# Female Injury Vulnerability in U.S. Motor Vehicle Crashes (2017-2021)

**Abstract**
The historical lack of representation of the female body in safety tests conducted by car manufacturers has led to a higher injury rate for females in motor vehicle crashes in previous years. However, according to the National Highway Traffic Safety Administration (NHTSA) in 2022, sex disparities in the fatality rate of car accidents have been significantly reduced in recent years. In our study, we performed an analysis of 13 potential explanatory variables using merged nationwide car crash data from 2017 to 2021, provided by the Fatality Analysis Reporting System (FARS). Likelihood ratio tests, the area under the ROC curve (AUC), residual analysis, and overall accuracy were considered to develop the final model. Our study shows that sex is not a determinant predictor of fatality rates in motor vehicle crashes, which is consistent with the 2022 study from NHTSA

## Background

Motor vehicle road safety is a critical issue that can affect people of all ages and genders. As more data on road accidents have been collected and more research has been done on this topic, studies found that gender could have an impact on the fatality rate in motor vehicle crashes. Research has shown that men, with relatively high car crash involvement, is explained by the difference in risk-taking behavior by age and gender (Turner & McClure, 2003). However, while males are likely to be responsible for more car accidents, women are often more vulnerable to injuries and fatalities in such incidents. As suggested by the 2013 National Highway Traffic Safety Administration (NHTSA) report, on average, the risk of fatality is 17.0 ± 1.5 percent higher for females than males of the same age, with a greater disparity observed among young adults and less difference among elderly occupants (Kahane, 2013). In specific, female drivers tend to have a higher likelihood of experiencing primary anatomic injuries in the abdomen, chest, lower extremities, and upper extremities compared to male drivers (Ryan et al., 2020). Additionally, studies have also indicated that there is gender-based difference in the effectiveness of protection systems. The odds for a belt-restrained female driver to sustain severe injuries were 47% (95% confidence interval = 28%, 70%) higher than those for a belt-restrained male driver involved in a comparable crash (Ryan et al., 2020).

Recently, however, a decrease in gender-based difference in fatality rate in motor vehicle crashes was reported in 2022 by NHTSA. As the study reflected, improvements in seatbelts and dual airbags in newer generations of cars have helped to reduce the fatality rate for females. Statistically, the difference between the female and male fatality risks decreased significantly, from 18% to 6.3%, in the case of vehicles manufactured between 2010 and 2020, and to 2.9% for those produced between 2015 and 2020 (Noh et al., 2022).

Thus, we believe that it is important to understand the existing impact of sex disparities on fatality rate, as it could provide people as well as the government entities and vehicle manufacturers with insights to further reduce the gender gap in the effectiveness of vehicle protection systems. To determine if there has been a significant improvement in the gender gap evident in car accidents over the years, we aim to assess whether sex is an effective predictor of the probability of getting fatally injured in motor vehicle crashes.

## Methods

*a. Dataset Collection and Processing*

We used the data provided by the Fatality Analysis Reporting System (FARS) operated by NHTSA. This database allows us to obtain a nationwide census regarding motor vehicle crashes with detailed information on occupants' demographics and injury outcomes, crash-related information, and the associated vehicle information. Our raw data has a sample size of 435,659, each corresponding to an occupant involved in the traffic crash. To better address the sex-specific disparity in passenger vehicles, we conducted our analysis on accidents involving motor vehicles intended for transportation purposes, and we restricted our dataset to occupants who were 18 years of age or older. Our final dataset has a sample size of 137665.

For explanatory variables, we identify a list of major indicators in addition to the sex of occupants (SEX). We relabeled and reclassified explanatory variables to better reflect their practical relevance to our study, including the usage of restraint equipment (REST_USE_M), airbags (AIR_USE_M), and substance (SUB_USE_M). Other key explanatory variables in our study included role of involved occupants (PER_TYP), model age of involved vehicle (MOD_AGE_M), and the number of cars involved in the accident (VEH_FORMS). For a comprehensive list of explanatory variables, please refer to the Appendix.

For the response variable, we created a binary variable that classifies crash outcomes as either fatal (=1) or not fatal (=0). The fatality classification is based on the categorical variable derived from the 'INJ_SEV' variable in the original dataset.

