Civilian Impact of U.S. Drone vs. Non-Drone Strikes in Somalia and Yemen

Assessing Humanitarian Impact with Count Regression Models.

Shanmei Wanyan[1], Daniel Dai[1], Keivan Bolouri[1], Itaru Fukushima[1], Linxue Guo[1] and Evelyn Isaka[1]

1. University of California, Los Angeles, Department of Statistics and Data Science, 8125 Math Sciences Bldg, Los Angeles, CA 90095

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https://keivanbolouri.github.io/finalProject140XP/

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1 Abstract

Since 2002, the United States has conducted largely hidden counterterrorism campaigns in countries such as Somalia and Yemen, raising ongoing concerns about their humanitarian impact. This project asks how the characteristics and civilian costs of U.S. strikes differ between these two theaters of war. Using open-source strike records compiled by independent monitoring organizations, including the Bureau of Investigative Journalism, We construct a combined dataset of U.S. actions in Somalia and Yemen and analyze casualty patterns with negative binomial regression. The analysis tests three hypotheses: whether civilian casualty rates differ by country, whether drone strikes have different effects across countries, and whether reporting uncertainty varies between regions. The results show that, controlling for strike characteristics and total fatalities, strikes in Yemen are associated with nearly five times the civilian casualties of strikes in Somalia. By contrast, there is no evidence that the impact of drone strikes on civilian harm differs between the two countries, nor that overall reporting uncertainty is systematically higher in one region than the other. However, uncertainty is greater for drone and unconfirmed strikes and lower when U.S. involvement is confirmed. These findings underscore the unequal humanitarian burdens across theaters of U.S. counterterrorism and highlight the need for more transparent and consistent casualty reporting.

2 Introduction

2.1

Since 2002, the United States has waged a largely clandestine drone war in countries such as Yemen and Somalia, often far from public scrutiny [1]. Although these counterterrorism strikes aim to eliminate militant targets while minimizing risk to U.S. personnel, their humanitarian consequences remain a pressing concern. The cost to civilian life can be substantial. For example, an investigation found that roughly one-third of those killed by U.S. drone strikes in Yemen in 2018 were likely civilians or pro-government allies [2].

This research addresses a central question: **Do the characteristics and human costs of U.S. counterterrorism strikes differ between Somalia and Yemen—and if so, how?** Understanding such differences is important both theoretically and practically.
Theoretically, comparing two distinct drone theaters can reveal how local conditions—such as insurgent behavior, intelligence quality, and terrain—shape strike outcomes. Practically, identifying where drone operations are less effective in sparing civilians can guide improvements in targeting procedures, transparency, and accountability mechanisms.

These operations are often carried out "out of sight," yet their humanitarian consequences are very real [1]. Official reporting has historically underestimated civilian casualties, prompting independent organizations to investigate and publish alternative estimates [2]. For instance, the U.S. government once claimed only 64–116 civilian deaths from drone strikes outside declared warzones between 2009 and 2015, whereas independent monitors estimated several times more [2].

In response to these discrepancies, numerous efforts have emerged to document the drone war's toll. Pitch Interactive's *Out of Sight, Out of Mind* visualization cataloged CIA drone strikes and casualties in Pakistan [1]. The Economist released infographics demonstrating large gaps between official and independent casualty estimates. UCLA's **Drone Wars** project created a cross-country dataset covering Afghanistan, Pakistan, Somalia, and Yemen using records from the Bureau of Investigative Journalism (BIJ) [3,4].

These initiatives highlight the need for **rigorous, comparative analysis**. Yet no study has systematically compared Somalia and Yemen with respect to strike characteristics and humanitarian outcomes. This paper fills that gap by leveraging detailed open-source strike records from both countries to quantitatively assess differences in civilian harm.

We explicitly test three hypotheses:

1. **Hypothesis 1 – Civilian Harm Difference:**
   Somalia and Yemen differ in their civilian casualty rates.
2. **Hypothesis 2 – Drone Effectiveness Across Countries:**
   The effect of drone strikes on civilian casualties differs between Somalia and Yemen.
3. **Hypothesis 3 – Reporting Uncertainty:**
   Casualty reporting uncertainty differs between regions.

To evaluate these hypotheses, we construct a comprehensive dataset of U.S. counterterrorism strikes in Somalia and Yemen from independent monitoring organizations such as BIJ [1]. Because fatality reporting is often uncertain, we use minimum–maximum casualty ranges [1]. Civilian casualty counts exhibit strong overdispersion, so we employ negative binomial regression to estimate the effects of region and strike characteristics. This modeling framework allows us to determine whether "country" remains a significant predictor of civilian harm once contextual factors are controlled for.

3 Literature Review

Researchers and monitoring groups have spent many years examining how many people are killed in U.S. drone strikes, but most work focuses on one country at a time rather than comparing Somalia and Yemen directly.

Columbia Law School's Human Rights Clinic, in *Counting Drone Strike Deaths*, shows that official U.S. numbers often underestimate civilian deaths. They recommend using casualty ranges (minimum–maximum) because information from the ground is often unclear [**3**].

The Bureau of Investigative Journalism (BIJ) collected open-source reports for every known strike in Yemen, Somalia, Pakistan, and Afghanistan. Their database records both minimum and maximum death counts and distinguishes civilians from militants when possible, noting that reports are often uncertain or contradictory [**5**].

New America's *Counterterrorism Wars* project compiles strike data from Yemen and Somalia, listing total strikes and casualty ranges and explaining how they classify victims when reports are vague or disputed [**6**].

Together, these sources show that:

1. Independent groups usually find **more civilian deaths** than official U.S. reports.
2. Although detailed data exist for Yemen and Somalia, most previous analyses summarize each country separately rather than compare them statistically.

Our study fits into this work by using open-source strike records to conduct a direct, quantitative comparison between Somalia and Yemen. Using negative binomial regression, we test whether the countries differ in civilian casualty rates and the uncertainty of reported casualties, controlling for strike characteristics.

