Facial Trauma Analysis Final Report

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Abstract:

This study is a retrospective review of trauma patients with craniofacial injuries data from 2016-2020 done in partnership with Maine Medical Center (MMC). The purpose of this report is to provide supplementary data analysis to this study with the main goal of analyzing the relationships between areas of facial trauma and numerous predictors, such as residency and mechanism of injury. In this analysis, we will apply the Generalized Linear Mixed-Effect Regression Model, which is best-fit for binary outcomes. We were able to make some preliminary inferences from the model, however, neither residency nor the majority of the injury mechanisms in this dataset appear to be great predictors of the area of facial trauma.

Introduction:

Facial Trauma, also called maxillofacial trauma, involves different facial trauma sites and injury mechanisms. In this report, our main focus is to explore a facial trauma database collected for any patient with facial trauma admitted in Maine Medical Center from 2016 to 2020. The goal of this project is to analyze the relationship between patient's injury sites and residency aiming to design specific facial trauma treatment plans for future patients with respect to their residency, from urban or rural areas; and provide efficient treatment corresponding to their facial trauma injury sites. For better access to facial trauma prediction, we are going to apply the Generalized Linear Mixed-Effect Regression Model which is best-fit for binary outcomes, non-Gaussian distribution variable predictors, and it allows us to add random slope and intercept effects which will also improve model fitting efficiency.

Data Cleaning and Processing:

For ICD codes: The major differences between the two coding systems include the number of characters involved. ICD-9 has up to five characters while ICD-10 has up to seven. ICD-10 adds laterality to the coding system, which ICD-9 lacks. ICD-10 offers much more specificity, including episodes of care, body area, etc. Also, the ICD-10 coding structure utilizes a dummy placeholder, which ICD-9 does not. Because the clients plan to analyze the injury area differences in facial trauma patients in urban and rural settings. Transformation of ICD codes is very important.

For cause of injury(Injury mechanism): From the data screening provided by the client, we found that there are 10 levels for injury mech in the dataset and some of them are same at some content, for example, there are several mechanisms for falls but with different falling height. We need to categorize them in order to tidy the dataset for further use.

For categorization of ICD10 codes: Now we have the ICD10 codes, but what we want to study is the relationship between areas of facial trauma instead of the codes. So we need to categorize the codes to specific areas of injury: as the client instructs, we categorize the codes into four levels: Midface, Mandible, Superior and other facial trauma sites for further use.

When we want to do ICD Code transformation Among 318 patients, we found that 158 of them are recorded with ICD 9, while 160 take ICD 10. When the client tried to convert ICD 9 code into ICD 10 code. He encountered two major problems: A) Not Convertible: 75 out of 432 ICD 9 code can not be converted to

ICD 10 code. B) Multiple Converted: 143 of the ICD 9 codes can be converted into multiple ICD 10 codes. In order to solve these two major problems. We plan to solve B first. After solving B, we can drop the codes mentioned in A and only leave the useful observations for further analysis.

To solve problem A. For the tidy dataset so far, we now have 211 patients with corresponding injury areas. For the rest of the observations, our client David conducted a more detailed investigation and he gave a table for the corresponding convertible codes for us to do the conversion. After finalizing the conversion, we are now having 292 observations for the further analysis. To solve problem B, we first let all the missing values be blank. And use for loops for each ICD9 code column, when the ICD9 column has the code that can be converted to useful ICD10 codes, then we assign the converted ICD10 codes to the corresponding ICD10 code column. Categorization of codes (ICD10) Among 318 patients, 311 of them have explicit injury mechanism records, 7 of them are blank or not clarified clearly. For 311 patients who have records, we extracted the key words of descriptions, and divided them into 6 categories:

Converted injury mechanism categories	Original injury mechanism
MVC	Motorcycle, MVC
Falls	Fall under 1m, Fall 1m-6m, Fall over 6m
Gun	Hand gun, Shotgun
Others	Other, Assault, Biting, Pedestrian, 0
Bicycle	Bicycle
Other_Blunt	Blunt Mechanism

Data Description:

Variable	Explanation	Description
Study.ID..	ID for Patients	Total 292 observations left
Age	Age information for patients	From 17 to 90
Gender	Gender information for patients	Male, Female
Race	Ethnicity information for patients	Asian, White, African American and Other Races
Urban.Rural	Living area information for patients	Urban and Rural
Superior	Dummy variable to check if patient was hurt on Superior site	Binary
Mandible	Dummy variable to check if patient was hurt on Mandible site	Binary
Midface	Dummy variable to check if patient was hurt on Midface site	Binary
Otherff	Dummy variable to check if patient was hurt on other face trauma site	Binary
Injury.Mech.category	Variable to check what mechanisms caused facial trauma	6 mechs as showed above