*b. Finding the Best Reduced Model*

First, we examined our selection of variables and created a correlation plot to examine the relationship between variables (See Appx. A). Since most of the explanatory variables are categorical, we also created pairwise mosaic plots to check the correlation as well as the observation size within each level (See Appx. A). The patterns of interaction provided insights into how the variables jointly influence the outcomes, and we excluded dependent variables with high degree of correlation.

Then, we used stepwise linear logistic regression, drop-in deviance test, and comparison of test statistics on predictive performance to get the reduced model with the best predictive power without explanatory variable SEX and its interaction terms. The key variables were maintained (See Appx. A). Due to the large dataset, the small standard

| | Accuracy | ROC analysis (AUC) | AIC | Residual deviance |
|---|---|---|---|---|
| Main Effect Reduced Model | 0.7266 (Threshold=0.5) | 0.782 | 148217 | 148179 |
| Interaction Effect Reduced Model | 0.7363 (Threshold=0.5) | 0.796 | 144516 | 144202 |

***Table 2.*** Evaluation metrics of Main Effect Reduced Model and Interaction Effect Reduced Model.

deviation resulted in small p-values for almost every drop-in deviance test. In our study, model selection primarily relied on the assessment of the accuracy at optimal threshold, AIC, and the ROC. Quadratic logistic regression was developed to include all interaction effects. We compared the single variable logistic regression model with the interaction model to determine our best reduced model based on the statistics mentioned above. We also applied the residual plots for both models to identify the outliers and compared the residual performance of each model (See Appx. A). Since the purpose of this step was to identify the reduced model with the best predictive power, rather than interpreting the model between actual value and predicted value. The decrease of residual deviance from 144202 to 144112 suggests that the model is able to explain more of the variability in the response variable. The confusion matrix for each model (See Appx. A) suggests that sensitivity increases from 0.8432 to 0.8458 and specificity decreases from 0.5583 to 0.5544. The overall accuracy at optimal thresholds for each model increased from 0.7364 (threshold = 0.5057) to 0.7366 (threshold = 0.509). Based on our ROC curve and confusion matrix, it is hard to tell whether the slight changes in sensitivity, specificity, and accuracy are practically significant.

| | Accuracy | ROC analysis (AUC) | AIC | Residual deviance |
|---|---|---|---|---|
| Reduced Model | 0.7364 (Threshold=0.5057) | 0.796 | 144516 | 144202 |
| Full Model | 0.7366 (Threshold=0.509) | 0.796 | 144464 | 144112 |

***Table 3.*** Evaluation metrics of Reduced Model and Full Model.

coefficient, we didn't further reduce the variables in the quadratic logistic regression. Instead, we retained all interaction terms, as suggested by test statistics. Our final reduced model includes a total of 10 variables, with 3 quantitative and 7 categorical, and all the interaction terms.

*c. Examination of variable 'SEX'*

To determine the contribution of the variable 'SEX', we tested the predictive model with sex and its interaction terms. The resulting test statistics displayed the difference between deviance in the full model with threshold=0.5057 (with SEX and SEX-related terms) and deviance in the reduced model with threshold=0.509 (without SEX and SEX-related terms). AUC, accuracy, and G-statistics were compared. The differences reflected whether sex is a key factor in determining the fatality rate.

## Results

After determining the best reduced model, we tested the effect of the 'SEX' variable and its interactions with all other variables on the predictive performance of the model. Due to the diminished practical meaning of p-value based on our large dataset, the following statistics were compared to assess the performance of model prediction.

The inclusion of the variable 'SEX' in our best reduced model, along with its interaction effects, resulted in a slight improvement in the predictive performance of our model.

The large size of our dataset diminishes the practical importance of p-value. Therefore, we used accuracy from the confusion matrix, AIC, and AUC obtained from the ROC curve to assess models with different variable selections. We observed a minor decrease in both AIC and residual deviance after adding the 'SEX' variable and its interaction effect. In the full model, AIC decreased from 144516 to 144464, suggesting the model adding the variable 'SEX' is a better fit to the data. Similarly, residual deviance helps us assess the goodness-of-fit of the model

## Discussion

*a. Adding SEX to Model - No Discernible Improvement*

The NHTSA 2022 report indicates that refinement in seat belts and dual airbag usage in newer-generation cars have significantly reduced sex disparities in the fatality rate of motor vehicle crashes (Noh et al., 2022). Our study findings align with this report, showing that adding sex to our best reduced model does not have statistically discernible improvement on the overall model performance (see *Results* section for details). However, our logistic model with interaction terms identifies a strong association between sex and other variables in our study. We further our study by looking into sex disparity for drivers and passengers given different conditions regarding to restraint usage, substance involvement, and air bag deployment.