4 Data Processing

4.0.1 Data Import and Cleaning

The dataset combines information on U.S. counterterrorism strikes in **Somalia** and **Yemen**, spanning Somalia (2007–present) and Yemen (2002–present). These data were originally compiled by investigative journalists tracking U.S. drone and air strikes, including casualties. In particular, the source appears to be the **Bureau of Investigative Journalism (TBIJ)**, which maintains detailed records of U.S. strikes in those countries[7]. Each country's data was provided in a separate Excel worksheet (titled *"All US actions"* for Somalia and Yemen respectively), containing reported strike dates, locations, strike types, and casualty counts (with minimum and maximum estimates).

4.0.2 Data Import and Cleaning

We imported two Excel datasets using `read_excel()` in R:

Somalia: `us-strikes-in-somalia-2007-to-present.xls`

Yemen: `us-strikes-in-yemen-2002-to-present.xlsx`
Each file was read from the "All US actions" sheet into `somalia_raw` and `yemen_raw`.

Using `dplyr::transmute()`, we extracted and standardized key variables to match across datasets. This included:

Assigning a `region` label (Somalia or Yemen)

- Converting `Date` fields to proper date format

  Creating indicators for drone strikes (`drone`) and U.S. confirmation (`us_confirmed`)

  Harmonizing strike and casualty counts (`min_/max_` values for killed, civilians, children, and injured)

These transformations produced two cleaned data frames with identical structures, enabling easy merging.

4.0.3 Combining and Preparing the Dataset

To support hypothesis testing, we created three key analytical variables from the cleaned and combined dataset. `civilian_casualties` represents the minimum number of civilians killed per strike, using the `min_civilians` field as a conservative estimate. `total_killed` captures the minimum total fatalities (`min_killed`) for each incident, providing a standardized baseline for analysis. `uncertainty_killed` quantifies reporting uncertainty by calculating the difference between `max_killed` and `min_killed`. These derived variables help assess both the scale of violence and the variability in casualty reporting across strikes and regions. All three were added to the dataset and are ready for descriptive analysis.

Table 4.1: Summary of Key Derived Variables by Region

Region	Avg. Civilian Casualties	Avg. Total Killed	Avg. Reporting Uncertainty
Somalia	0.08	6.54	1.56
Yemen	0.64	4.67	1.84

4.0.4 Finalizing the Dataset for Analysis

The last step shown is the creation of `combined_model`, which is a filtered version of the data ready for modeling or statistical analysis. Here we **restrict to complete cases** for the key outcome variables of interest. The code `filter(!is.na(civilian_casualties), !is.na(uncertainty_killed), !is.na(min_strikes), !is.na(total_killed))` removes any strikes that still have missing values in those crucial fields.

In practice, because we already replaced NAs with 0 or other values for most of these, there may be very few records dropped. However, this filter is a safety measure to ensure that the modeling dataset doesn't include any undefined values. For example, if a particular entry had an entirely missing civilian casualty field in the raw data (and somehow our earlier replacement didn't catch it), or if any event lacks data on number of strikes or total killed, it will be excluded. The end result `combined_model` contains only strikes with valid `civilian_casualties`, `total_killed`, `uncertainty_killed`, and `min_strikes` values. This will be the dataset used in subsequent analysis and hypothesis testing.

5 Methods

5.1 Statistical Methods

5.1.1 Hypothesis Tests

5.1.2 Hypothesis 1: Civilian Harm Difference

H_0 : Drone strikes have the same civilian impact in Somalia and Yemen.
H_1 : Drone strikes have different civilian impacts across the two regions.

To test whether Somalia and Yemen differ in civilian casualty outcomes, we estimate the model:

$$\begin{aligned} E(\text{civilian casualties}) = {} & \beta_0 + \beta_1(\text{region}) + \beta_2(\text{drone}) + \beta_3(\text{US confirmed}) + \beta_4(\text{minimum strikes}) \\ & + \beta_5(\text{total killed}) \end{aligned}$$

Table 5.1: Variable Definitions

Variable	Description
Civilian casualties	Number of civilians reported killed in the strike (outcome variable).
Region	Country where the strike occurred (Somalia or Yemen).
Drone	Indicates whether the strike was carried out by a drone (1 = drone).
US confirmed	Whether the strike was officially confirmed by the U.S. government.
Minimum strikes	Minimum number of strike events associated with the record.
Total killed	Minimum number of total fatalities (civilians + militants).

5.1.3 Hypothesis 2: Drone Effectiveness Across Countries

H_0 : Drone use affects civilian casualties in the same way in both Somalia and Yemen.
H_1 : Drone use affects civilian casualties differently across Somalia and Yemen.

To evaluate whether the civilian impact of drone strikes varies by region, we include an interaction term between drone use and region:

$$\begin{aligned} E(\text{civilian casualties}) = \beta_0 + \beta_1(\text{drone}) + \beta_2(\text{region}) + \beta_3(\text{drone} \times \text{region}) \\ + \beta_4(\text{US confirmed}) + \beta_5(\text{minimum strikes}) + \beta_6(\text{total killed}) \end{aligned}$$

5.1.4 Hypothesis 3: Reporting Uncertainty Difference

H_0 : Reporting uncertainty does not differ between Somalia and Yemen.
H_1 : Reporting uncertainty differs between Somalia and Yemen.

To assess whether casualty reporting uncertainty differs between regions, we model the uncertainty metric. We modeled casualty reporting uncertainty (defined as `max_killed - min_killed`) region and strike characteristics as predictors.

$$E(\text{Uncertainty in casualties}) = \beta_0 + \beta_1\,\text{Region} + \beta_2\,\text{Drone} + \beta_3\,\text{US confirmed} + \beta_4\,\text{Minimum strikes}$$

where:

$$\text{Uncertainty in casualties} = \text{Maximum killed} - \text{Minimum killed}$$

6 Model Selection

Because our prediction variable is a count—specifically, the number of civilians killed in each strike—we use statistical models designed for count data. A natural starting point is the **Poisson regression**, which assumes that the mean and variance of the outcome are equal $E(x) = \text{Var}(x)$. However, in our dataset the variance is much larger than the mean, a condition known as **overdispersion**. When overdispersion is present, Poisson regression underestimates the true variability and produces misleadingly small standard errors. To address this, we use a **negative binomial regression**, which adds a dispersion parameter that allows the variance to exceed the mean. This makes the negative binomial model much better suited for modeling drone-strike casualty counts and provides more reliable estimates of how factors such as region, drone use, and confirmation status relate to civilian harm.

```r
mean_civ <- mean(combined_model$civilian_casualties)
var_civ  <- var(combined_model$civilian_casualties)

c(mean = mean_civ, variance = var_civ)
```

```
     mean  variance 
0.4338521 8.0043879 
```

Showt that our data is overdispersion: $E(x) < \text{Var}(x)$

In our combined Somalia–Yemen dataset, civilian casualties have a mean of **0.43** and a variance of **8.00**, so the variance is about **18 times** larger than the mean. This large variance-to-mean ratio indicates substantial overdispepersion.