In order to show the information of the data set and the relationship between various variables more intuitively, let's move to our EDA part:

EDA:

After data cleaning and processing, we started our exploratory data analysis. As shown in Figure 1, 2, 3, and 4, there are more data samples collected from midface injury patients than the other three facial trauma sites. Among all four facial trauma sites, falls and motor vehicle accidents are the two major types of injury mechanisms for both residency areas. It is hard not to notice that people in rural areas have more facial trauma caused by MVCs than people with facial trauma in urban areas. In addition, we have a small sample size for the injury mechanism of "Gun" which makes sense because gunshot accidents are rare in our daily life and gunshot accidents can cause immediate death that do not even have a chance to be admitted into hospital for treatment and gunshots are majorly targets on midface and superior.

Figure 5 is a bar plot which compares the different population sizes of people with facial trauma and bars are filled with color coded facial injury mechanism categories. From the bar plot, we can see that the database consists of more male patients than female patients. Falls and motor vehicle accidents are the two major types of injury mechanisms for both female and male patients.

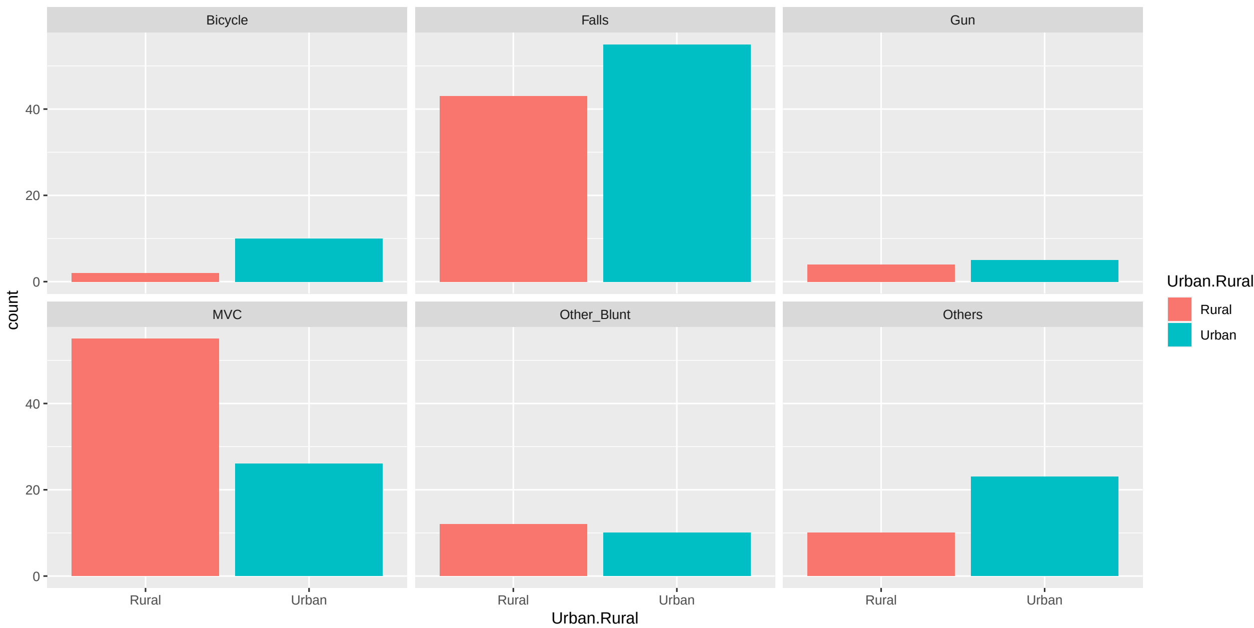

Figure 1: Midface area injured patient number vs. demographic information

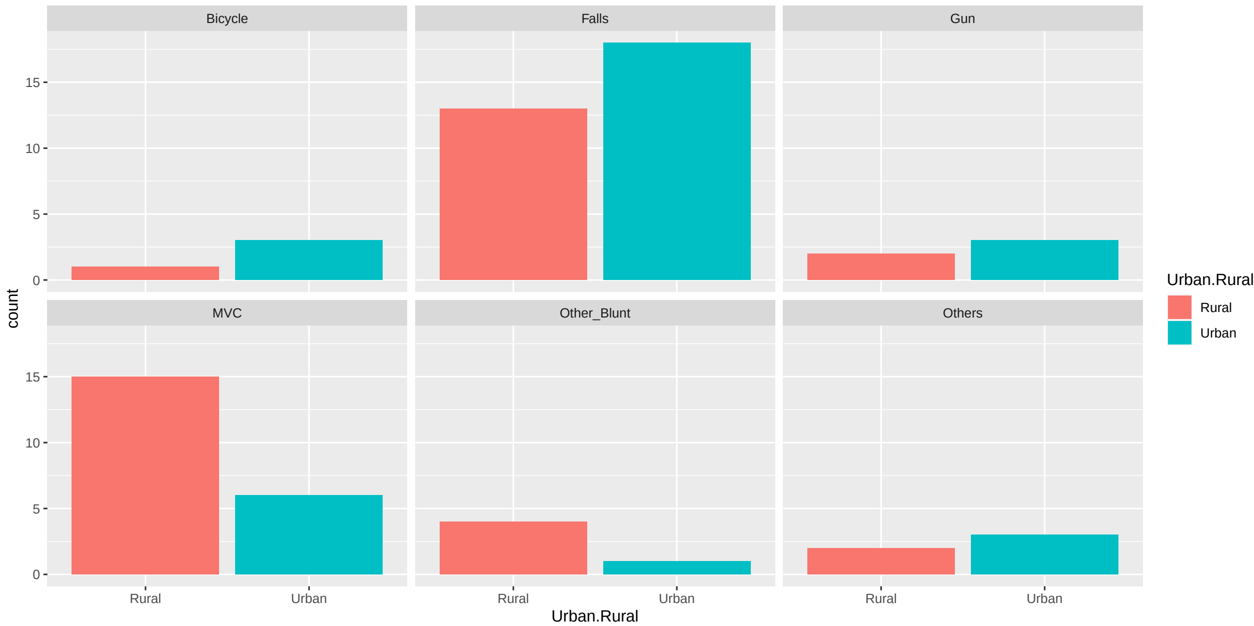

Figure 2: Superior area injured patient number vs. demographic information

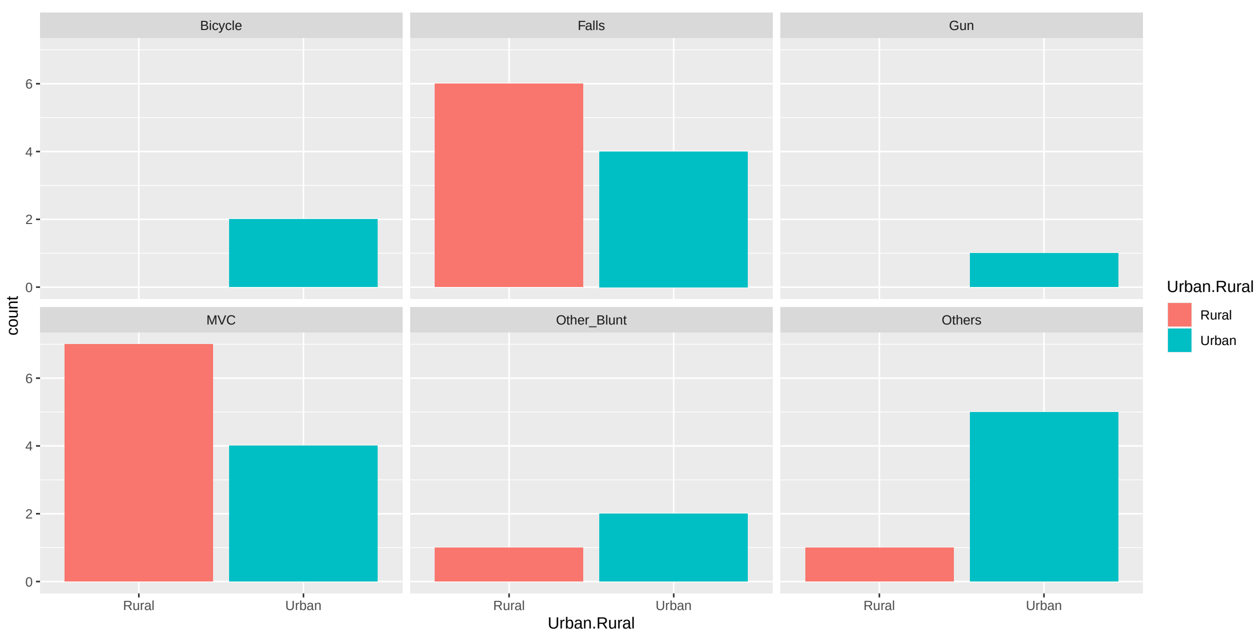

Figure 3: Mandible area injured patient number vs. demographic information

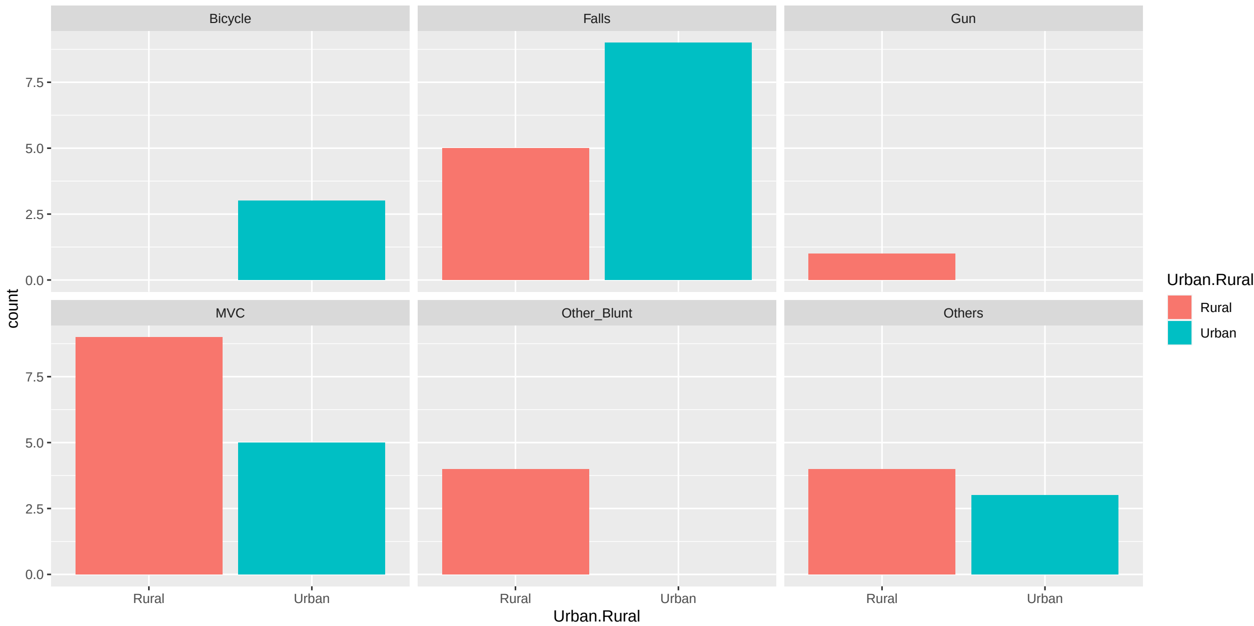

Figure 4: Other facial trauma sites injured patient number vs. demographic information

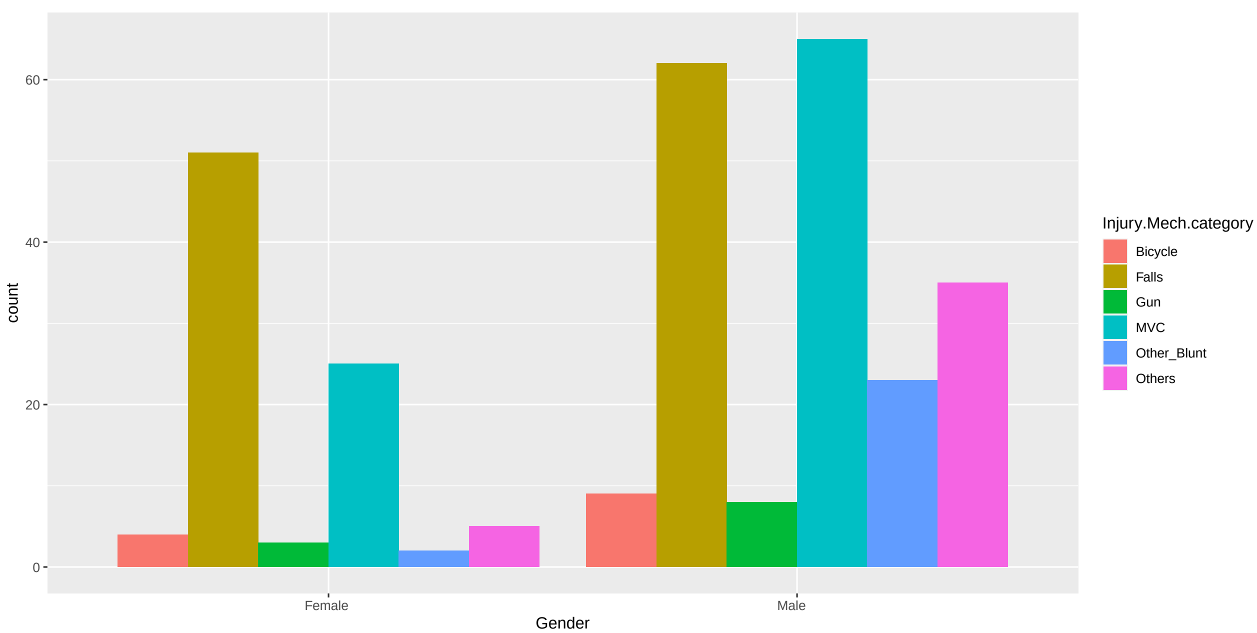

Figure 5: Distribution for injury mech for different gender

Model Fitting:

Based on finding from our EDAs, we use the Generalized Linear Mixed-Effects Regression Model to estimate the mixed effects of getting facial trauma in one of four trauma sites using "Urban.Rural", "Gender", and "Injury.Mech.category" as the predictors, add "Urban.Rural" for the random slope effect, and use "Injury.Mech.catergory" as the random intercept. The function of the model is shown below:

$$stan\_glmer(''Traumasite'' \sim Urban.Rural + Gender + Injury.Mech.category$$
$$+(1 + Urban.Rural|Injury.Mech.category), family = binomial(link = ''logit''))$$

By arranging all four fitted models into one plot in Figure 6, we can see the same model generates different results in different trauma sites. For mandible facial trauma site (upper left), we can see that "Urban.Rural" and "Injury.Mech.category Others" have positive effect on it. For the superior facial trauma site (upper right), "Gender Male" and "Injury.Mech.category Gun" have greater positive effect on it. For midface facial trauma site (lower left), only the intercept shows a positive result which means people have higher probability of getting hurt on midface regardless of other predictors. For other facial trauma site (lower right), only "Gender Male" shows positive effect. One reason that can cause this discrepancy in midface is that all other three trauma sites have very small sample sizes and bigger sample size can help improving the model fitting effect. Table 3, 4, 5, 6 show us the numeric result of fixed effect of each predictor on the trauma site. We also need validation to further assess the effectiveness of this model.

Generalized Linear Mixed-Effects Regression Models are validated by posterior predictive checks and binned residual plots. Figure 7 is the posterior predictive checks plot which displays the comparison distribution of the observed outcome of trauma site(y) and simulated outcome of trauma site(y_rep) in which both distributions match well in the pattern, but simulated y_rep show more predicted zero which means there are less proportion of getting facial trauma in superior, mandible and other trauma sites in the simulation. Again, from Table 6 we can see that there are higher response effect on midface trauma than other three trauma sites.

On the other hand, Figure 8 is the binned residual plots which shows that almost all the points lie inside the confidence limits for all four trauma sites and there is no obvious pattern in the plots. Therefore, the generalized linear mixed-effects model fits well overall in assessing the prediction of relationship between all four trauma sites and patients residencies as validated by the posterior predictive checks plots and binned residual plot. But other models should be taken into consideration.

Table 3: Fixed effects of Mandible

	x
(Intercept)	-1.8893555
Urban.RuralUrban	0.2795753
GenderMale	-0.4531176
Injury.Mech.categoryFalls	-0.2708036
Injury.Mech.categoryGun	-0.7798593
Injury.Mech.categoryMVC	0.1986243
Injury.Mech.categoryOther_Blunt	0.0018478
Injury.Mech.categoryOthers	0.2649054

Table 4: Fixed effects of superior

	x
(Intercept)	-1.1409340
Urban.RuralUrban	-0.2246427
GenderMale	0.6596456

	x
Injury.Mech.categoryFalls	-0.1179664
Injury.Mech.categoryGun	0.6054417
Injury.Mech.categoryMVC	-0.4921415
Injury.Mech.categoryOther__Blunt	-0.8002720
Injury.Mech.categoryOthers	-1.3153604

Table 5: Fixed effects of midface

	x
(Intercept)	2.9776090
Urban.RuralUrban	0.0530611
GenderMale	-0.4174494
Injury.Mech.categoryFalls	-0.8736861
Injury.Mech.categoryGun	-0.9240347
Injury.Mech.categoryMVC	-0.4308041
Injury.Mech.categoryOther__Blunt	-0.5007044
Injury.Mech.categoryOthers	-1.0422883

Table 6: Fixed Effects of other

	x
(Intercept)	-1.5250992
Urban.RuralUrban	-0.3806473
GenderMale	0.4211833
Injury.Mech.categoryFalls	-0.6063963
Injury.Mech.categoryGun	-1.1814356
Injury.Mech.categoryMVC	-0.3863268
Injury.Mech.categoryOther__Blunt	-0.3734653
Injury.Mech.categoryOthers	-0.0692480

Result:

Comparison:

From the estimates of model fitting, we can use 1/4 beta principle to do some preliminary inferences as below, all percentages are multiple effects:

Firstly, a patient's age has no influence on facial trauma sites, which means, we donot have enough evidence to believe people with different ages have different possibilities to getting hurt on different facial trauma sites. So we remove it from our model.

Secondly, for patients with the same injury mechanism and from the same residency, men have 16% more possibility to get hurt at superior and 10% at other facial sites compared with women. Similarly, women are more likely to get hurt at mandible and midface, the effect levels are 11% and 10%.