*b. Consider SEX-related Associations*

For drivers, the impact of restraint usage exhibits minimal disparity between sex indicated by Figure 1. This suggests that both male and female drivers experience similar levels of fatalities, regardless of whether restraints are used. Although there is a 3.7% higher fatality percentage for female drivers who are reported no restraint is applied than male driver under comparable restraint usage condition, there is no consistent trend that we could identify.

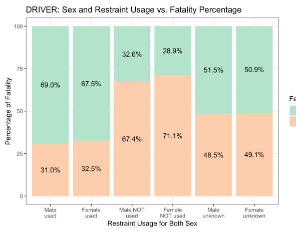


***Figure 1.*** Driver | Sex & Restraint Usage v.s. % Fatality

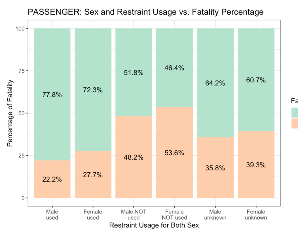


***Figure 2.*** Passenger | Sex & Restraint Usage v.s. % Fatality

However, when considering passengers, a distinct pattern emerges, as demonstrated in Figure 2 higher fatality percentage ranging from 4% to 6% for female passengers. Figure 2 shows that when restraints are applied, the fatality percentage of female passengers is 5.5% higher than male passengers, and when restraints are reported not used, the fatality percentage of female passengers is still 5.4% higher. This identifiable pattern suggests that when both males and females are subjected to similar circumstances in terms of safety restraint usage, female passengers are at a greater risk of experiencing fatal outcomes.

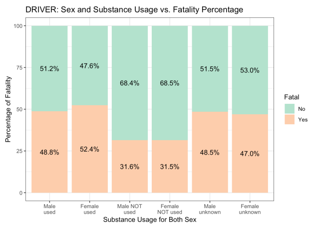


***Figure 3.*** Driver | Sex & Substance Usage v.s. % Fatality

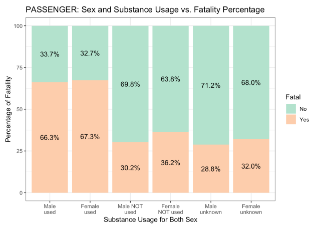


***Figure 4.*** Passenger | Sex & Substance Usage v.s. % Fatality

Besides, substance engagement follows the similar pattern between sex (male or female) and person type (driver or passengers). Figure 4 highlights that among passengers who do not engage in substance (drug or alcohol) use, the fatality percentage for female passengers is 6% higher than that of male passengers who engage in substance use. We observed that the disparity in fatality percentages based on sex becomes especially pronounced among passengers when comparable conditions of restraint usage and substance engagement are considered.

We proceeded to analyze the influence of airbag deployment on both male and female drivers and passengers. In our examination, we focused solely on situations where the airbag was deployed. This is because cases where the airbag was not deployed can be attributed to a range of factors that are unable to identify, including minimal impact or the absence of installed protective measures, which result in distinct injury outcomes.

Once again, this gap persists among male and female passengers. In cases where the airbag is activated with female passengers having 4.4% higher fatality percentage. Further exploration of these two or three-way associations indicates that females are more susceptible to vulnerability under specific conditions related to the protective systems of vehicles in car crashes.

