# Final Report

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Reading Data and Data Clean Up:

```
spending <- read.csv("../data/spending_data_unzip/IHME_DEX_ED_SPENDING_2006_2016_DATA_Y2021M09D23.CSV")
```

Emergency spending

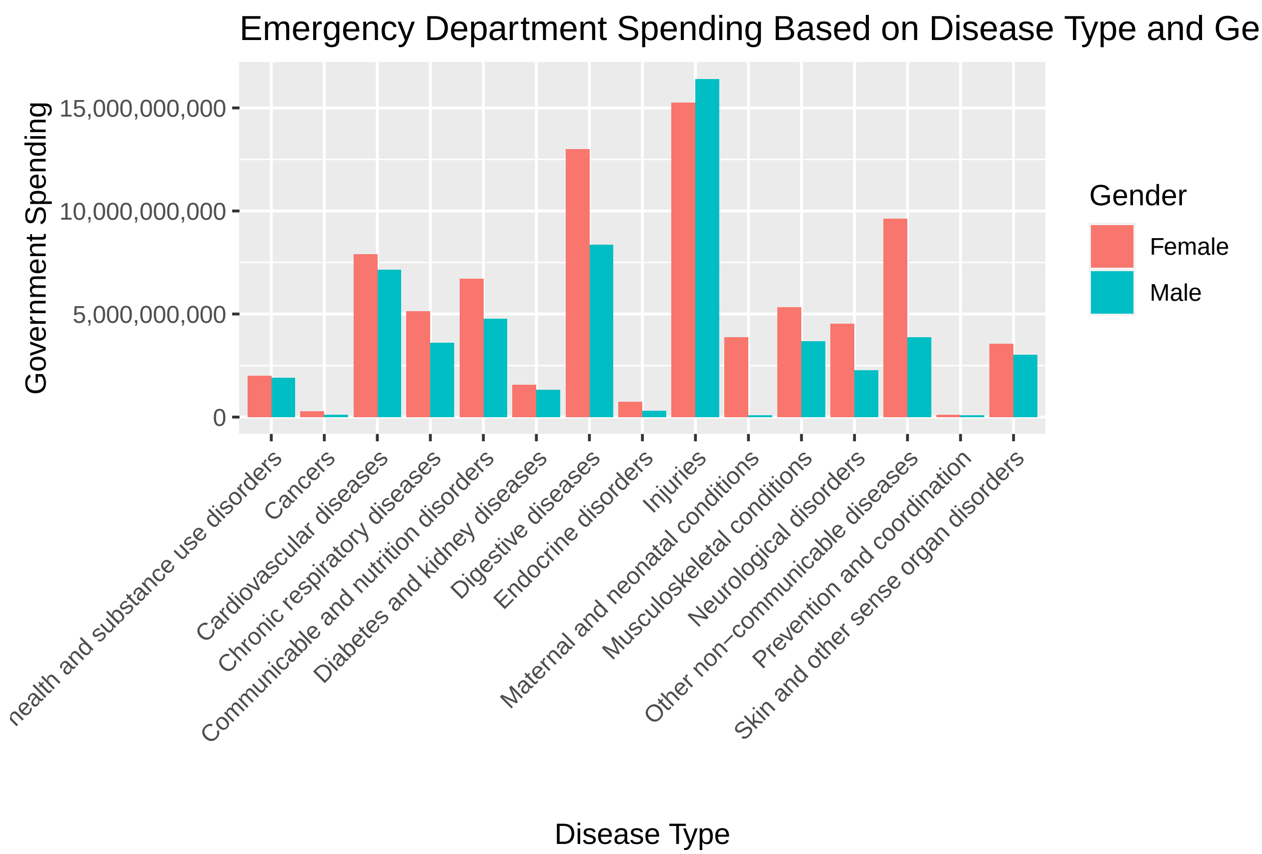
## Gender

Does the emergency department spend a different amount of money on males and females? This is looking at all spending, not taking into account type of insurance.

```
spending_malefemale <- spending %>%
  filter(sex %in% c("Female", "Male"))
```

Here is a boxplot showing the distribution of Emergency Department Government spending based on disease type and gender. ADD interpretation

```
ggplot(data = spending_malefemale, aes(x = agg_cause, y = mean_all, fill = sex)) +
  geom_bar(position = "dodge", stat = "identity") +
  theme(axis.text.x = element_text(angle = 45,hjust = 1)) +
  scale_y_continuous(labels = scales::comma) +
  labs(
    x = "Disease Type",
    y = "Government Spending",
    title = "Emergency Department Spending Based on Disease Type and Gender",
    fill = "Gender"
       )
```




```
  t.test(spending_malefemale$mean_all~spending_malefemale$sex) %>%
  print()
```

```
##
##  Welch Two Sample t-test
##
## data:  spending_malefemale$mean_all by spending_malefemale$sex
## t = 4.0269, df = 6416.2, p-value = 5.717e-05
## alternative hypothesis: true difference in means between group Female and group Male is not equal to
## 95 percent confidence interval:
##   56638431 164092573
## sample estimates:
## mean in group Female   mean in group Male
##            413610916            303245414
```