Thirdly, injury mechanisms also show their impacts on facial trauma sites. For patients with the same gender and from the same residency, they are 29% less likely to get hurt at other facial trauma site if they are hurt by a gun. For patients hurt by falls, they are 22% less likely to get hurt at midface. For patients hurt because of motorcycles, there are no significant effect on the facial trauma site.For patients with other blunt and other

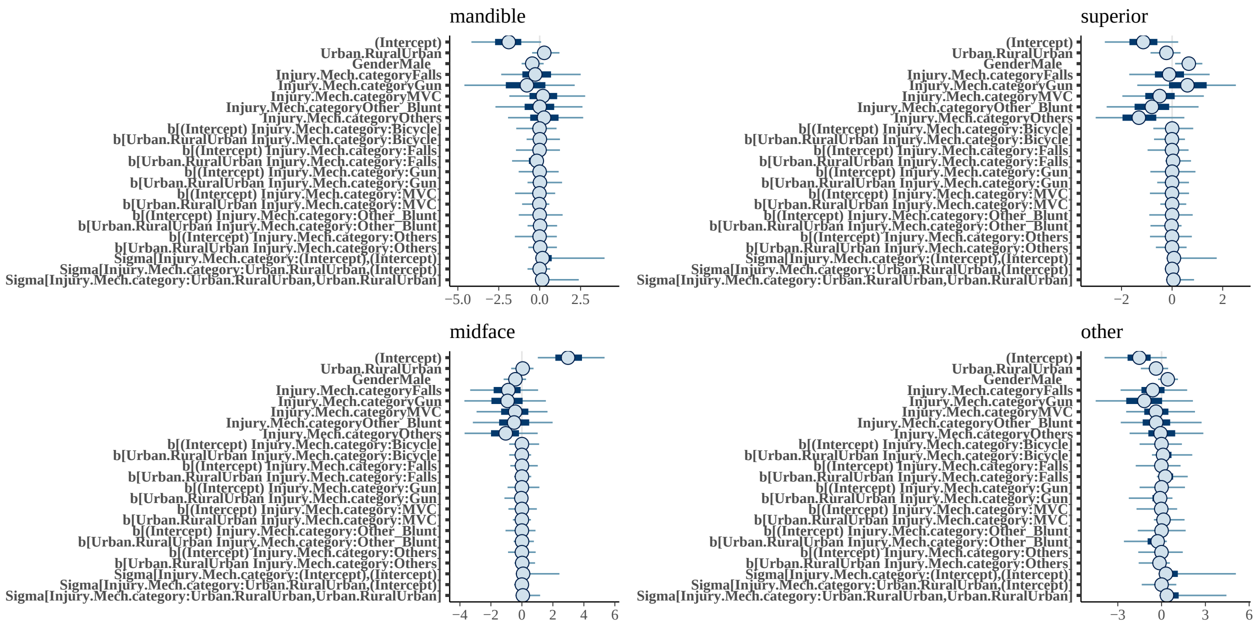

Figure 6: Plots of model fitting for four trauma sites

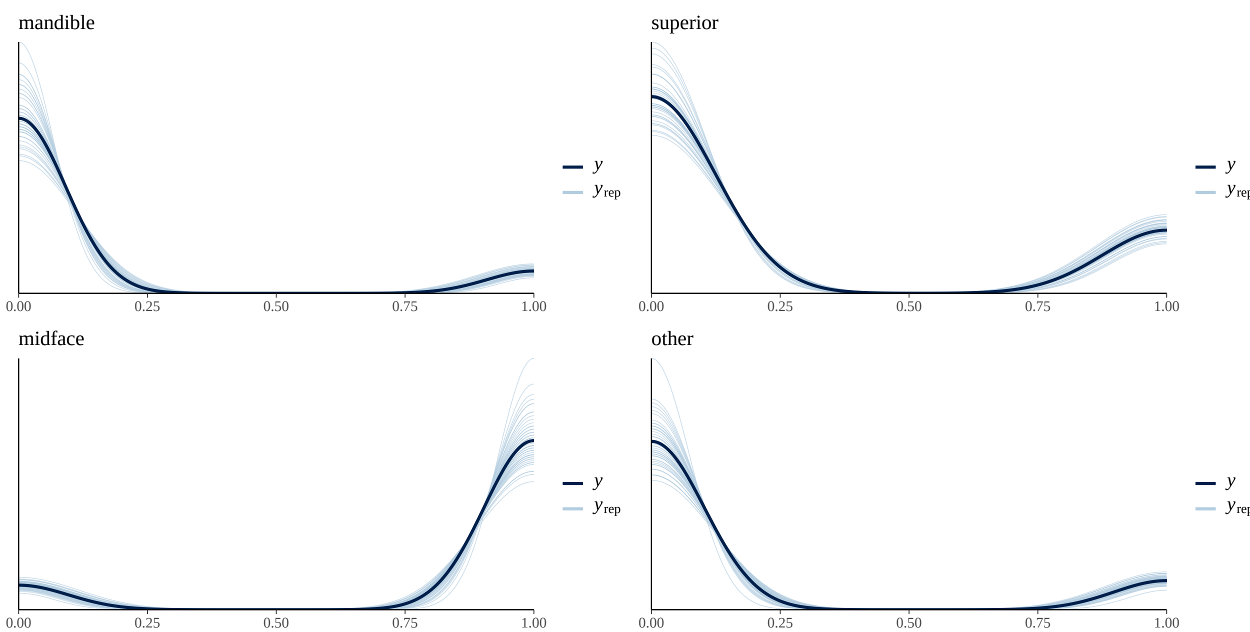

Figure 7: Posterior Predictive Checks Plots for Four Trauma Sites

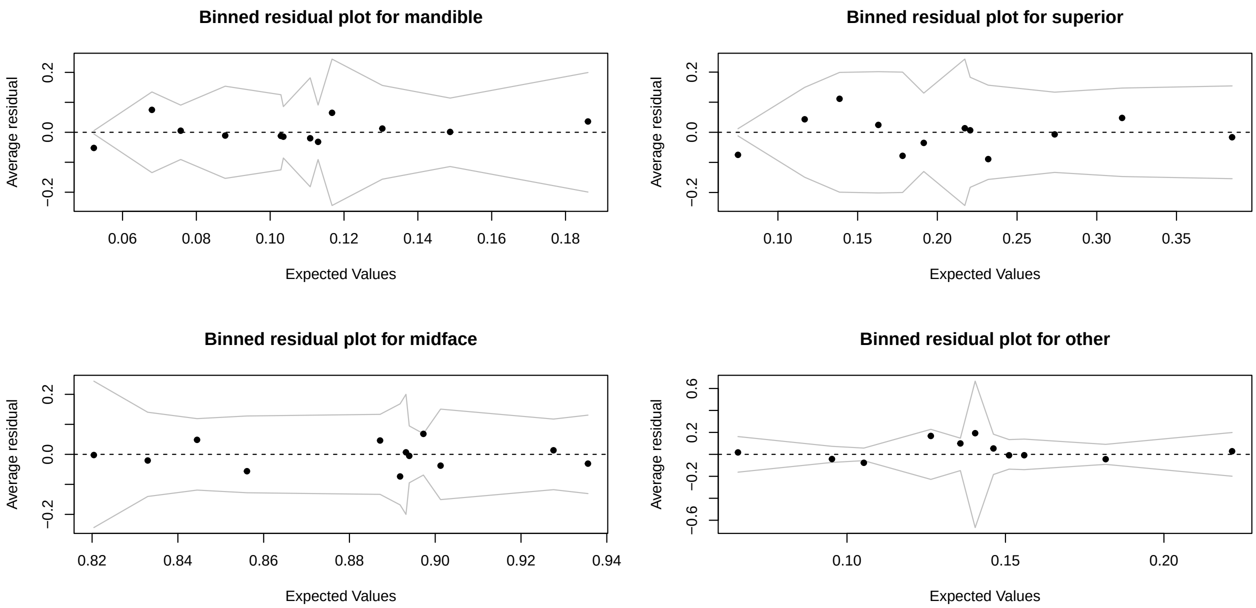

Figure 8: Binned Residual Plots for Model Fitting

injury mechanisms in our sample, they show 19% and 31% less possibility of getting hurt at superior face. What's more, other injury type also shows -27% effect on midface.

Fourthly, for patients with the same gender and same injury mechanism, if the accidents occur in urban areas, patients are approximately 7% more likely to get hurt at mandible face, and 5% or so less likely at superior face. For patients hurt by falls/ MVC/ bicycle/ Gun/ other/ other blunt, urban patients have approximately 3%/ 5%/ 7%/ 12%/ 13%/ 16% less possibility get hurt at other trauma site than patients with same injury type from rural. Because injury mechanisms will influence the effect level of residency, so this is why we choose residency as our random slope. For midface trauma site, patients' residency shows no significant difference.

