Pilot Study - 2x3 Design (Cond x Base)

October 28, 2025

Items

Read Data

```
# Set this to TRUE if you have API access, FALSE if using CSV
USE_API <- T

if(USE_API) {
  ## Pull directly from Qualtrics API
  qual_data <- fetch_survey(surveyID='SV_dpbDBoF9oHm8TXw',  # Pilot Study ID
                            start_date = "2025-10-27",
                     force_request = T)
} else {
  # Read the processed data directly from CSV
  d0 <- read.csv('pilot-study.csv', check.names = F)
  num_excluded <- unique(d0$num_excluded_total)
}

# Define the categories based on the JavaScript feedback code
# Low base categories (3 authors each) - SetA
categories_low <- list(
  women = c('Zadie Smith','J.K. Rowling','Jane Austen'),
  poets = c('George Orwell','Flann O\'Brien','Neil Gaiman'),
  oldies = c('Ernest Hemingway','Nathaniel Hawthorne','F. Scott Fitzgerald'),
  books = c('John Steinbeck','Michael Crichton','Kurt Vonnegut')
)

# Medium base categories (6 authors each) - SetB
categories_med <- list(
  women = c('Zadie Smith','J.K. Rowling','Jane Austen','Joyce Carol Oates','Sylvia
  ↪  Plath','Virginia Woolf'),
  poets = c('Charles Dickens','George Orwell','Sylvia Plath','Flann O\'Brien','Neil
  ↪  Gaiman','Oscar Wilde'),
  oldies = c('Charles Dickens','Ernest Hemingway','Nathaniel Hawthorne','F. Scott
  ↪  Fitzgerald','Virginia Woolf','Oscar Wilde'),
  books = c('Charles Dickens','John Steinbeck','Joyce Carol Oates','Michael
  ↪  Crichton','Ray Bradbury','Kurt Vonnegut')
)

# High base categories (9 authors each) - SetC
categories_high <- list(
  women = c('Zadie Smith','J.K. Rowling','Jane Austen','Maya Angelou','Joyce Carol
  ↪  Oates','Sylvia Plath','Lucy Maud','Isabel Allende','Virginia Woolf'),
  poets = c('Charles Dickens','Victor Hugo','George Orwell','Maya Angelou','Sylvia
  ↪  Plath','Flann O\'Brien','Jorge Luis Borges','Neil Gaiman','Oscar Wilde'),
  oldies = c('Charles Dickens','Ernest Hemingway','Victor Hugo','Nathaniel
  ↪  Hawthorne','Lucy Maud','F. Scott Fitzgerald','Jorge Luis Borges','Virginia
  ↪  Woolf','Oscar Wilde'),
  books = c('Charles Dickens','John Steinbeck','Joyce Carol Oates','Lucy Maud','Isabel
  ↪  Allende','Jorge Luis Borges','Ray Bradbury','Kurt Vonnegut','Michael Crichton')
)

if(USE_API) {
  # Process the API data with new category definitions
  d0 <- qual_data |>
    filter(!is.na(`choice-7`), !is.na(PROLIFIC_PID)) |>
```

```r
  mutate(
    # Extract base condition from embedded data
    base_condition = tolower(base),

    # Gender feedback detection (cond == "treat")
    gender_feedback = as.numeric(cond == "treat"),

    # Attribute feedback detection based on JavaScript code
    poets_shown = as.numeric(grepl("wrote poetry", feedbackItem1) |
                 grepl("wrote poetry", feedbackItem2) |
                 grepl("wrote poetry", feedbackItem3)),

    oldies_shown = as.numeric(grepl("born in the 1800s", feedbackItem1) |
                  grepl("born in the 1800s", feedbackItem2) |
                  grepl("born in the 1800s", feedbackItem3)),

    books_shown = as.numeric(grepl("wrote more than 10 books", feedbackItem1) |
                  grepl("wrote more than 10 books", feedbackItem2) |
                  grepl("wrote more than 10 books", feedbackItem3)),

    women_shown = as.numeric(grepl("were women", feedbackItem1) |
                 grepl("were women", feedbackItem2) |
                 grepl("were women", feedbackItem3))
  )

# Calculate picks based on the appropriate category list
for(i in 1:nrow(d0)) {
  if(d0$base_condition[i] == "high") {