To verify whether a Poisson model was appropriate for our outcome variable, we formally tested for overdispersion. We first fit a Poisson regression using civilian casualties as the count outcome and calculated the dispersion statistic by dividing the residual deviance by the residual degrees of freedom.

6.0.1 Poisson dispersion test

$$
\begin{aligned}
H_0 &: \text{dispersion} = 1 \quad \text{(Poisson adequate)} \\
H_a &: \text{dispersion} > 1 \quad \text{(overdispersion)}
\end{aligned}
$$

```r
library(MASS)
library(AER)   # for dispersiontest

# Poisson version of H1 model
pois_h1 <- glm(
  civilian_casualties ~ region + drone + us_confirmed
  + min_strikes + total_killed,
  family = poisson(link = "log"),
  data = combined_model
)

# 3a. Quick dispersion estimate: residual deviance / df
dispersion_est <- pois_h1$deviance / pois_h1$df.residual
dispersion_est
```

```
[1] 1.945971
```

```r
# 3b. Formal test
dispersiontest(pois_h1)
```

```

	Overdispersion test

data:  pois_h1
z = 2.3989, p-value = 0.008222
alternative hypothesis: true dispersion is greater than 1
sample estimates:
dispersion
  11.36617
```

The resulting value of approximately **1.95** already suggested that the variance in the data was nearly twice as large as the Poisson model allows. We then conducted a formal **overdispersion test** using `dispersiontest()` from the *AER* package. The test returned a z-value of **2.40** with a p-value of **0.008**, indicating statistically significant overdispersion. In other words, the Poisson assumption that the mean equals the variance is violated. Because the data exhibit much greater variability than the Poisson model can accommodate, this test confirms that a **negative binomial regression**—which includes an additional.

Consequently, we use negative binomial regression, which relaxes the equidispersion assumption and is more appropriate for these data.

7 Statistical Testing

Hypothesis Test 1

```r
library(dplyr)
library(stringr)
library(MASS)
library(broom)



model_h1 <- glm.nb(
  civilian_casualties ~ region
  + drone + us_confirmed + min_strikes + total_killed,
  data = combined_model
)

summary(model_h1)
```

```

Call:
glm.nb(formula = civilian_casualties ~ region + drone + us_confirmed +
    min_strikes + total_killed, data = combined_model, init.theta = 0.04945140151,
    link = log)

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept)  -2.08959    1.02564  -2.037   0.0416 *
regionYemen   1.59150    0.64403   2.471   0.0135 *
drone        -0.00298    0.58431  -0.005   0.9959
us_confirmed -0.19350    0.56118  -0.345   0.7302
min_strikes  -1.02747    0.68030  -1.510   0.1310
total_killed  0.14571    0.01948   7.481 7.39e-14 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for Negative Binomial(0.0495) family taken to be 1)
```

```
    Null deviance: 143.44  on 513  degrees of freedom
Residual deviance: 107.17  on 508  degrees of freedom
AIC: 469.8

Number of Fisher Scoring iterations: 1


              Theta:  0.0495
          Std. Err.:  0.0102
Warning while fitting theta: alternation limit reached

 2 x log-likelihood:  -455.8010
```

```
tidy(model_h1, exponentiate = TRUE, conf.int = TRUE)
```

```
# A tibble: 6 × 7
  term         estimate std.error statistic  p.value conf.low conf.high
  <chr>           <dbl>     <dbl>     <dbl>    <dbl>    <dbl>     <dbl>
1 (Intercept)     0.124    1.03     -2.04    4.16e- 2   0.0185      1.21
2 regionYemen     4.91     0.644     2.47    1.35e- 2   1.57       15.6
3 drone           0.997    0.584    -0.00510 9.96e- 1   0.326       2.80
4 us_confirmed    0.824    0.561    -0.345   7.30e- 1   0.246       2.40
5 min_strikes     0.358    0.680    -1.51    1.31e- 1   0.0657      1.03
6 total_killed    1.16     0.0195    7.48    7.39e-14  NA          NA
```

7.0.1 Rsult for Hypothesis 1: Civilian Harm Differences

Strikes in **Yemen** show significantly higher civilian casualties than those in Somalia. The coefficient for Yemen is **1.59** ($p = 0.0135$), corresponding to an IRR of **4.9**, meaning Yemen strikes produce nearly **5**$\times$ the civilian casualties of Somalia.
Total fatalities are also positively associated with civilian casualties (coef = **0.146**, $p < 0.001$).
Conclusion: Civilian harm is significantly higher in Yemen $\rightarrow$ *H1 supported*

