My title*

My subtitle if needed

First author   Another author

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First sentence. Second sentence. Third sentence. Fourth sentence.

1 Model

1.0.1 Model Set-Up

This analysis seeks to understand the influence of political ideology and media framing on the public's policy support concerning opioid abuse treatment. A logistic regression model was constructed to predict the likelihood of favouring government-funded treatment over favouring arrest (`policy`) as a function of political ideology and media framing. The model includes two main ideology predictors: `conservative` and `liberal`. Additionally, the model incorporates media framing variables: `sympathetic_white` and `sympathetic_black` which represent sympathetic media narratives towards opioid users of different races, and `unsympathetic_white` and `unsympathetic_black`, representing unsympathetic narratives.

The terms `conservative:media_frames` and `liberal:media_frames` are designed to detect whether the relationship between media framing and policy support differs across the ideological spectrum. The response variable `Policy` is binary, indicating whether an individual supports or rejects treatment-focused intervention for opioid abuse. Therefore, a logistic regression model (logit model) is employed to predict the probability of policy support, which is suitable for binary outcome data. The logit model is defined as:

```
policy ~ conservative + liberal + sympathetic_white + sympathetic_black +
    unsympathetic_white + unsympathetic_black + conservative *
    sympathetic_white + conservative * sympathetic_black + conservative *
    unsympathetic_white + conservative * unsympathetic_black +
    liberal * sympathetic_white + liberal * sympathetic_black +
```

*Code and data are available at: LINK.

```
liberal * unsympathetic_white + liberal * unsympathetic_black
```

The next step after setting up the logistic regression model is understanding how people's ideological beliefs and the various ways the media frames opioid use impact their support for policy . To do this, a coefficient table (Table 2) was produced to capture the essence of the relationships between predictor variables. The goal is to quantify the relationship between each predictor variable (ideological beliefs, media framings, etc.) and interaction term (like conservative:media_frames) and the corresponding likelihood of policy support.

The coefficients, for instance, point to whether a factor, like political leaning or a specific type of media narrative, nudges public opinion towards or away from a certain policy stance, and importantly, how strong that nudge is. It also looks at standard errors, z-values, and p-values to check the confidence in these effects—are they solid or could they be just chance findings? And those 95% confidence intervals give a ballpark figure, showing where the true effect likely falls. Table 1 summarizes each term found in the coefficient table. Furthermore, the model's fit statistics (Table 3), including AIC and BIC among others, offer a snapshot of the model's overall performance and suitability for the data at hand.

Table 1: Explanation of Terms in the Coefficient Table

Term	Description
Estimate	The coefficient estimate indicates the change in the log odds of the outcome for a one-unit increase in the predictor. Positive values indicate an increase in the likelihood of policy support, while negative values suggest a decrease.
Std.Error	The standard error of the coefficient estimate provides a measure of the estimate's precision. Smaller values indicate more precise estimates.
Statistic	The test statistic (usually a Z-value) used to assess the significance of the predictor is derived from the coefficient estimate divided by its standard error.
P.Value	The p-value associated with the test statistic indicates the probability of observing the data, or something more extreme, under the null hypothesis that the coefficient is zero. A p-value below a certain threshold (e.g., 0.05) suggests statistical significance.
Conf.Low	The lower bound of the 95% confidence interval for the coefficient estimate provides a range within which we are 95% confident that the true coefficient value lies.
Conf.High	The upper bound of the 95% confidence interval for the coefficient estimate, together with the lower bound, offers insight into the estimate's uncertainty; narrower intervals indicate more precise estimates.

Table 2: Logistic regression coefficient estimates, standard errors, z-values, p-values, and 95% confidence intervals.