    d0$female_pick[i] <- as.numeric(d0$`choice-7`[i] %in% categories_high$women)
    d0$poets_pick[i] <- as.numeric(d0$`choice-7`[i] %in% categories_high$poets)
    d0$oldies_pick[i] <- as.numeric(d0$`choice-7`[i] %in% categories_high$oldies)
    d0$books_pick[i] <- as.numeric(d0$`choice-7`[i] %in% categories_high$books)

    # Calculate base counts for initial selections
    d0$base_gender[i] <- sum(d0$`choice-1`[i] %in% categories_high$women,
                             d0$`choice-2`[i] %in% categories_high$women,
                             d0$`choice-3`[i] %in% categories_high$women,
                             d0$`choice-4`[i] %in% categories_high$women,
                             d0$`choice-5`[i] %in% categories_high$women,
                             d0$`choice-6`[i] %in% categories_high$women)
    d0$base_poets[i] <- sum(d0$`choice-1`[i] %in% categories_high$poets,
                            d0$`choice-2`[i] %in% categories_high$poets,
                            d0$`choice-3`[i] %in% categories_high$poets,
                            d0$`choice-4`[i] %in% categories_high$poets,
                            d0$`choice-5`[i] %in% categories_high$poets,
                            d0$`choice-6`[i] %in% categories_high$poets)
    d0$base_oldies[i] <- sum(d0$`choice-1`[i] %in% categories_high$oldies,
                             d0$`choice-2`[i] %in% categories_high$oldies,
                             d0$`choice-3`[i] %in% categories_high$oldies,
                             d0$`choice-4`[i] %in% categories_high$oldies,
                             d0$`choice-5`[i] %in% categories_high$oldies,
                             d0$`choice-6`[i] %in% categories_high$oldies)
    d0$base_books[i] <- sum(d0$`choice-1`[i] %in% categories_high$books,
                            d0$`choice-2`[i] %in% categories_high$books,
```

```
                         d0$`choice-3`[i] %in% categories_high$books,
                         d0$`choice-4`[i] %in% categories_high$books,
                         d0$`choice-5`[i] %in% categories_high$books,
                         d0$`choice-6`[i] %in% categories_high$books)
} else if(d0$base_condition[i] == "med") {
  d0$female_pick[i] <- as.numeric(d0$`choice-7`[i] %in% categories_med$women)
  d0$poets_pick[i] <- as.numeric(d0$`choice-7`[i] %in% categories_med$poets)
  d0$oldies_pick[i] <- as.numeric(d0$`choice-7`[i] %in% categories_med$oldies)
  d0$books_pick[i] <- as.numeric(d0$`choice-7`[i] %in% categories_med$books)

  # Calculate base counts for initial selections
  d0$base_gender[i] <- sum(d0$`choice-1`[i] %in% categories_med$women,
                          d0$`choice-2`[i] %in% categories_med$women,
                          d0$`choice-3`[i] %in% categories_med$women,
                          d0$`choice-4`[i] %in% categories_med$women,
                          d0$`choice-5`[i] %in% categories_med$women,
                          d0$`choice-6`[i] %in% categories_med$women)
  d0$base_poets[i] <- sum(d0$`choice-1`[i] %in% categories_med$poets,
                         d0$`choice-2`[i] %in% categories_med$poets,
                         d0$`choice-3`[i] %in% categories_med$poets,
                         d0$`choice-4`[i] %in% categories_med$poets,
                         d0$`choice-5`[i] %in% categories_med$poets,
                         d0$`choice-6`[i] %in% categories_med$poets)
  d0$base_oldies[i] <- sum(d0$`choice-1`[i] %in% categories_med$oldies,
                          d0$`choice-2`[i] %in% categories_med$oldies,
                          d0$`choice-3`[i] %in% categories_med$oldies,
                          d0$`choice-4`[i] %in% categories_med$oldies,