Hypothesis Test 2

```
model_h2 <- glm.nb(
  civilian_casualties ~ drone * region +
    us_confirmed + min_strikes + total_killed,
  data = combined_model
)

summary(model_h2)
```

```
Call:
glm.nb(formula = civilian_casualties ~ drone * region + us_confirmed +
    min_strikes + total_killed, data = combined_model, init.theta = 0.04963878986,
    link = log)

Coefficients:
                  Estimate Std. Error z value Pr(>|z|)
(Intercept)       -2.15732    1.03711  -2.080   0.0375 *
drone              0.33091    1.00164   0.330   0.7411
regionYemen        1.80725    0.83212   2.172   0.0299 *
us_confirmed      -0.21220    0.55986  -0.379   0.7047
min_strikes       -1.02119    0.66922  -1.526   0.1270
total_killed       0.14319    0.01965   7.288 3.14e-13 ***
drone:regionYemen -0.49367    1.22774  -0.402   0.6876
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for Negative Binomial(0.0496) family taken to be 1)

    Null deviance: 143.81  on 513  degrees of freedom
Residual deviance: 107.26  on 507  degrees of freedom
AIC: 471.63

Number of Fisher Scoring iterations: 1

              Theta:  0.0496
          Std. Err.:  0.0103
Warning while fitting theta: alternation limit reached

 2 x log-likelihood:  -455.6270
```

```
tidy(model_h2, exponentiate = TRUE, conf.int = TRUE)
```

```
# A tibble: 7 × 7
  term              estimate std.error statistic  p.value conf.low conf.high
  <chr>                <dbl>     <dbl>     <dbl>    <dbl>    <dbl>     <dbl>
1 (Intercept)          0.116    1.04      -2.08  3.75e- 2   0.0171      1.14
2 drone                1.39     1.00       0.330 7.41e- 1   0.215      11.5
3 regionYemen          6.09     0.832      2.17  2.99e- 2   1.38       32.8
4 us_confirmed         0.809    0.560     -0.379 7.05e- 1   0.241       2.36
5 min_strikes          0.360    0.669     -1.53  1.27e- 1   0.0671      1.02
6 total_killed         1.15     0.0196     7.29  3.14e-13  NA          NA
```

```
7 drone:regionYemen    0.610    1.23      -0.402 6.88e- 1   0.0500      5.87
```

7.0.2 Result for Hypothesis 2: Drone Effectiveness by Country

The key interaction term **drone × region (Yemen)** is **not significant** (coef $= -0.49$, $p = 0.688$).
Drone use alone is also not significant (coef $= 0.33$, $p = 0.741$).
Conclusion: Drones do not affect civilian casualties differently across countries → *H2 not supported.*

Hypothesis Test 3

```r
model_h3 <- glm.nb(
  uncertainty_killed ~ region +
    drone + us_confirmed + min_strikes,
  data = combined_model
)
summary(model_h3)
```

```

Call:
glm.nb(formula = uncertainty_killed ~ region + drone + us_confirmed +
    min_strikes, data = combined_model, init.theta = 0.2157180244,
    link = log)

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept)   0.64763    0.30943   2.093  0.03635 *
regionYemen  -0.16294    0.26446  -0.616  0.53781
drone         0.61827    0.24966   2.476  0.01327 *
us_confirmed -0.69343    0.25255  -2.746  0.00604 **
min_strikes   0.08520    0.05284   1.612  0.10687
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for Negative Binomial(0.2157) family taken to be 1)

    Null deviance: 400.69  on 513  degrees of freedom
Residual deviance: 385.48  on 509  degrees of freedom
AIC: 1571.1

Number of Fisher Scoring iterations: 1
```

```
              Theta:  0.2157
          Std. Err.:  0.0218

 2 x log-likelihood:  -1559.1480
```

```r
tidy(model_h3, exponentiate = TRUE, conf.int = TRUE)
```

```
# A tibble: 5 × 7
  term         estimate std.error statistic p.value conf.low conf.high
  <chr>           <dbl>     <dbl>     <dbl>   <dbl>    <dbl>     <dbl>
1 (Intercept)     1.91     0.309      2.09  0.0363     1.13      3.34
2 regionYemen     0.850    0.264     -0.616 0.538      0.536     1.33
3 drone           1.86     0.250      2.48  0.0133     1.18      2.91
4 us_confirmed    0.500    0.253     -2.75  0.00604    0.305     0.793
5 min_strikes     1.09     0.0528     1.61  0.107      0.990     1.28
```

```r
combined_model %>%
  group_by(region, drone) %>%
  summarise(
    mean_civilian_casualties = mean(civilian_casualties, na.rm = TRUE),
    n = n(),
    .groups = "drop"
  )
```

```
# A tibble: 4 × 4
  region  drone mean_civilian_casualties     n
  <fct>   <int>                    <dbl> <int>
1 Somalia     0                   0.0753   146
2 Somalia     1                   0.114     44
3 Yemen       0                   1.38      76
4 Yemen       1                   0.411    248
```

```r
combined_model %>%
  group_by(region) %>%
  summarise(
    mean_uncertainty = mean(uncertainty_killed, na.rm = TRUE),
    n = n(),
    .groups = "drop"
  )
```

```
# A tibble: 2 × 3
  region  mean_uncertainty     n
  <fct>              <dbl> <int>
1 Somalia             1.56   190
2 Yemen               1.84   324
```

