

# Risk Factors for Injury Severity in Road Accidents

2025-06-27

This kaggle dataset provides the research collected by the Addis Adaba Sub-city police department of road traffic accidents from 2017 through 2020. <https://www.kaggle.com/datasets/kanuriviveknag/road-accidents-severity-dataset>

My goal is to identify significant predictors of injury occurrence in road traffic accidents using logistic regression.

```
library(tidyverse)
```

```
## -- Attaching core tidyverse packages ----- tidyverse 2.0.0 --
## v dplyr      1.1.4      v readr      2.1.5
## v forcats    1.0.0      v stringr    1.5.1
## v ggplot2     3.5.1      v tibble     3.2.1
## v lubridate  1.9.3      v tidyr      1.3.1
## v purrr       1.0.2
```

```
## -- Conflicts ----- tidyverse_conflicts() --
```

```
## x dplyr::filter() masks stats::filter()
```

```
## x dplyr::lag()      masks stats::lag()
```

```
## i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become errors
```

```
library(readr)
```

```
library(car)
```

```
## Warning: package 'car' was built under R version 4.3.3
```

```
## Loading required package: carData
```

```
##
```

```
## Attaching package: 'car'
```

```
##
```

```
## The following object is masked from 'package:dplyr':
```

```
##
```

```
##      recode
```

```
##
```

```
## The following object is masked from 'package:purrr':
```

```
##
```

```
##      some
```

```
library(dplyr)
```

```
library(ggplot2)
```

```
Data = read_csv("RTA Dataset 2.csv"); count(Data)
```

```
## Rows: 12316 Columns: 32
```

```
## -- Column specification -----
```

```
## Delimiter: ","
```

```
## chr  (29): Day_of_week, Age_band_of_driver, Sex_of_driver, Educational_level...
```

```
## dbl  (2): Number_of_vehicles_involved, Number_of_casualties
```

```
## time (1): Time
```

```
##
```

```

## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.

## # A tibble: 1 x 1
##       n
##   <int>
## 1 12316

# Given over 12,300 entries, I want to first organize my data set and select only the subset of variables I need.

Data = read_csv("RTA Dataset 2.csv") %>%
  select(Accident_severity, Sex_of_driver, Area_accident_occured, Light_conditions, Educational_level, Number_of_vehicles_involved, Number_of_casualties, Time_of_accident) %>%
  rename(Severity = Accident_severity, Sex = Sex_of_driver, Area = Area_accident_occured, Light = Light_conditions, Education = Educational_level, Vehicles = Number_of_vehicles_involved, Casualties = Number_of_casualties, Time = Time_of_accident) %>%
  drop_na() %>%
  filter(!Sex %in% c("Unknown"), !Education %in% c("Unknown"), !Area %in% c("Unknown"), !Light %in% c("Unknown"), !Vehicles %in% c("Unknown"), !Casualties %in% c("Unknown"), !Time %in% c("Unknown"))

## Rows: 12316 Columns: 32
## -- Column specification -----
## Delimiter: ","
## chr  (29): Day_of_week, Age_band_of_driver, Sex_of_driver, Educational_level...
## dbl  (2): Number_of_vehicles_involved, Number_of_casualties
## time (1): Time
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.

# To sparse the data I dropped all unknowns within the variables.

Data = Data %>%
  mutate(Area = fct_collapse(as.factor(Area), "Urban_institutions" = c("Hospital areas", "Office areas", "Industrial areas", "Commercial areas", "Residential areas"),
    Light = ifelse(Light == "Daylight", "Daylight", "Low Visibility"), Light = as.factor(Light),
    Road = fct_collapse(as.factor(Road), "Severe" = c("Flood over 3cm. deep", "Snow"), "Wet" = "Wet or dry", "Dry" = "Dry"),
    Sex = as.factor(Sex),
    Injury = ifelse(Severity %in% c("Slight Injury", "Serious Injury", "Fatal Injury"), 1, 0))

# Above, I continued to clean the data by combining similar entries into broader categories. I then factored the variables.

logit_model = glm(Injury ~ Sex + Area + Light + Road, family = binomial, data = Data);summary(logit_model)

##
## Call:
## glm(formula = Injury ~ Sex + Area + Light + Road, family = binomial,
##      data = Data)
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)    5.0988     0.4656  10.951 < 2e-16 ***
## SexMale       -0.5987     0.4585  -1.306  0.1916
## AreaUrban_institutions 0.2660     0.1889   1.409  0.1590
## AreaRural      0.5371     0.7185   0.748  0.4548
## AreaRecreational -0.6990     0.3751  -1.863  0.0624 .
## LightLow Visibility -0.8445     0.1747  -4.835 1.33e-06 ***
## RoadSevere     13.3165    477.9144   0.028  0.9778
## RoadWet        0.2995     0.2094   1.430  0.1527
## ---