                          d0$`choice-5`[i] %in% categories_med$oldies,
                          d0$`choice-6`[i] %in% categories_med$oldies)
  d0$base_books[i] <- sum(d0$`choice-1`[i] %in% categories_med$books,
                         d0$`choice-2`[i] %in% categories_med$books,
                         d0$`choice-3`[i] %in% categories_med$books,
                         d0$`choice-4`[i] %in% categories_med$books,
                         d0$`choice-5`[i] %in% categories_med$books,
                         d0$`choice-6`[i] %in% categories_med$books)
} else {
  d0$female_pick[i] <- as.numeric(d0$`choice-7`[i] %in% categories_low$women)
  d0$poets_pick[i] <- as.numeric(d0$`choice-7`[i] %in% categories_low$poets)
  d0$oldies_pick[i] <- as.numeric(d0$`choice-7`[i] %in% categories_low$oldies)
  d0$books_pick[i] <- as.numeric(d0$`choice-7`[i] %in% categories_low$books)

  # Calculate base counts for initial selections
  d0$base_gender[i] <- sum(d0$`choice-1`[i] %in% categories_low$women,
                          d0$`choice-2`[i] %in% categories_low$women,
                          d0$`choice-3`[i] %in% categories_low$women,
                          d0$`choice-4`[i] %in% categories_low$women,
                          d0$`choice-5`[i] %in% categories_low$women,
                          d0$`choice-6`[i] %in% categories_low$women)
  d0$base_poets[i] <- sum(d0$`choice-1`[i] %in% categories_low$poets,
                         d0$`choice-2`[i] %in% categories_low$poets,
                         d0$`choice-3`[i] %in% categories_low$poets,
                         d0$`choice-4`[i] %in% categories_low$poets,
                         d0$`choice-5`[i] %in% categories_low$poets,
                         d0$`choice-6`[i] %in% categories_low$poets)
```

```r
      d0$base_oldies[i] <- sum(d0$`choice-1`[i] %in% categories_low$oldies,
                               d0$`choice-2`[i] %in% categories_low$oldies,
                               d0$`choice-3`[i] %in% categories_low$oldies,
                               d0$`choice-4`[i] %in% categories_low$oldies,
                               d0$`choice-5`[i] %in% categories_low$oldies,
                               d0$`choice-6`[i] %in% categories_low$oldies)
      d0$base_books[i] <- sum(d0$`choice-1`[i] %in% categories_low$books,
                              d0$`choice-2`[i] %in% categories_low$books,
                              d0$`choice-3`[i] %in% categories_low$books,
                              d0$`choice-4`[i] %in% categories_low$books,
                              d0$`choice-5`[i] %in% categories_low$books,
                              d0$`choice-6`[i] %in% categories_low$books)
    }
  }

  # Continue processing demographics
  d0 <- d0 |>
    mutate(
      # Demographics
      gender_code = case_when(gender=="Man" ~ 1, TRUE ~ 0),
      race_code = case_when(str_detect(race, "White / Caucasian") ~ 1, TRUE ~ 0)
    ) |>
    dplyr::select(cond, base_condition, gender_feedback, poets_shown, oldies_shown,
↪   books_shown, women_shown,
                  female_pick, poets_pick, oldies_pick, books_pick,
                  base_gender, base_poets, base_oldies, base_books,
↪   `choice-1`:`choice-7`,
                  race, gender, age, gender_code, race_code)

  # Calculate the number of excluded participants
  num_excluded <- nrow(qual_data) - nrow(d0)

  # Save num_excluded in d0
  d0$num_excluded_total <- num_excluded  # As a column

  # Write the API-pulled data into a CSV file
  write.csv(d0, 'pilot-study.csv', row.names = FALSE, quote = TRUE)
}
```