7.0.3 Result for Hypothesis 3: Reporting Uncertainty

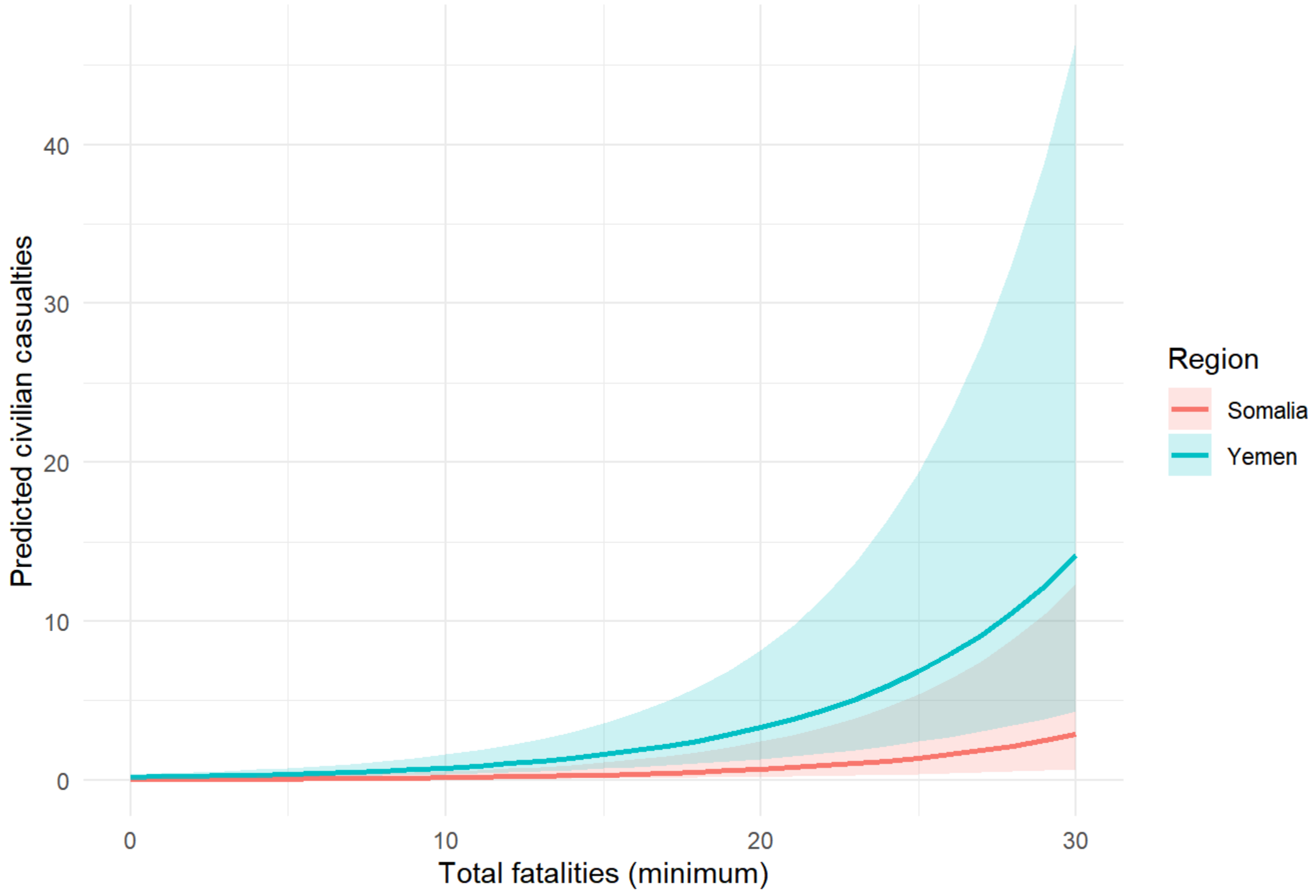
Reporting uncertainty does **not** differ between regions (Yemen coef = -0.16, $p = 0.538$). However, drone strikes show **higher uncertainty** (coef = 0.62, IRR = **1.86**, $p = 0.013$), while confirmed U.S. strikes show **lower uncertainty** (coef = -0.69, IRR = **0.50**, $p = 0.006$).
Conclusion: No regional difference in uncertainty → *H3 not supported*, though uncertainty varies by strike type.

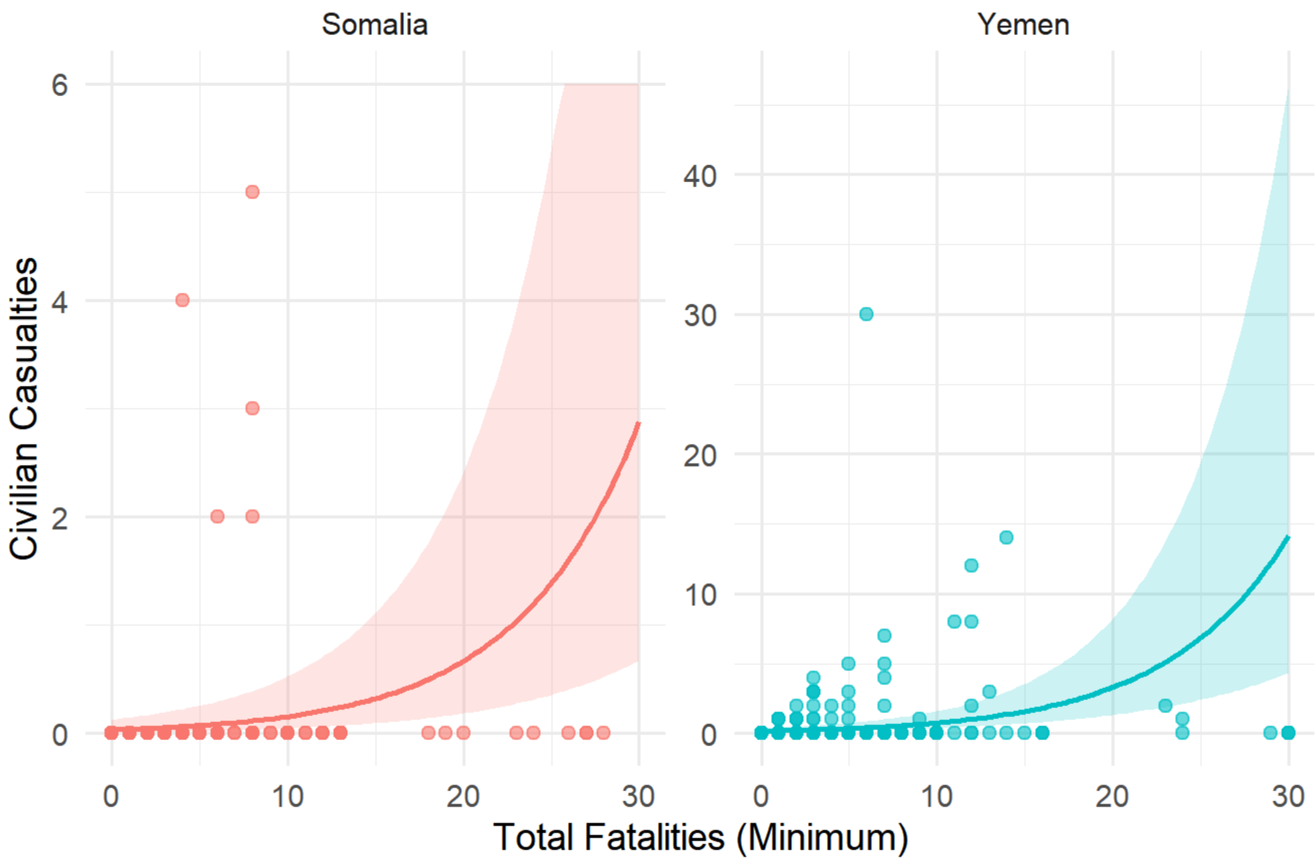
8 Visualizations

8.1 Visualization (Test 1)

$$H_0 : \text{Drone strikes have the same civilian impact in Somalia and Yemen.}$$
$$H_1 : \text{Drone strikes have different civilian impacts across the two regions.}$$

$$\begin{aligned} E(\text{civilian casualties}) = \beta_0 &+ \beta_1(\text{region}) + \beta_2(\text{drone}) + \beta_3(\text{US confirmed}) + \beta_4(\text{minimum strikes}) \\ &+ \beta_5(\text{total killed}) \end{aligned}$$