Linear regression model for gender and government spending model

```
spending_malefemale_fit <- linear_reg() %>%
  set_engine("lm") %>%
  fit(mean_all~sex, data = spending_malefemale)
```

```
augment_spendinggenderfit <- augment(spending_malefemale_fit$fit)
```

```
augment_spendinggenderfit %>%
  ggplot(aes(x = .fitted,
             y = .resid)) +
  geom_point() +
  scale_y_continuous(labels = scales::comma) +
```

```
  scale_x_continuous(labels = scales::comma) +
  labs(x = "Predicted Government Spending",
       y = "Residual",
       title = "Residual Plot for Linear Regression of Gender and Goverment Spending")
```


The graph of residuals vs the fitted linear lines shows a pattern of clumping around two areas – slightly above 300,000,000 and slightly below 420,000,000. The clumping pattern indicates a linear model is not a good fit to model the relationship here.

!!not sure what else to do for gender since the lin regression is so bad

##Disease category and gov spending

ANOVA: null hypothesis: means of spending the same for each disease category assume outcomes are normally distributed, same variance, and samples are independent

```
summary(aov(mean_all~agg_cause,data=spending_malefemale))
```

```
##                Df    Sum Sq   Mean Sq F value Pr(>F)
## agg_cause      14 7.432e+20 5.309e+19   47.08 <2e-16 ***
## Residuals    6563 7.400e+21 1.128e+18
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Based on the p-value here of these data or more extreme data it is highly unlikely the null hypothesis is true. Therefore, we perform step-down tests using a Holm correction for multiple comparisons

```
diseasepair <- pairwise.t.test(spending_malefemale$mean_all,    spending_malefemale$agg_cause, p.adj =
sigpairs <- broom::tidy(diseasepair) %>%
  filter(p.value<0.05) %>%
```

```r
  arrange(group1,group2)
nrow(sigpairs)
```

```
## [1] 61
```

The step-down t tests indicate 61 disease category pairs are different out of ?? ## hey i'm just making this blue so you'll see but i'm pretty sure that the possible pairs is just the combination formula with all the fun factorial stuff, so if there are 15 groups as indicated in ur overall test, then there are 105 possible combinations. but also idk if the "all ages" group will mess u up because it changed the response in my age comparison my brain is kinda foggy though , indicating most disease categories do differ in the amount of government spending by the emergency department.

## Age

!! had to take out the observations with "All Ages" because I think it will just mess up the pairs but let me know what you think or whether you think there's anything we can do with that group

```r
spending_noall <- spending_malefemale %>%
  filter(age_group_name != "All Ages")
```

We wonder whether there is a correlation between government healthcare expenditures in the emergency department and age. The age variable is categorical, split into 19 groups that generally include 5 years each, apart from the first (<1 year) and last (85 plus) groups.

To address this question, we began by using an overall test with ANOVA.

Below is an overall test of the null hypothesis that all of the means for age groups across the years are equal, as opposed to the alternative that at least one mean is different.

```r
summary(aov(mean_all~age_group_name,data = spending_noall))
```

```
##                  Df    Sum Sq   Mean Sq F value Pr(>F)
## age_group_name   18 2.712e+19 1.507e+18   28.26 <2e-16 ***
## Residuals      6229 3.321e+20 5.331e+16
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

In this F-test (ndf = 18, ddf = 6229), a significant difference among age groups was identified. Our p-value tells us that this data (or data more extreme) would be very unlikely if the null hypothesis were true because it shows statistical significance at an alpha well below 0.05. Therefore, we reject the null hypothesis that the mean expenditures for all age groups are equal.

To see which specific means may be different from one another, we used planned step-down tests with a Holm correction to minimize Type I errors.

```r
agepair <- pairwise.t.test(spending_noall$mean_all, spending_noall$age_group_name, p.adj = "holm")
sigagepairs <- broom::tidy(agepair) %>%
  filter(p.value<0.05) %>%
  arrange(group1,group2)
nrow(sigagepairs)
```

```
## [1] 97
```

The pairwise t-tests used for our ANOVA step-down tests suggest that there are 97 different age pairs out of the 171 possible combinations. This tells us that more age pairs are different than are similar and that therefore the majority of age group pairs differ in terms of mean expenditures.