Variable Names

Variable	Description
cond	Treatment condition (control or treat).
base_condition	Base condition (low = 3 authors, med = 6 authors, high = 9 authors per category).
gender_feedback	Binary indicator of whether participant was in treatment condition (cond = treat).
female_pick	Binary indicator of whether participant selected a female author for seventh selection.
poets_pick	Binary indicator of whether participant selected an author who wrote poetry.
oldies_pick	Binary indicator of whether participant selected an author born in the 1800s.
books_pick	Binary indicator of whether participant selected an author who wrote 10+ books.
base_gender	Count of female authors selected in initial six authors.
base_poets	Count of poets selected in initial six authors.
base_oldies	Count of 1800s-born authors selected in initial six authors.
base_books	Count of 10+ book authors selected in initial six authors.
choice-1 to choice-7	The selected authors.
gender	Self-selected gender.
race	Self-selected race.
age	Self-entered age.
gender_code	Dummy code for gender (male = 1).
race_code	Dummy code for race (white = 1).

Demographics

```
## Excluded Participants: 38

##                        Percentage gender
## 1                             Woman  51.55
## 2                               Man  46.90
## 3                        Non-binary   1.11
## 4 Another gender not listed here:   0.44

##                          Percentage  Race
## 1 American Indian or Alaskan Native  0.44
## 2          Asian / Pacific Islander  7.52
## 3         Black or African American 10.62
## 4                 Hispanic / Latinx  7.52
## 5                 White / Caucasian 73.89

## # A tibble: 1 x 2
##   mean_age sd_age
##      <dbl>  <dbl>
## 1     44.1   13.2

##
## --- Initial Selections (Women) ---

## Mean (num of initial women selected):  1.87

## SD (num of initial women selected):  1.18

## Percentage (initial women selected):  31.19 %

##
## --- Balance Checks by Condition ---

## # A tibble: 2 x 2
##   gender_feedback mean_women
##             <dbl>      <dbl>
## 1               0      0.317
## 2               1      0.307

##
##  Welch Two Sample t-test
##
## data:  base_gender/6 by gender_feedback
## t = 0.5556, df = 448.82, p-value = 0.5788
## alternative hypothesis: true difference in means between group 0 and group 1 is not equal to 0
## 95 percent confidence interval:
##  -0.02619505  0.04684401
## sample estimates:
## mean in group 0 mean in group 1
##       0.3171091       0.3067847
```

```
##
## --- Balance by Base Condition ---

## # A tibble: 3 x 6
##   base_condition     n mean_women mean_poets mean_oldies mean_books
##   <chr>          <int>      <dbl>      <dbl>       <dbl>      <dbl>
## 1 high             151      0.406      0.352       0.368      0.357
## 2 low              149      0.223      0.126       0.186      0.188
## 3 med              152      0.306      0.257       0.305      0.339
```

Primary Analysis

Low Base Condition (3 authors per category)

```
# Create condition-specific datasets
d0_low <- d0 |> filter(base_condition == "low")
d0_med <- d0 |> filter(base_condition == "med")
d0_high <- d0 |> filter(base_condition == "high")

# Effect of gender feedback in low base condition
r_low <- lm(female_pick ~ gender_feedback, data=d0_low)

cat("Effect in Low Base Condition (3 authors per category):\n")
```

```
## Effect in Low Base Condition (3 authors per category):
```

```
robust_summary(r_low)
```

```
##
## Call:
## lm(formula = female_pick ~ gender_feedback, data = d0_low)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.14667 -0.14667 -0.09459 -0.09459  0.90541
##
## Coefficients:
##                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)      0.09459    0.03449   2.743  0.00685 **
## gender_feedback  0.05207    0.05388   0.966  0.33544
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.3271 on 147 degrees of freedom
## Multiple R-squared:  0.006382,   Adjusted R-squared:  -0.0003773
## F-statistic: 0.9442 on 1 and 147 DF,  p-value: 0.3328
```

```
robust_confint(r_low)
```

```
##                       2.5 %    97.5 %
## (Intercept)      0.02644145 0.1627477
## gender_feedback -0.05441477 0.1585589
```

Medium Base Condition (6 authors per category)

```r
# Effect of gender feedback in medium base condition
r_med <- lm(female_pick ~ gender_feedback, data=d0_med)

cat("Effect in Medium Base Condition (6 authors per category):\n")
```

```
## Effect in Medium Base Condition (6 authors per category):
```

```r
robust_summary(r_med)
```

```
##
## Call:
## lm(formula = female_pick ~ gender_feedback, data = d0_med)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -0.3684 -0.3684 -0.3026  0.6316  0.6974
##
## Coefficients:
##                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)      0.30263    0.05340   5.667 7.21e-08 ***
## gender_feedback  0.06579    0.07743   0.850    0.397
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.4742 on 150 degrees of freedom
## Multiple R-squared:  0.004853,   Adjusted R-squared:  -0.001781
## F-statistic: 0.7316 on 1 and 150 DF,  p-value: 0.3937
```

```r
robust_confint(r_med)
```

```
##                       2.5 %    97.5 %
## (Intercept)      0.19712005 0.4081431
## gender_feedback -0.08720381 0.2187828
```

High Base Condition (9 authors per category)

```r
# Effect of gender feedback in high base condition
r_high <- lm(female_pick ~ gender_feedback, data=d0_high)

cat("Effect in High Base Condition (9 authors per category):\n")
```

```
## Effect in High Base Condition (9 authors per category):
```

```r
robust_summary(r_high)
```

```
##
## Call:
## lm(formula = female_pick ~ gender_feedback, data = d0_high)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -0.4210 -0.4210 -0.3733  0.5789  0.6267
##
## Coefficients:
##                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)      0.42105    0.05739   7.337 1.31e-11 ***
## gender_feedback -0.04772    0.08061  -0.592    0.555
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.492 on 149 degrees of freedom
## Multiple R-squared:  0.002377,   Adjusted R-squared:  -0.004318
## F-statistic: 0.3551 on 1 and 149 DF,  p-value: 0.5522
```

```r
robust_confint(r_high)
```

```
##                      2.5 %    97.5 %
## (Intercept)      0.3076500 0.5344553
## gender_feedback -0.2070043 0.1115657
```