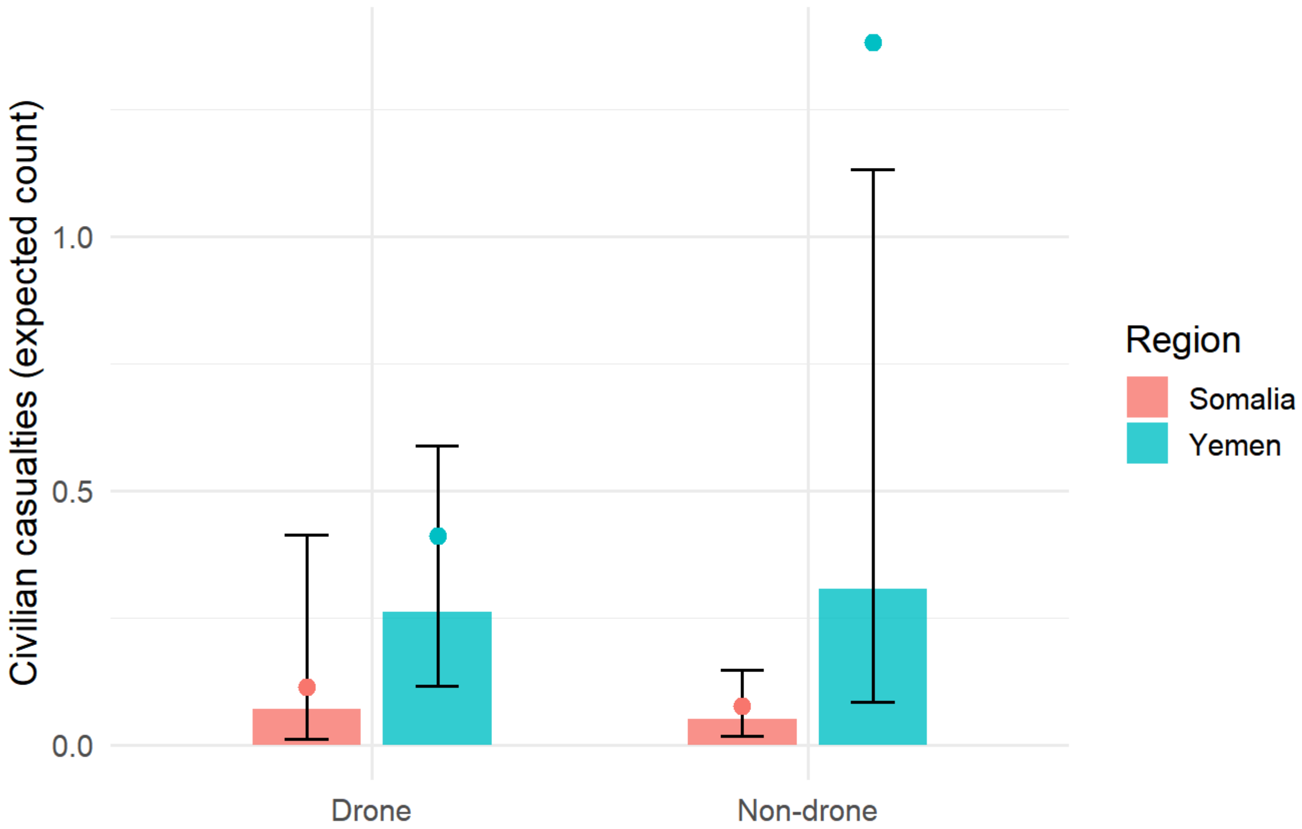

Predicted civilian casualties
40
30
20
10
0
0
10
20
30
Total fatalities (minimum)
Region
Somalia
Yemen