```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##    Null deviance: 1502.4  on 11086  degrees of freedom
## Residual deviance: 1470.4  on 11079  degrees of freedom
## AIC: 1486.4
##
## Number of Fisher Scoring iterations: 16
# A large standard error of 477.9144 for Road Severity indicates great uncertainty in the estimation of

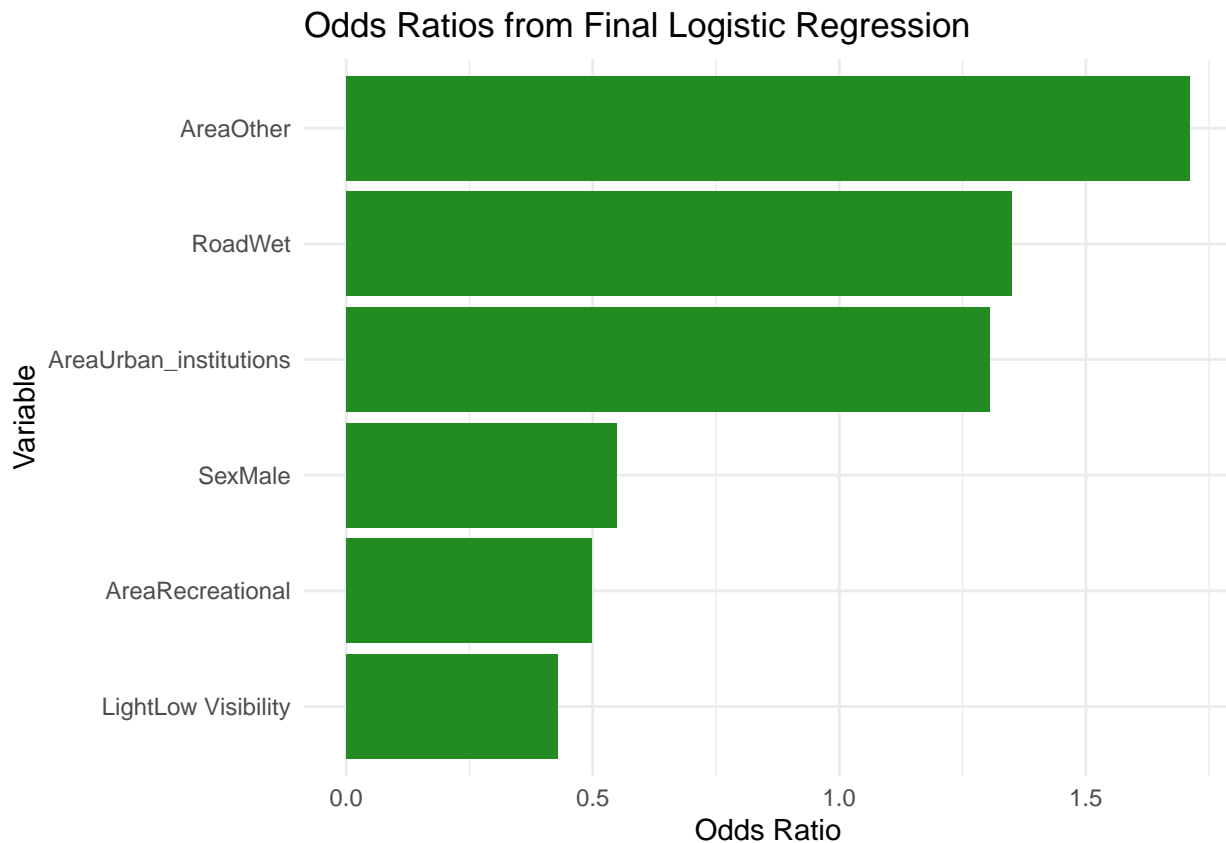
Data = Data %>%
  mutate(Area = fct_lump(Area, n = 3, other_level = "Other"), Road = fct_lump(Road, n = 2, other_level = "Other"),
         filter(Road != "Other") # Remove overly sparse Road category)

logit_model = glm(Injury ~ Sex + Area + Light + Road, family = binomial, data = Data);summary(logit_model)