Interaction Model

```r
# Full 2x3 factorial model testing interaction
# Factor base_condition with reference category
d0$base_condition_factor <- factor(d0$base_condition, levels = c("low", "med", "high"))

r_factorial <- lm(female_pick ~ gender_feedback * base_condition_factor, data=d0)

cat("2x3 Factorial Design: Gender Feedback x Base Condition\n")
```

```
## 2x3 Factorial Design: Gender Feedback x Base Condition
```

```r
robust_summary(r_factorial)
```

```
##
## Call:
## lm(formula = female_pick ~ gender_feedback * base_condition_factor,
##     data = d0)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -0.4210 -0.3684 -0.1467  0.5789  0.9054
##
## Coefficients:
##                                          Estimate Std. Error t value Pr(>|t|)
## (Intercept)                               0.09459    0.03449   2.743  0.00633
## gender_feedback                           0.05207    0.05388   0.966  0.33438
## base_condition_factormed                  0.20804    0.06357   3.273  0.00115
## base_condition_factorhigh                 0.32646    0.06695   4.876 1.51e-06
## gender_feedback:base_condition_factormed  0.01372    0.09433   0.145  0.88445
## gender_feedback:base_condition_factorhigh -0.09979    0.09696  -1.029  0.30394
##
## (Intercept)                              **
## gender_feedback
## base_condition_factormed                 **
## base_condition_factorhigh                ***
## gender_feedback:base_condition_factormed
## gender_feedback:base_condition_factorhigh
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.4379 on 446 degrees of freedom
## Multiple R-squared:  0.07227,    Adjusted R-squared:  0.06187
## F-statistic: 6.949 on 5 and 446 DF,  p-value: 2.9e-06
```

```r
robust_confint(r_factorial)
```

```
##                                                 2.5 %     97.5 %
## (Intercept)                               0.02681859 0.16237059
## gender_feedback                          -0.05382549 0.15796964
```

```
## base_condition_factormed                    0.08310879 0.33296518
## base_condition_factorhigh                   0.19487294 0.45804313
## gender_feedback:base_condition_factormed  -0.17167565 0.19911045
## gender_feedback:base_condition_factorhigh -0.29034728 0.09076454
```

Testing Differences in Effects Across Base Conditions

```
# Test whether the effect of gender feedback differs significantly
# across the three base conditions

# Extract interaction coefficients
rob_sum <- robust_summary(r_factorial)
rob_ci <- robust_confint(r_factorial)

cat('\nInteraction Effects (relative to Low base):\n\n')
```

```
##
## Interaction Effects (relative to Low base):
```

```
# Medium vs Low
if('gender_feedback:base_condition_factormed' %in% rownames(rob_sum$coefficients)) {
  interaction_coef_med <-
↪  rob_sum$coefficients['gender_feedback:base_condition_factormed', 'Estimate']
  interaction_se_med <- rob_sum$coefficients['gender_feedback:base_condition_factormed',
↪  'Std. Error']
  interaction_p_med <- rob_sum$coefficients['gender_feedback:base_condition_factormed',
↪  'Pr(>|t|)']

  cat('Medium vs Low:\n')
  cat('  Difference in effects:', round(interaction_coef_med * 100, 2), 'percentage
   ↪  points\n')
  cat('  Robust standard error:', round(interaction_se_med * 100, 2), '\n')
  cat('  p-value:', round(interaction_p_med, 4), '\n\n')
}
```

```
## Medium vs Low:
##   Difference in effects: 1.37 percentage points
##   Robust standard error: 9.43
##   p-value: 0.8844
```

```
# High vs Low
if('gender_feedback:base_condition_factorhigh' %in% rownames(rob_sum$coefficients)) {
  interaction_coef_high <-
↪  rob_sum$coefficients['gender_feedback:base_condition_factorhigh', 'Estimate']
  interaction_se_high <-
↪  rob_sum$coefficients['gender_feedback:base_condition_factorhigh', 'Std. Error']
  interaction_p_high <- rob_sum$coefficients['gender_feedback:base_condition_factorhigh',
↪  'Pr(>|t|)']

  cat('High vs Low:\n')
  cat('  Difference in effects:', round(interaction_coef_high * 100, 2), 'percentage
   ↪  points\n')
  cat('  Robust standard error:', round(interaction_se_high * 100, 2), '\n')
  cat('  p-value:', round(interaction_p_high, 4), '\n\n')
}
```

```
## High vs Low:
##   Difference in effects: -9.98 percentage points
##   Robust standard error: 9.7
##   p-value: 0.3039
```

```r
# Joint F-test for interaction terms
library(car)
cat('\nJoint test of interaction terms:\n')
```