term	estimate	std.error	statistic	p.value	Confidence Interval conf.low	conf.high
(Intercept)	0.6678294	0.2750291	2.4282132	0.0151734	0.1411158	1.2259861
conservative	-0.9814869	0.3481201	-2.8193920	0.0048115	-1.6774510	-0.3086062
liberal	0.4097295	0.3428255	1.1951547	0.2320266	-0.2703181	1.0788210
sympathetic_white	0.6990469	0.4149361	1.6847099	0.0920446	-0.1051626	1.5311750
sympathetic_black	0.5217547	0.4108634	1.2698982	0.2041209	-0.2772228	1.3422341
unsympathetic_white	0.0741080	0.3865883	0.1916974	0.8479793	-0.6862842	0.8352658
unsympathetic_black	-0.1859913	0.3907324	-0.4760068	0.6340696	-0.9565777	0.5808922
conservative_sympathetic_white	0.3550107	0.5151322	0.6891643	0.4907199	-0.6640394	1.3613041
conservative_sympathetic_black	0.1246086	0.5094497	0.2445945	0.8067704	-0.8819534	1.1203956
conservative_unsympathetic_white	0.0819206	0.4901231	0.1671430	0.8672575	-0.8802856	1.0445048
conservative_unsympathetic_black	0.4996488	0.4897806	1.0201482	0.3076582	-0.4599725	1.4633501
liberal_sympathetic_white	0.8624515	0.6059047	1.4234113	0.1546170	-0.3056957	2.0873183
liberal_sympathetic_black	0.0299270	0.5200971	0.0575411	0.9541142	-0.9955244	1.0492711
liberal_unsympathetic_white	0.1620568	0.4920280	0.3293650	0.7418798	-0.8028944	1.1298208
liberal_unsympathetic_black	0.2950135	0.4894581	0.6027349	0.5466851	-0.6644274	1.2579679

Table 3: Model fit statistics including Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and other relevant measures.

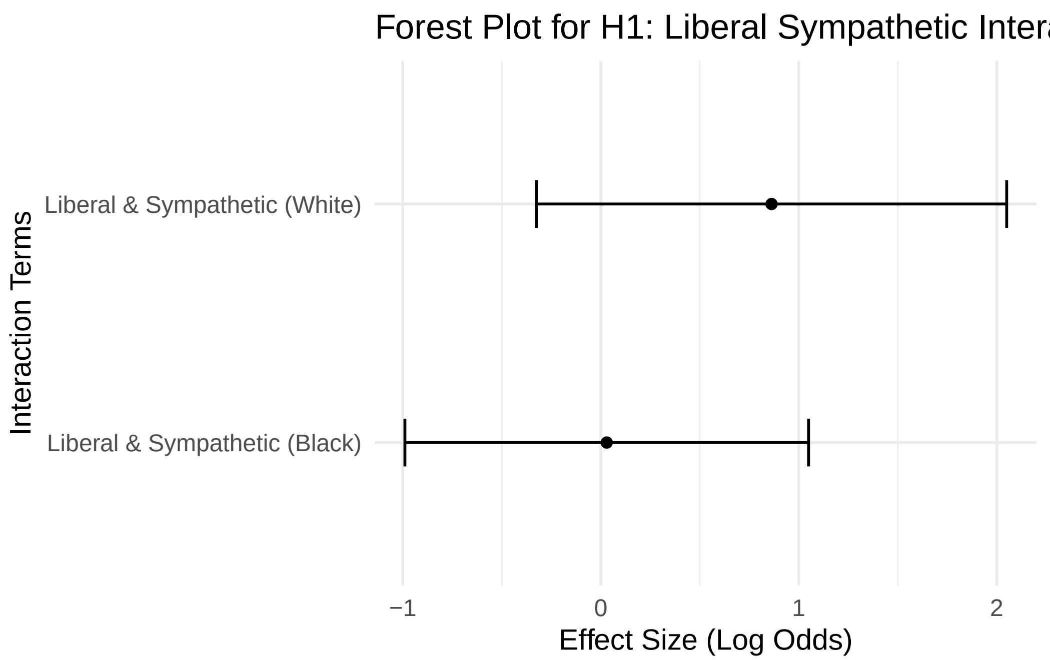
null.deviance	df.null	logLik	AIC	BIC	deviance	df.residual	nobs
1675.942	1356	-769.6327	1569.265	1647.461	1539.265	1342	1357