Prediction:

Based on our model, we did posterior prediction about each factors, the output shows below:

Table 7: Prediction of probability of getting hurt on facial sites

Gender	Urban.Rural	Injury.Mech.category	mandible	superior	midface	other
Female	Rural	Bicycle	0.1525000	0.2710000	0.9360000	0.2032500
Female	Rural	Falls	0.1135568	0.2191250	0.8860682	0.1017727
Female	Rural	Gun	0.1032500	0.3810000	0.8567500	0.1055000
Female	Rural	MVC	0.1514844	0.1661562	0.9208125	0.1242188
Female	Rural	Other_Blunt	0.1427500	0.1307500	0.9102500	0.1570000
Female	Rural	Others	0.1727500	0.0970000	0.8557500	0.1931250
Female	Urban	Bicycle	0.1925000	0.2140833	0.9351667	0.1846667
Female	Urban	Falls	0.1040862	0.2009310	0.8945086	0.1019397
Female	Urban	Gun	0.1285000	0.3333750	0.8498750	0.0517500
Female	Urban	MVC	0.1819444	0.1425000	0.9231944	0.1149444
Female	Urban	Other_Blunt	0.2082500	0.1020000	0.9112500	0.0785000
Female	Urban	Others	0.2223333	0.0690000	0.8748333	0.1056667
Male	Rural	Bicycle	0.1147500	0.4052500	0.8972500	0.2647500
Male	Rural	Falls	0.0763036	0.3458125	0.8414107	0.1456607

Gender	Urban.Rural	Injury.Mech.category	mandible	superior	midface	other
Male	Rural	Gun	0.0703333	0.5231667	0.8122500	0.1360833
Male	Rural	MVC	0.1012000	0.2746944	0.8898500	0.1732278
Male	Rural	Other_Blunt	0.0977692	0.2285769	0.8710192	0.2111538
Male	Rural	Others	0.1152045	0.1576818	0.8067273	0.2564091
Male	Urban	Bicycle	0.1408750	0.3366562	0.9093750	0.2459687
Male	Urban	Falls	0.0699706	0.3213309	0.8499706	0.1472279
Male	Urban	Gun	0.0884000	0.4780500	0.7956000	0.0769000
Male	Urban	MVC	0.1236250	0.2355750	0.8914000	0.1635125
Male	Urban	Other_Blunt	0.1383750	0.1783500	0.8797000	0.1062250
Male	Urban	Others	0.1577708	0.1231875	0.8271458	0.1461771

Discussion:

Logistic Mixed-Effects Regression Models

When using this model, we can use the confidence interval to evaluate the statistical significance of variable effects. Age has a non-significant effect on four facial trauma sites, but gender has statistical significant effect on all facial trauma sites at a significant level of 0.5. For injury mechanisms, on one shows significant effect on mandible face, but for superior face, all injury mechanisms are significant except falls. And for midface, falls, gun, others are have significant effect, but for other facial taruma sites, only gun shows significant negative effect. Here we set significant level at 0.5 because our data will not show any statistically significant effect if we use higher confidence level. In this case, one might explore this further by using larger sample. Repeating the study with a larger sample would certainly not guarantee a statistically significant result, but it would provide a more precise estimate.

To interpret the random effect, as we mentioned above, each injury mechanism has its own intercept and slope, which means, there exists difference within each sample group of different injury mechanisms. From the plot above, we can see the coefficient of random effects are not significantly different from 0, which means, the multilevel model's shrink effect is not so well, so in the future, we can try logistic regression without random effect and add some interactions terms.

Phenomena and future Steps:

Firstly, the data we used was collected from one hospital in one state. We understand that this data collection approach will allow hospitals to tailor treatments for facial injury patients from different residential areas to local characteristics in Maine. However, if our client wants to extend this method of improving diagnostic efficiency to the entire East Coast and even the entire United States, we suggest that we can select representative hospitals in each state to collect data and conduct more overall data analysis and modeling.

Secondly, after we cleaned the data set we got, we found that there were only 3-4 factors we can use for building models for checking the relationship between patients' living areal information and the facial trauma sites they got hurt. And we also noticed the information about the patient's place of residence. Our customer divides it into urban and rural areas. We understand that in this way, we can more efficiently derive the relationships that our customers want. But this will also limit our model construction and overly generalize the patient's residence information. Because the diversity of residence will also have a certain impact on the injured area of the patient's face. If our clients want to allow the hospital to formulate more accurate treatment methods for patients with facial trauma from different living areas, we suggest that we can add some residential information.

Last but not least, we also found some imbalances in the amount of data caused by objective factors. For example, the number of patients with injuries to the middle face and upper forehead is much more than in the other two weeks. And because of the regional characteristics of Maine, the number of patients injured by guns and bicycles is far less than the number of patients caused by other reasons. These are imbalances that are hard to avoid. The positive aspect is that the imbalance of these data volumes can reflect local characteristics, and the negative aspect is that it will cause some obstacles to model selection. Our suggestion is that, if possible, we hope that more local information can be collected in the future that can contribute more factores in order to make our research results more convincing. Because of the limited time, we did not try more statistical models, but based on the current data situation. Knowledge of machine learning should be helpful.

References:

1. https://icdcodelookup.com/icd-10/codes
2. https://www.rdocumentation.org/packages/lme4/versions/1.1-27.1/topics/glmer
3. https://stats.idre.ucla.edu/r/dae/mixed-effects-logistic-regression/