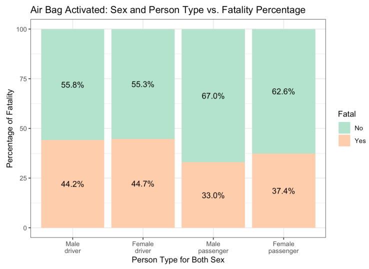


***Figure 5.*** Air Bag Activated | Sex & Person Type v.s. % Fatality

In conclusion, our findings provide sufficient evidence to suggest that the sex of vehicle occupants is no longer the determining factor in predicting the probability of fatality in the United States from 2017 to 2021. This could be attributed to the implementation of advanced safety technologies in recent years, resulting in a reduction in the overall fatality rate. However, despite these advancements, we continue to observe a persistent trend in the gender gap, specifically on the vulnerability of female passengers compared to male passengers under similar conditions of restraint usage, substance involvement, and airbag deployment. Given the fact that the first female dummies in car crash tests were not introduced until 2022, it is worth considering the potential implications of this fact in addressing the specific safety needs of female occupants, despite being beyond the scope of this study.

## Limitation and Future Research

It is important to acknowledge the limitations of our study and the need for further research to address them. Firstly, while our dataset was collected from a nationwide yearly census and is considered exhaustive and reliable, our study does not account for confounding variables that are either unavailable or difficult to analyze, such as the occurrence time and weather conditions of the accident, occupants' BMI, previous health conditions, and driving duration. The absence of these variables could potentially bias our results. Additionally, our dataset was restricted to adult occupants of motor vehicles in transit, resulting in missing data and potentially limiting the generalizability of our results.

To improve future investigations, we recommend the inclusion of additional variables, such as occupants' previous health conditions and occupants’ BMI, as they are related to sex and could affect the predictive model of the fatality rate in motor vehicle crashes. It is crucial to acknowledge the limitations of our study and incorporate more comprehensive data to provide a more accurate understanding of the factors that influence the fatality rate in motor vehicle crashes.

**References**

Bose, D., Segui-Gomez, M., & Crandall, J. R. (2011). Vulnerability of female drivers involved in motor vehicle crashes: an analysis of US population at risk. *American journal of public health, 101*(12), 2368–2373. https://doi.org/10.2105/AJPH.2011.300275

Kahane, C. J. (2013, May). *Injury vulnerability and effectiveness of occupant protection technologies for older occupants and women*. (Report No. DOT HS 811 766). Washington, DC: National Highway Traffic Safety Administration.

Noh, E. Y., Atwood, J. R. E., Lee, E., & Craig, M. J. (2022, August) *Female crash fatality risk relative to males for similar physical impacts* (Report No. DOT HS 813 358). Washington, DC: National Highway Traffic Safety Administration.

Ryan, A., Tainter, F., Fitzpatrick, C., Gazzillo, J., Riessman, R., & Knodler, M. (2020). The impact of sex on Motor Vehicle Crash Injury Outcomes. *Journal of Transportation Safety & Security, 14*(5), 818–842. http://doi.org/10.1080/19439962.2020.1834478

Turner, C., & McClure, R. (2003). Age and gender differences in risk-taking behaviour as an explanation for high incidence of motor vehicle crashes as a driver in young males. *Injury Control and Safety Promotion*, *10*(3), 123–130. https://doi.org/10.1076/icsp.10.3.123.14560