##
## Call:
## glm(formula = Injury ~ Sex + Area + Light + Road, family = binomial,
##      data = Data)
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)      5.0988     0.4656  10.951 < 2e-16 ***
## SexMale          -0.5987     0.4584  -1.306  0.1916
## AreaUrban_institutions  0.2660     0.1888   1.409  0.1590
## AreaRecreational    -0.6990     0.3751  -1.863  0.0624 .
## AreaOther           0.5371     0.7184   0.748  0.4547
## LightLow Visibility  -0.8445     0.1747  -4.835 1.33e-06 ***
## RoadWet            0.2995     0.2094   1.430  0.1527
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##    Null deviance: 1500.7  on 11020  degrees of freedom
## Residual deviance: 1470.4  on 11014  degrees of freedom
## AIC: 1484.4
##
## Number of Fisher Scoring iterations: 7
# Calculate and visualize Odds Ratios
Odds = data.frame(Variable = names(coef(logit_model)), OR = exp(coef(logit_model))); Odds

##              Variable              OR
## (Intercept) (Intercept) 163.8239317
## SexMale      SexMale    0.5495322
## AreaUrban_institutions AreaUrban_institutions 1.3047416
## AreaRecreational AreaRecreational 0.4971033
## AreaOther     AreaOther  1.7109973
## LightLow Visibility LightLow Visibility 0.4297621
## RoadWet       RoadWet    1.3491626
```

```
ggplot(Odds[-1,], aes(x = reorder(Variable, OR), y = OR)) +
  geom_bar(stat = "identity", fill = "forestgreen") +
  coord_flip() +
  labs(title = "Odds Ratios from Final Logistic Regression", x = "Variable", y = "Odds Ratio") +
  theme_minimal()
```



From the above model, we see that male drivers had about a 45.05% lower odds of injury, but this result is not statistically significant ( $p=0.1916$ ). Urban areas had a 30.47% higher chance of injury compared to residential areas, but again, this is not significant ( $p=.0159$ ). Marginally lower injury odds occur in recreational areas (50.29%), which may reflect that individuals drive slower speeds through these areas. These odds are not statistically significant ( $p=.0624$ ), but they are the closest value to the goal  $p=0.05$ . Other yielded a  $p=.4547$  implying great uncertainty, but this was to be expected with this category representing a grouping of underrepresented occurrences. For low visibility, there are statistically significantly lower odds of injury (57.02%;  $p<.05$ ). This may reflect more cautious driving at night, as expected. Finally, there is a 34.92% higher chance of injury on wet roads, but this is not significant ( $p=.1527$ ).