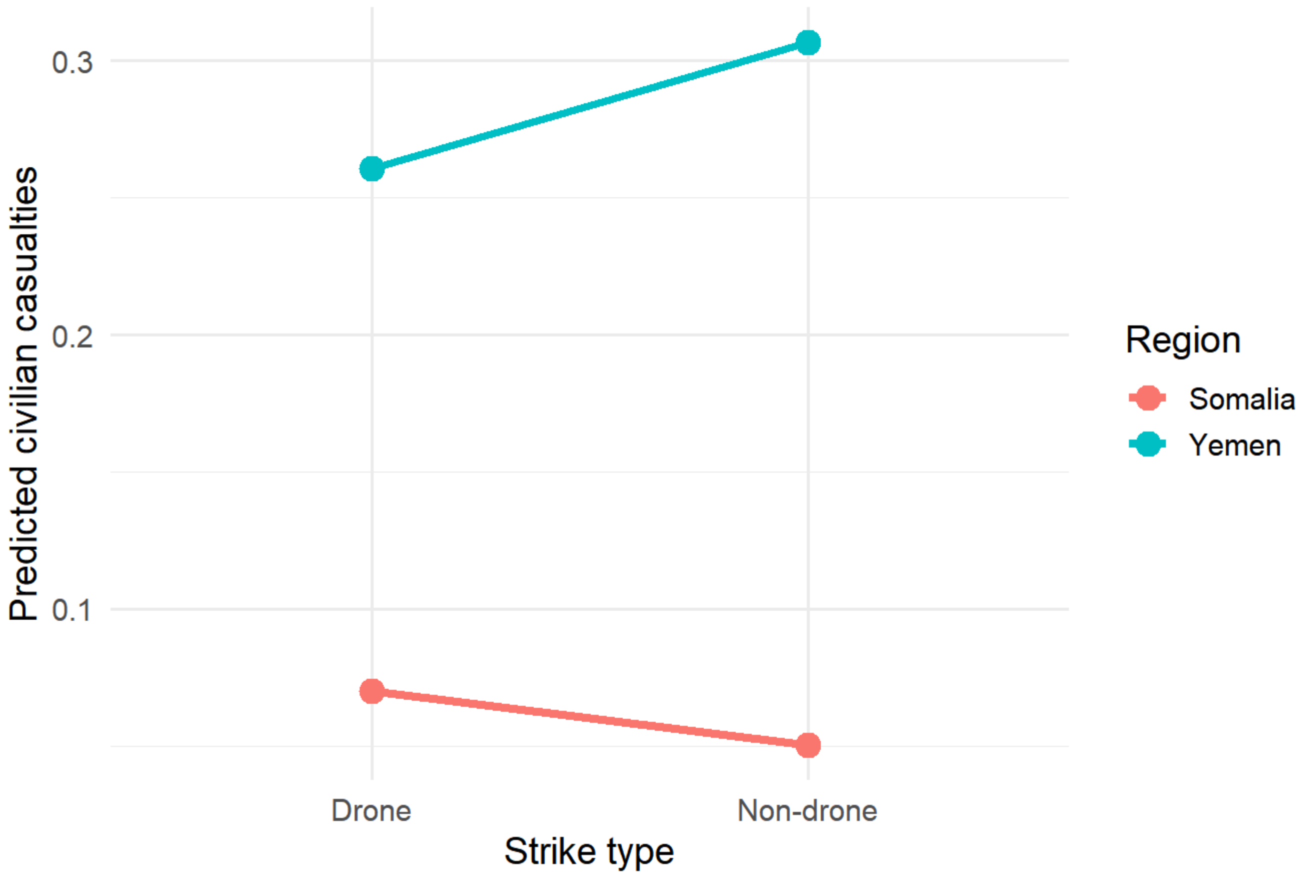


8.2 Visualization (Test 2)

H_0 : Drone use affects civilian casualties in the same way in both Somalia and Yemen.
H_1 : Drone use affects civilian casualties differently across Somalia and Yemen.

$$\begin{aligned} E(\text{civilian casualties}) = &\ \beta_0 + \beta_1(\text{drone}) + \beta_2(\text{region}) + \beta_3(\text{drone} \times \text{region}) \\ &+ \beta_4(\text{US confirmed}) + \beta_5(\text{minimum strikes}) + \beta_6(\text{total killed}) \end{aligned}$$

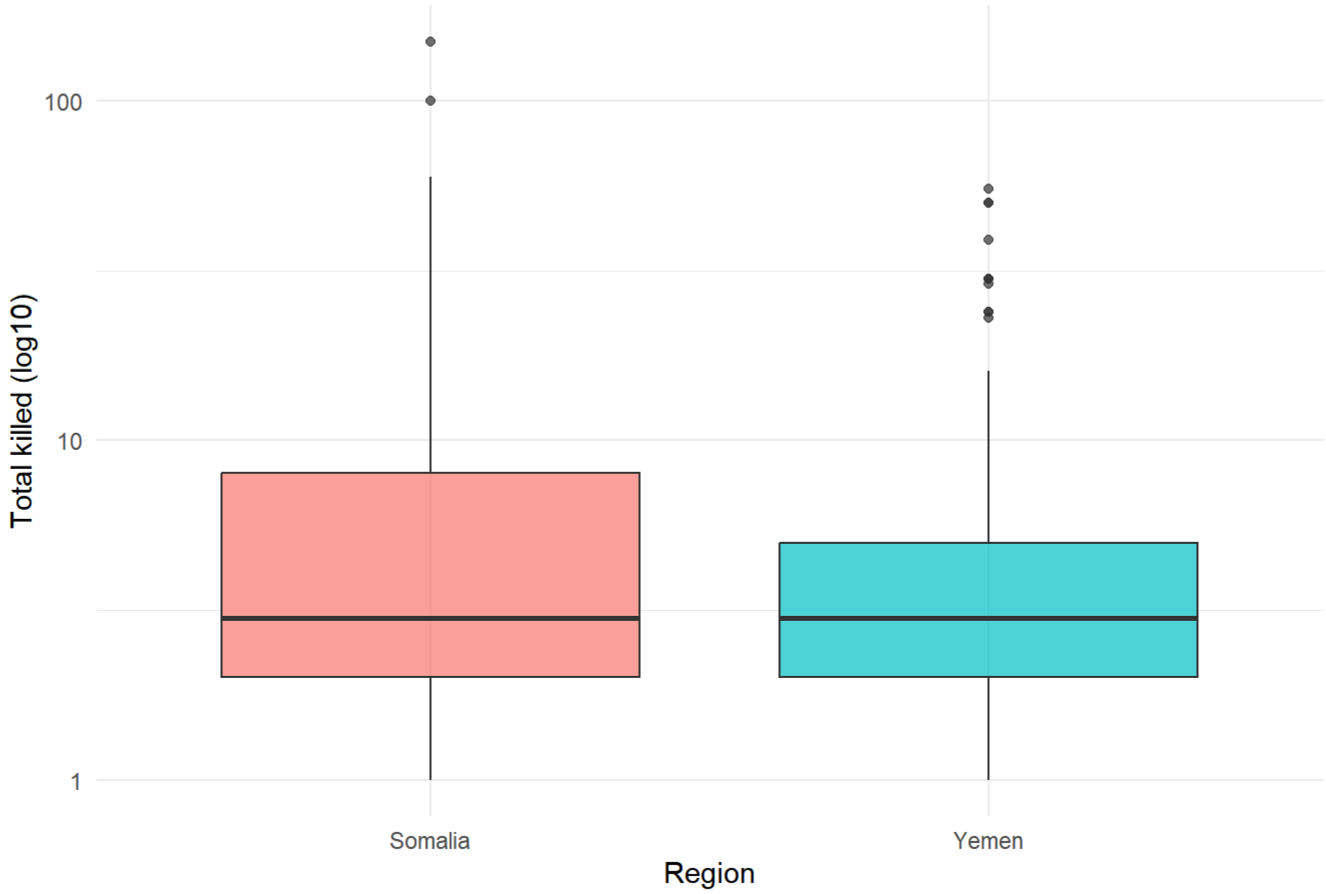

Civilian casualties (expected count)
1.0
0.5
0.0
Drone
Non-drone
Region
Somalia
Yemen