**Acknowledgment**
The authors are grateful for the guidance and assistance of Professor Shonda Kuiper on this project.

## Appendix A

*a. Correlation plots*

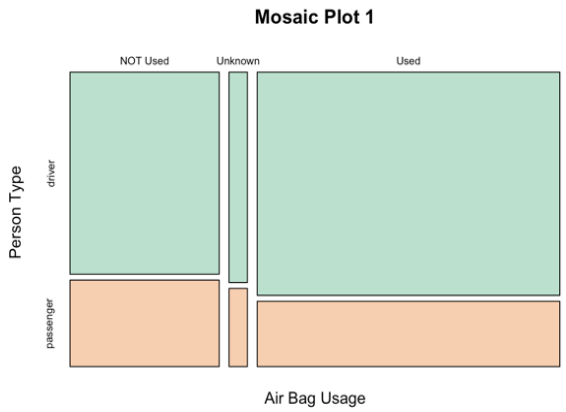


***Figure 1.*** Mosaic Plot of Air Bag Usage and Person Type.

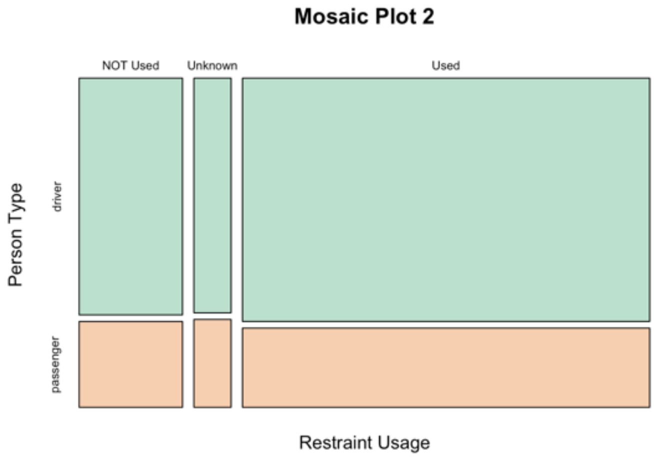


***Figure 2***. Mosaic Plot of Restraint Usage and Person Type.

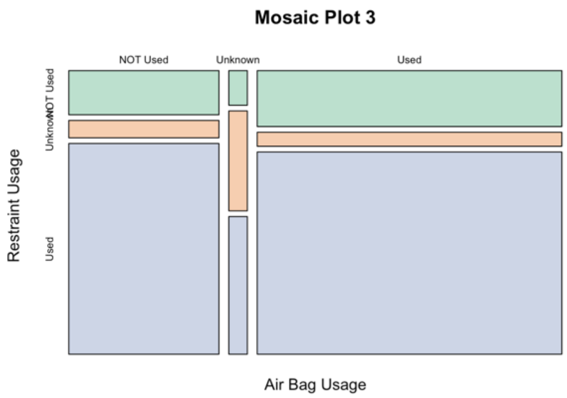


***Figure 3.*** Mosaic Plot of Air Bag Usage and Restraint Usage.

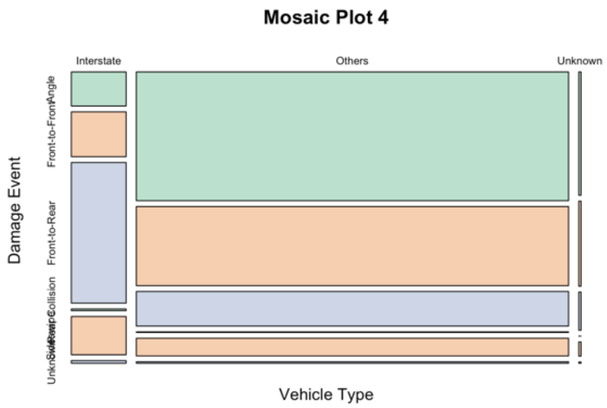


***Figure 4***. Mosaic Plot of Vehicle Type and Damage Event.

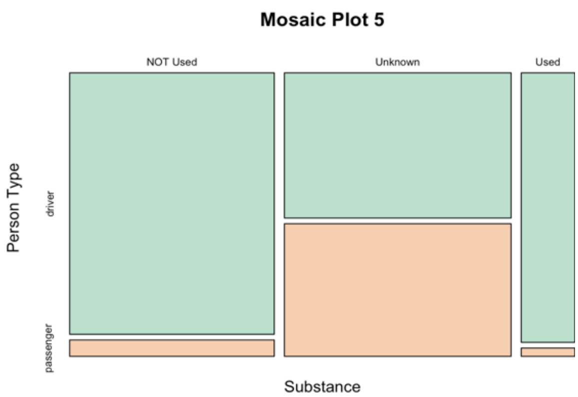


***Figure 5.*** Mosaic Plot of Substance and Person Type.

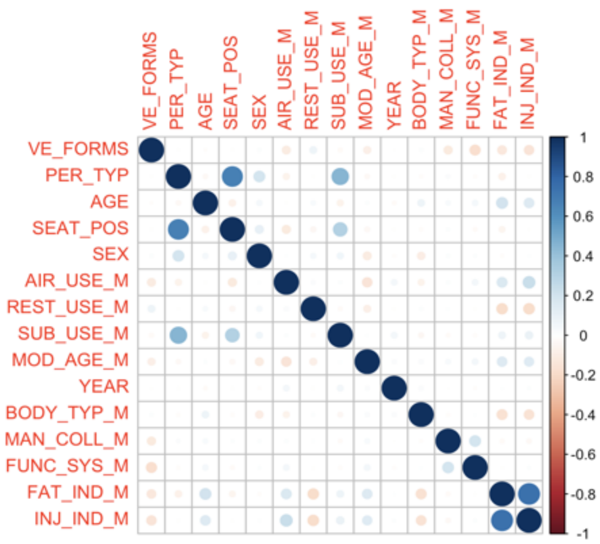


***Figure 6.*** Correlation plot of our explanatory variables to identify variables with high correlation.

*b. Residual & ROC plots*

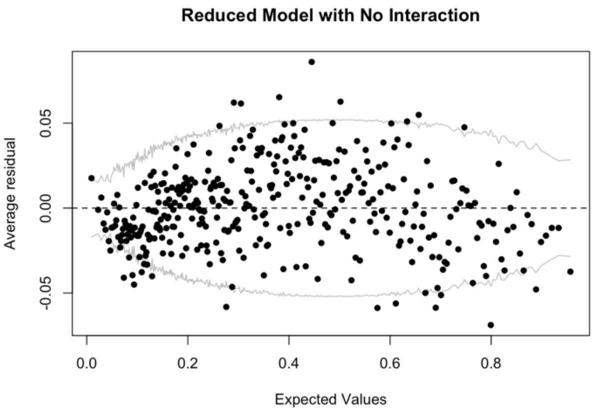


***Figure 7.*** Residual plot - reduced model (no interaction) (performance 91%).

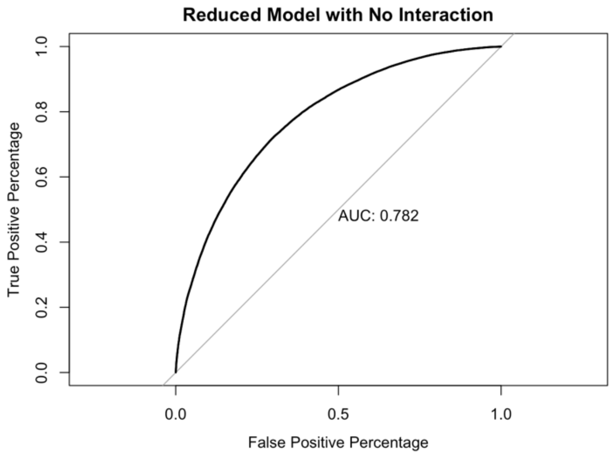


***Figure 8.*** ROC curve - reduced model (no interaction).

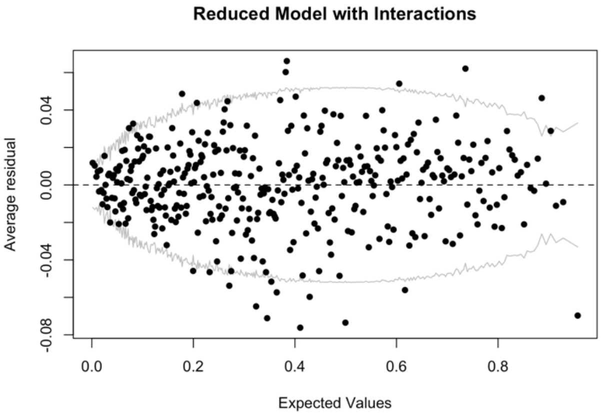