```
Data = Data %>%
  filter(Area %in% c("Residential/Market", "Urban_institutions")) %>%
  droplevels()
```

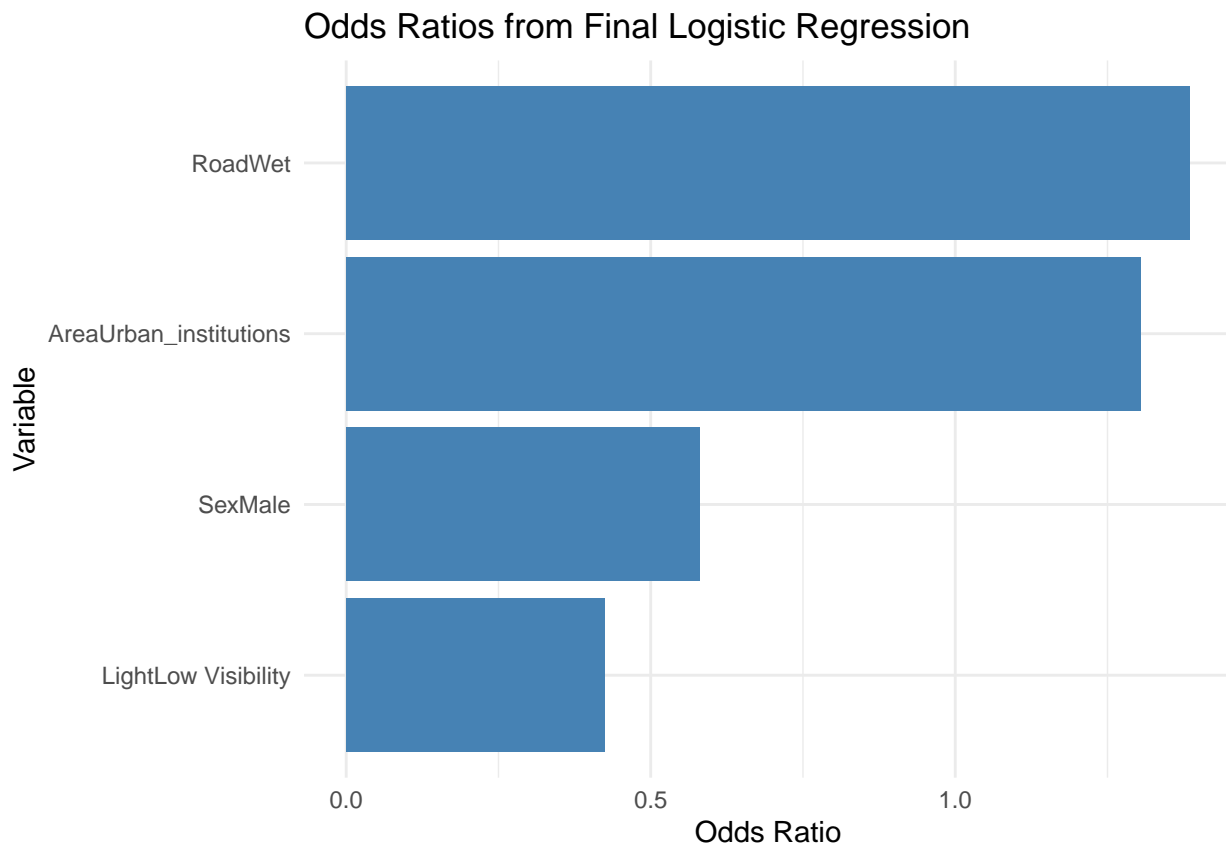
```
logit_model1 = glm(Injury ~ Sex + Area + Light + Road, family = binomial, data = Data);summary(logit_model1)
```

```
##
## Call:
## glm(formula = Injury ~ Sex + Area + Light + Road, family = binomial,
##      data = Data)
##
```

```
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)      5.0476    0.4666  10.819 < 2e-16 ***
## SexMale          -0.5453    0.4592  -1.188   0.235
## AreaUrban_institutions  0.2660    0.1889   1.409   0.159
## LightLow Visibility -0.8574    0.1810  -4.737 2.17e-06 ***
## RoadWet           0.3259    0.2193   1.486   0.137
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##    Null deviance: 1399.1  on 10455  degrees of freedom
## Residual deviance: 1374.0  on 10451  degrees of freedom
## AIC: 1384
##
## Number of Fisher Scoring iterations: 7
```

```
Odds = data.frame(Variable = names(coef(logit_model1)), OR = exp(coef(logit_model1)))
```

```
ggplot(Odds[-1,], aes(x = reorder(Variable, OR), y = OR)) +
  geom_bar(stat = "identity", fill = "steelblue") +
  coord_flip() +
  labs(title = "Odds Ratios from Final Logistic Regression", x = "Variable", y = "Odds Ratio") +
  theme_minimal()
```



```
vif_values = vif(logit_model)
print(vif_values)
```

```
##          GVIF Df GVIF^(1/(2*Df))
## Sex    1.003437  1      1.001717
## Area   1.001359  3      1.000226
## Light  1.044547  1      1.022031
## Road   1.042553  1      1.021055
```

```
# Variance Inflation Factors were all near 1, indicating no evidence of multicollinearity among predict
```

## Overall Findings

*In this project, I analyzed over 12,000 road traffic incidents to identify key risk factors for injury using logistic regression. I cleaned and recoded categorical data, merged sparse categories, and ensured model stability through exploratory data checks. My analysis revealed that injury risk was significantly reduced in low-visibility conditions, highlighting the importance of driver behavior over raw environmental danger. The results were visualized using odds ratio plots and I interpreted said data for both practical meaning and model reliability. Its also important to note that recreational and “Other” areas were removed entirely. While this improves model stability, this makes Area strictly binary, not often a common occurrence in real life. Similarly, the original severity variable contained ordinal levels, but I collapsed then into a binary outcome(method I am educated in). This discards potentially valuable distinctions between minor and fatal injuries, potentially affecting conclusions. Also recall that some sparse levels had inflated standard errors, which were removed and/or merged, which could obscure true effects. While their are currently limitations, I look forward to continuing my journey of learning R and practicing my data wrangling skills.*