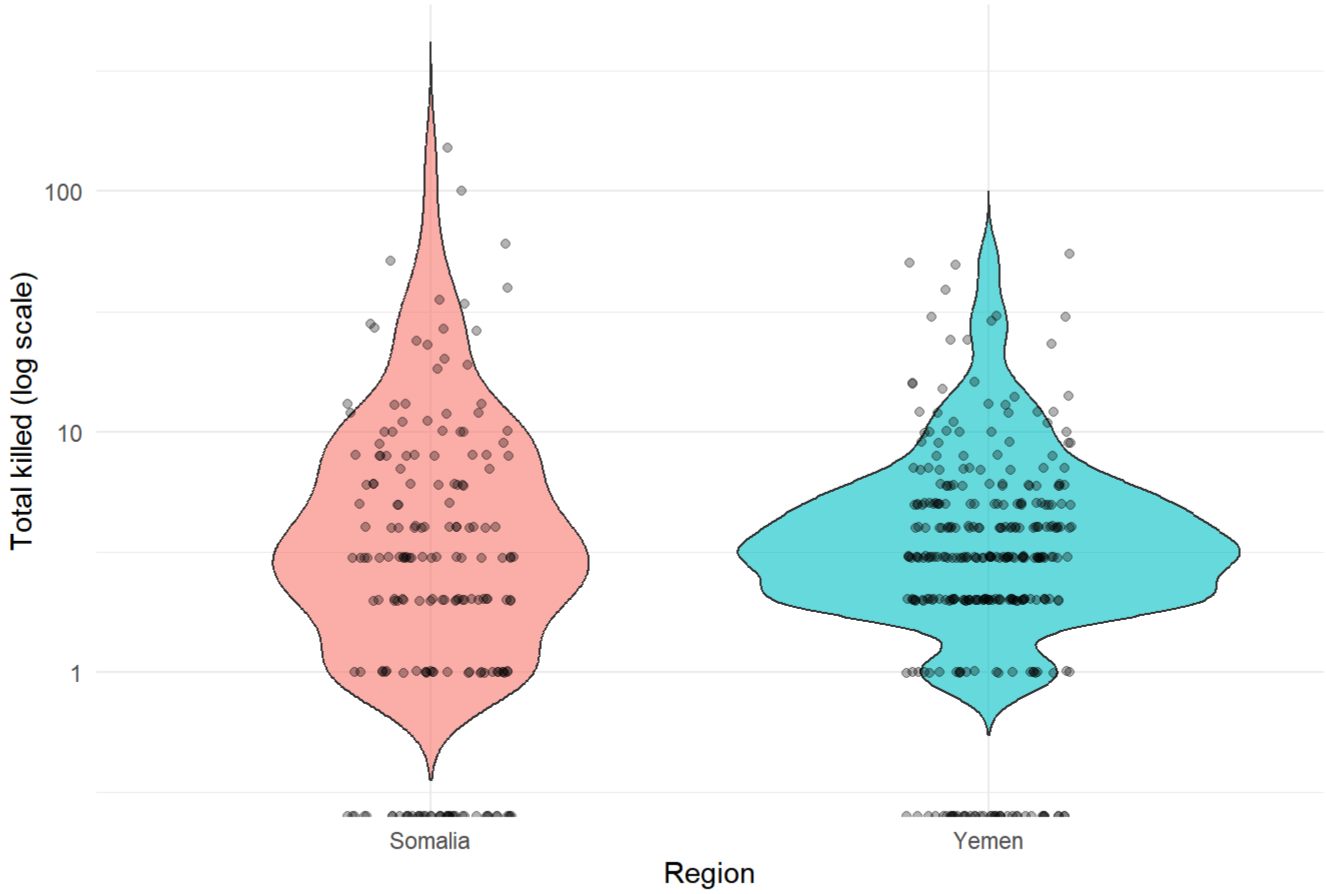


8.3 Visualization (Test 3)

H_0 : Reporting uncertainty does not differ between Somalia and Yemen.
H_1 : Reporting uncertainty differs between Somalia and Yemen.

$$E(\text{Uncertainty in casualties}) = \beta_0 + \beta_1 \text{ Region} + \beta_2 \text{ Drone} + \beta_3 \text{ US confirmed} + \beta_4 \text{ Minimum strikes}$$


100
10
1
Total killed (log10)
Somalia
Yemen
Region



Total killed (log scale)
100
10
1
Somalia
Yemen
Region

9 Conclusion

Our analysis shows clear and meaningful differences in the humanitarian impact of U.S. counterterrorism strikes in Somalia and Yemen. Using negative binomial regression to account for overdispersed count data, we find that strikes in Yemen are associated with nearly five times the civilian casualties of those in Somalia, even after controlling for drone use, confirmation status, and strike characteristics. Contrary to expectations, drone strikes do not have significantly different effects across the two countries, suggesting that broader regional factors—not simply weapon type—shape civilian outcomes. We also find no regional difference in reporting uncertainty, although uncertainty is higher for drone and unconfirmed strikes. Together, these results highlight the importance of transparent casualty reporting and the need to consider local conflict conditions when evaluating the effectiveness and humanitarian cost of U.S. strikes.

10 Author Contributions

In this project, the team collaborated effectively by distributing key responsibilities across members. Daniel Dai and Keivan Bolouri led the design and preparation of the poster, while Evelyn Isaka and Shanmei Wanyan delivered the main presentation. The written report was developed by Shanmei Wanyan, Keivan Bolouri, and Linxue Guo, ensuring clear documentation of the project's methods and results. Coding and analytical implementation were carried out by Itaru Fukushima and Daniel Dai, whose contributions supported the project's computational aspects.

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