***Figure 9.*** Residual plot - reduced model with interactions (performance 94%).

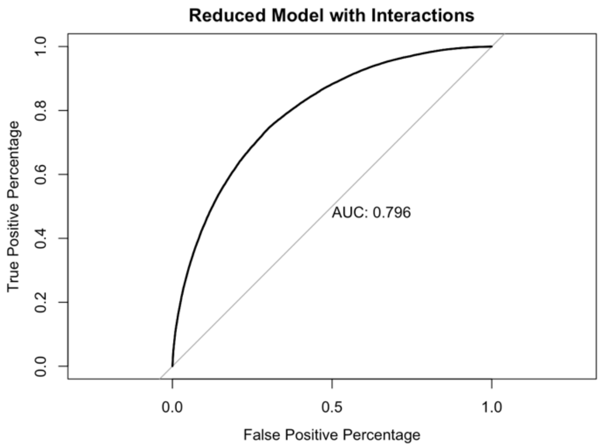


***Figure 10.*** ROC curve - reduced model (no interaction).

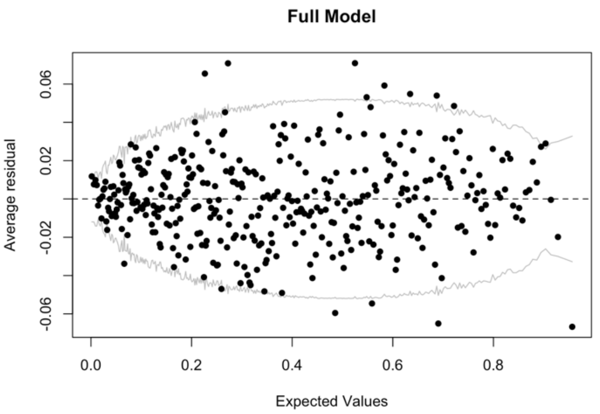


***Figure 11.*** Residual plot - Full Model included interaction (performance 95%)..

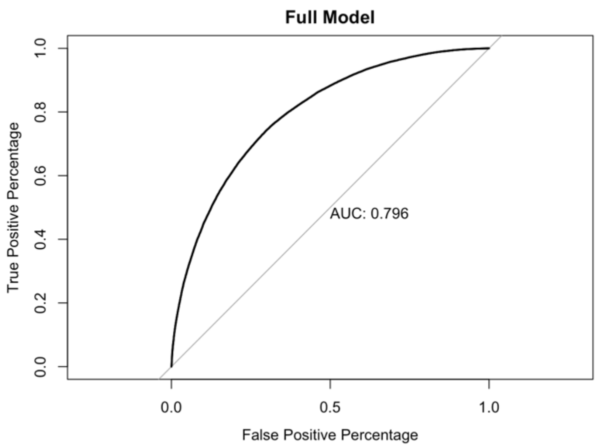


***Figure 12.*** ROC curve - Full Model included interaction.

*c. Logistic Model - Variables and Coefficients*

```
Call:
glm(formula = FAT_IND_M ~ VE_FORMS + as.factor(PER_TYP) + AGE +
    as.factor(BODY_TYP_M) + as.factor(FUNC_SYS_M) + as.factor(MAN_COLL_M) +
    as.factor(AIR_USE_M) + as.factor(REST_USE_M) + as.factor(SUB_USE_M) +
    MOD_AGE_M, family = "binomial", data = fat.red.data)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-3.3596  -0.8374  -0.5046   0.9471   4.0596

Coefficients:
                        Estimate Std. Error z value Pr(>|z|)
(Intercept)           -1.1828600  0.1289460  -9.173  < 2e-16 ***
VE_FORMS              -0.3018702  0.0092713 -32.560  < 2e-16 ***
as.factor(PER_TYP)2   -0.5903146  0.0170107 -34.703  < 2e-16 ***
AGE                    0.0321173  0.0003391  94.707  < 2e-16 ***
