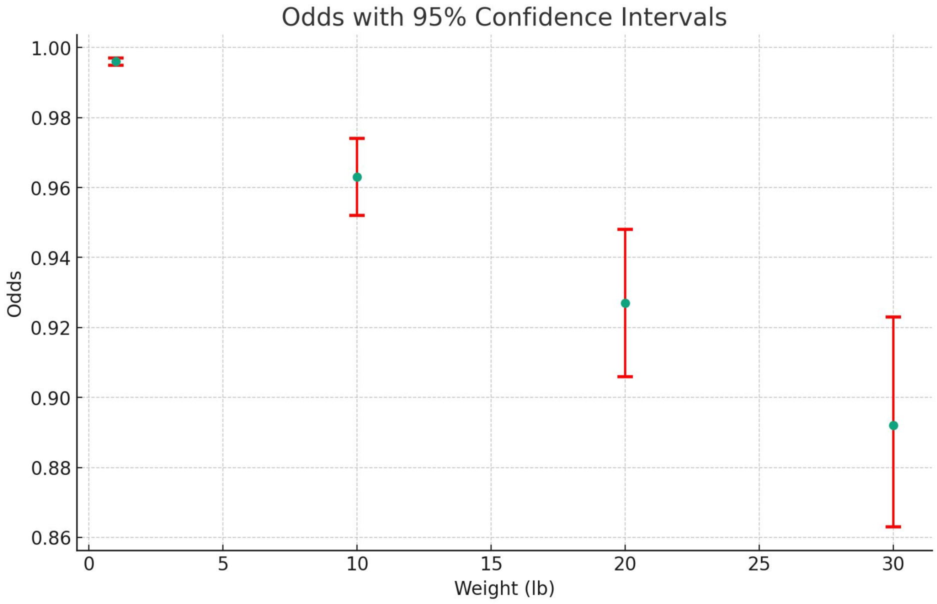
# Final Model - Odds Ratio

| | Odds | 95% CI |
|---|---|---|
| (Intercept) | 3.48 | (2.31, 5.30) |
| Weight | 0.996 | (0.995, 0.997) |
| Response_priority2 | 0.68 | (0.57, 0.82) |
| Response_priority3 | 0.53 | (0.41, 0.69) |
| Transportation_priority2 | 1.17 | (0.98, 1.40) |
| Transportation_priority3 | 0.86 | (0.71, 1.05) |
| Intervention_post | 1.55 | (1.37, 1.76) |
| Crash | 0.31 | (0.22, 0.44) |
| Fall | 0.25 | (0.17, 0.35) |
| Gun Shot | 1.05 | (0.72, 1.53) |
| Other | 0.45 | (0.31, 0.65) |
| Stab | 1.27 | (0.87, 1.86) |
| Arrival_Time_of_DayEvening | 1.02 | (0.86, 1.21) |
| Arrival_Time_of_DayMorning | 0.84 | (0.70, 1.01) |
| Arrival_Time_of_DayNight | 0.76 | (0.65, 0.90) |



# Weight - Odds Ratios

| Change in Weight (lb) | Odds | 95% CI |
|---|---|---|
| 1 | 0.996 | (0.995, 0.997) |
| 10 | 0.963 | (0.952, 0.974) |
| 20 | 0.927 | (0.906, 0.948) |
| 30 | 0.892 | (0.863, 0.923) |



# Conclusion

- There is not much significant difference between the two models and their performance is very similar. We determined that keeping the simpler model (without the interaction effect) would be the correct course of action.

- The odds of meeting our 10 minute scene time increased by 55% in our final model after the intervention.

- Weight, response priority, intervention, and method of injury were all significant predictors in determining scene time compliance.

- Additionally, transportation priority did not contribute significantly to general time compliance.

# Recommendations/Limitations

- Our final logistic regression model's prediction accuracy is about 65% with 10-folds cross validation which is moderate based on our real world data set.
- Having more observations after the Intervention 12/18/2014 would give us more balanced data.
- Potential use of Lasso(L1) or Ridge(L2) regression would've been useful in determining predictor selection/penalty to avoid overfitting.
- Considering more interaction pairs.

# Citations

*CCEMSA policies and procedures*. County of Fresno. (n.d.). https://www.fresnocountyca.gov/Departments/Public-Health/Emergency-Services/CCEMSA-Policies-and-Procedures

*Central California Emergency M Services - Fresno County, California. (n.d.). https://www2.co.fresno.ca.us/5620/ems/2008_pdfs/811.pdf*

Encyclopædia Britannica, inc. (n.d.-a). Encyclopædia Britannica. https://www.britannica.com/dictionary/eb/qa/parts-of-the-day-early-morning-late-morning-etc

*Children's books: I have A question*. website-1. (n.d.). https://www.ihaveaquestionbook.com/

# Additional Resources

**Code Book:**
https://docs.google.com/spreadsheets/d/1sWpSrF3EvbRQVGcHPKPhNgGBm3RtlZw7/edit?usp=sharing&ouid=101944088105331792577&rtpof=true&sd=true

**Cleaned Data:**
https://docs.google.com/spreadsheets/d/1txw3kX34Y8pnTJttUaKrEtuaTbCvDjs20mioGmyWdOM/edit?usp=sharing

**Code:**
https://drive.google.com/drive/folders/135Ty_a-19UdEAkEQeu4x1XvjPcPWW4fy?usp=sharing

# Thank you!!!