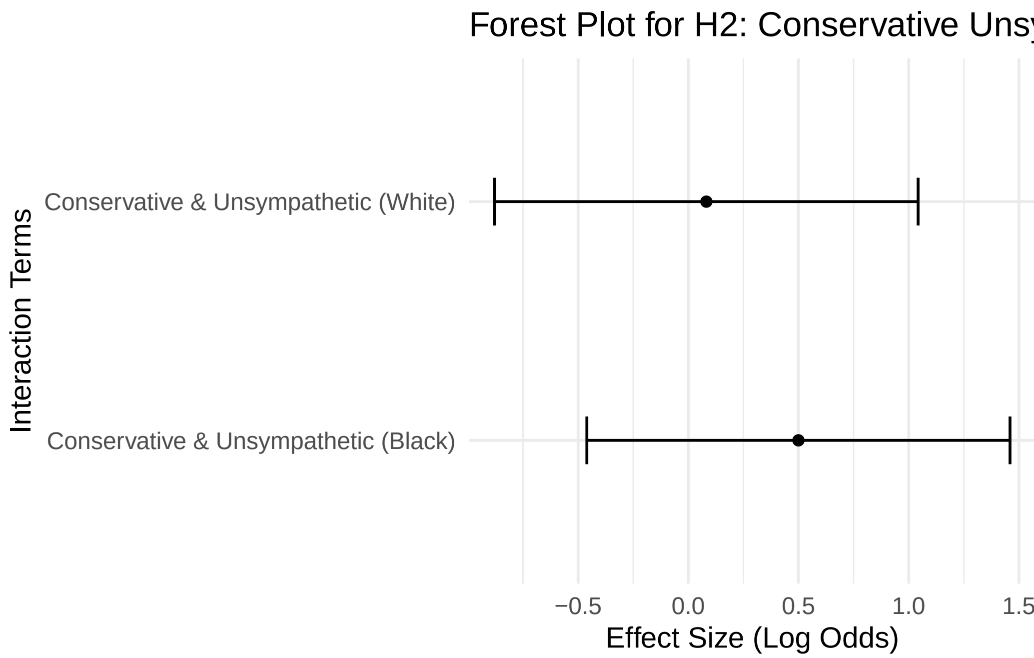
Note: Control condition for media frames = no story, control condition for ideology = moderate

1.0.2 Model Justification

The remainder of this paper will specifically examine the interaction effects to understand how the influence of media framing on policy support for opioid abuse treatment varies according to the political ideology of respondents. This approach aims to uncover how different ideological perspectives (conservative versus liberal) shape the effect that sympathetic or unsympathetic media narratives about opioid users have on an individual's likelihood to support treatment-focused policies. This analysis is guided by the following hypotheses:

H_0: There is no interaction effect between political ideology (conservative or liberal) and media framing (sympathetic or unsympathetic, towards white or black opioid users) on the support for policy regarding opioid abuse treatment. The effect of media framing on policy support does not differ across the ideological spectrum (conservative versus liberal). H_1: There is a significant interaction effect between political ideology and sympathetic media framing on policy support for opioid abuse treatment, with liberals showing a stronger positive response towards treatment-focused policies than conservatives when exposed to sympathetic narratives (towards white or black opioid users). This suggests that sympathetic framing will be more effective in increasing support for treatment-focused policies among liberals compared to conservatives. H_2: There is a significant interaction effect between political ideology and unsympathetic media framing on policy support for opioid abuse treatment, with liberals again expected to have a stronger response towards treatment-focused policies (i.e., moving towards supporting treatment over arrest) than conservatives when exposed to unsympathetic narratives. However, in this context, the "stronger response" could be interpreted as being less swayed by unsympathetic framing towards punitive measures and maintaining or increasing their support for treatment-focused interventions.






```r
# Your coefficients and standard errors here
coefficients <- c(0.35501, 0.86245, 0.12461, 0.02993, 0.08192, 0.16206, 0.49965, 0.29501)
std_errors <- c(0.51513, 0.60590, 0.50945, 0.52010, 0.49012, 0.49203, 0.48978, 0.48946)
terms <- c("Conservative & Sympathetic White", "Liberal & Sympathetic White",
           "Conservative & Sympathetic Black", "Liberal & Sympathetic Black",
           "Conservative & Unsympathetic White", "Liberal & Unsympathetic White",
           "Conservative & Unsympathetic Black", "Liberal & Unsympathetic Black")

# Create a dataframe
df <- data.frame(term = terms, estimate = coefficients, std_error = std_errors)

# Add lower and upper confidence intervals
df <- df %>%
  mutate(lower_ci = estimate - 1.96 * std_error,
         upper_ci = estimate + 1.96 * std_error)

# Check the dataframe
print(df)
```