as.factor(BODY_TYP_M)2 -0.8815795  0.0130330 -67.642  < 2e-16 ***
as.factor(FUNC_SYS_M)1  0.4822224  0.0955355   5.048 4.47e-07 ***
as.factor(FUNC_SYS_M)2  0.0451916  0.0934644   0.484 0.628729
as.factor(MAN_COLL_M)1  0.1123401  0.0839238   1.339 0.180702
as.factor(MAN_COLL_M)2  0.3090206  0.0832312   3.713 0.000205 ***
as.factor(MAN_COLL_M)3 -0.0733785  0.0829925  -0.884 0.376611
as.factor(MAN_COLL_M)4  0.0222353  0.0858074   0.259 0.795535
as.factor(MAN_COLL_M)5  0.2332917  0.1536335   1.518 0.128890
as.factor(AIR_USE_M)1   0.7840423  0.0155064  50.562  < 2e-16 ***
as.factor(AIR_USE_M)2   1.1959178  0.0339926  35.182  < 2e-16 ***
as.factor(REST_USE_M)1 -1.4523182  0.0165036 -88.000  < 2e-16 ***
as.factor(REST_USE_M)2 -0.8301170  0.0276937 -29.975  < 2e-16 ***
as.factor(SUB_USE_M)1   0.5047421  0.0212341  23.770  < 2e-16 ***
as.factor(SUB_USE_M)2   0.5541602  0.0153167  36.180  < 2e-16 ***
MOD_AGE_M               0.0489153  0.0009462  51.697  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 182108  on 137664  degrees of freedom
Residual deviance: 148179  on 137646  degrees of freedom
AIC: 148217

Number of Fisher Scoring iterations: 5
```

***Table 1.*** Summary of Logistic Model of Single Variables

*d. Confusion Matrices and Accuracy Table*

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction     0     1
##          0 72580 22786
##          1 13500 28799
##
##                Accuracy : 0.7364
##                  95% CI : (0.7341, 0.7387)
##     No Information Rate : 0.6253
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.4165
##
##  Mcnemar's Test P-Value : < 2.2e-16
##
##             Sensitivity : 0.8432
##             Specificity : 0.5583
##          Pos Pred Value : 0.7611
##          Neg Pred Value : 0.6808
##              Prevalence : 0.6253
##          Detection Rate : 0.5272
##    Detection Prevalence : 0.6927
##       Balanced Accuracy : 0.7007
##
##        'Positive' Class : 0
##
```

***Table 4.*** Confusion Matrix and Statistics for Best Reduced Model

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction     0     1
##          0 72806 22984
##          1 13274 28601
##
##                Accuracy : 0.7366
##                  95% CI : (0.7343, 0.7389)
##     No Information Rate : 0.6253
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.4159
##
##  Mcnemar's Test P-Value : < 2.2e-16
##
##             Sensitivity : 0.8458
##             Specificity : 0.5544
##          Pos Pred Value : 0.7601
##          Neg Pred Value : 0.6830
##              Prevalence : 0.6253
##          Detection Rate : 0.5289
##    Detection Prevalence : 0.6958
##       Balanced Accuracy : 0.7001
##
##        'Positive' Class : 0
##
```

***Table 5.*** Confusion Matrix and Statistics for Full model

**Appendix B**

**Code Book of Clean Data (n=137665)**

| Variable | Code | Count | %Total |
|---|---|---|---|
| VE_FORMS | Continuous (1-12) | | |
| SEX | 1=Male | 82251 | 59.75% |
| | 2=Female | 55414 | 40.25% |
| AGE | Continuous (18-107) | | |
| REST_USE_M | 0=No restraint use | 25982 | 18.87% |
| | 1=Restraint use | 102347 | 74.34% |
| | 2=Unkown/Unreported | 9336 | 6.78% |
| SEAT_POS | 11=Front Left | 103079 | 74.88% |
| | 13=Front Right | 26792 | 19.46% |
| | 21=Back Left | 3069 | 2.23% |
| | 22=Back Middle | 715 | 0.52% |
| | 23=Back Right | 4010 | 2.91% |
| AIR_USE_M | 0= Not deployed air bag | 43675 | 31.73% |
| | 1= Deployed air bag | 88601 | 64.36% |
| | 2=Unkown/Unreported | 5389 | 3.91% |
| SUB_USE_M | 0=No drug and no alcohol use | 58074 | 42.19% |
| | 1=Drug or alcohol use | 15247 | 11.08% |
| | 2=Unkown/Unreported | 64344 | 46.74% |
| FUNC_SYS_M | 0=Unkown | 644 | 0.47% |
| | 1=Interstate | 15417 | 11.20% |
| | 2=Other | 121604 | 88.33% |
| MAN_COLL_M | 0=Unknown | 830 | 0.60% |
| | 1=Front-to-Rear | 24414 | 17.73% |
| | 2=Front-to-Front | 39550 | 28.73% |
| | 3=Angle | 62032 | 45.06% |
| | 4=Sideswipe | 10502 | 7.63% |
| | 5=Rear Collison | 337 | 0.24% |
| BODY_TYP_M | 1=Passenger cars | 71254 | 51.76% |
| | 2=Light trucks/vans | 66411 | 48.24% |
| MOD_AGE_M | Continuous (0-98) | | |
| PER_TYP | 1=Driver | 103060 | 74.86% |
| | 2=Passenger | 34605 | 25.14% |
| YEAR | Continuouus(2017-2022) | | |