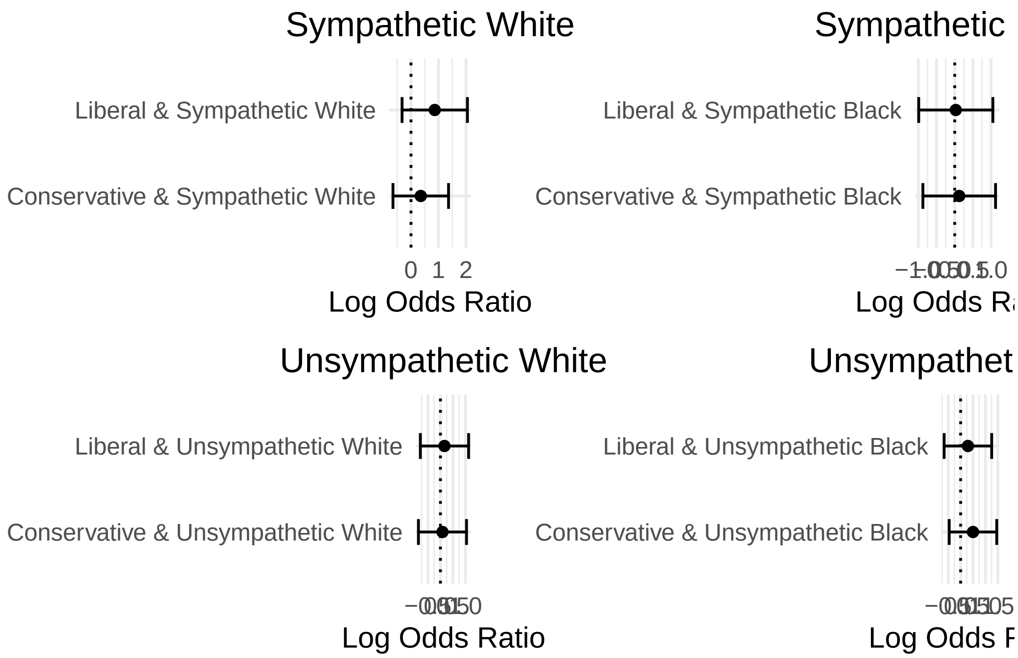
```
                                term estimate std_error   lower_ci upper_ci
1   Conservative & Sympathetic White  0.35501   0.51513 -0.6546448 1.364665
2        Liberal & Sympathetic White  0.86245   0.60590 -0.3251140 2.050014
3   Conservative & Sympathetic Black  0.12461   0.50945 -0.8739120 1.123132
```

```
4        Liberal & Sympathetic Black  0.02993   0.52010 -0.9894660 1.049326
5 Conservative & Unsympathetic White  0.08192   0.49012 -0.8787152 1.042555
6      Liberal & Unsympathetic White  0.16206   0.49203 -0.8023188 1.126439
7 Conservative & Unsympathetic Black  0.49965   0.48978 -0.4603188 1.459619
8      Liberal & Unsympathetic Black  0.29501   0.48946 -0.6643316 1.254352
```

```r
# Function to make a forest plot
make_forest_plot <- function(df, title) {
  p <- ggplot(df, aes(y = term, x = estimate)) +
    geom_point() +
    geom_errorbarh(aes(xmin = lower_ci, xmax = upper_ci), height = 0.3) +
    geom_vline(xintercept = 0, linetype = "dotted") +
    theme_minimal() +
    labs(title = title, x = "Log Odds Ratio", y = "") +
    theme(plot.title = element_text(hjust = 0.5))
  return(p)
}

# Create plots for each set of terms
p1 <- make_forest_plot(df[df$term %in% c("Conservative & Sympathetic White", "Liberal & Sy
p2 <- make_forest_plot(df[df$term %in% c("Conservative & Sympathetic Black", "Liberal & Sy
p3 <- make_forest_plot(df[df$term %in% c("Conservative & Unsympathetic White", "Liberal &
p4 <- make_forest_plot(df[df$term %in% c("Conservative & Unsympathetic Black", "Liberal &

# Arrange the plots in a 2x2 grid and display them
library(gridExtra)
```

```
Attaching package: 'gridExtra'

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

    combine
```

```r
grid.arrange(p1, p2, p3, p4, nrow = 2)
```



2 References