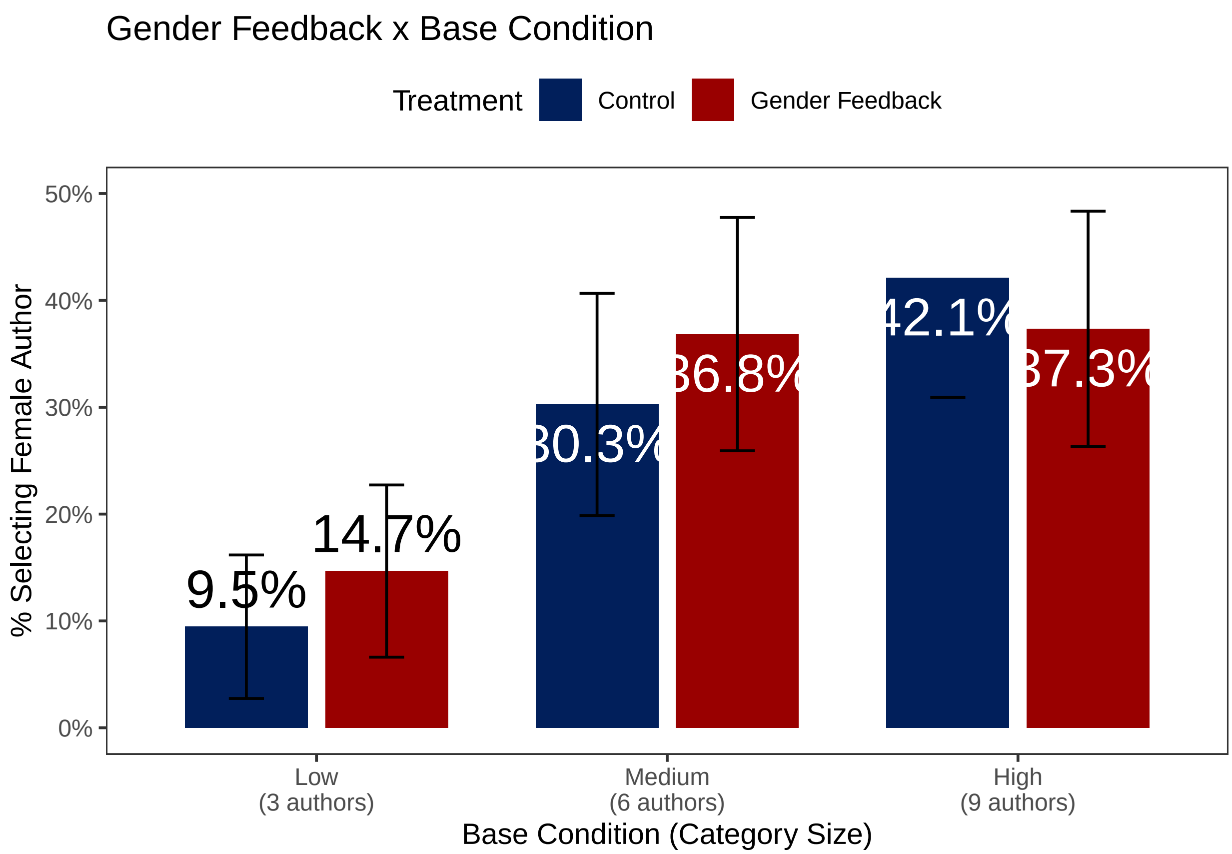
```
##
## Joint test of interaction terms:
```

```r
linearHypothesis(r_factorial, c("gender_feedback:base_condition_factormed = 0",
                                "gender_feedback:base_condition_factorhigh = 0"),
                 vcov = vcovHC(r_factorial, type = "HC3"))
```

```
##
## Linear hypothesis test:
## gender_feedback:base_condition_factormed = 0
## gender_feedback:base_condition_factorhigh = 0
##
## Model 1: restricted model
## Model 2: female_pick ~ gender_feedback * base_condition_factor
##
## Note: Coefficient covariance matrix supplied.
##
##   Res.Df Df      F Pr(>F)
## 1    448
## 2    446  2 0.6536 0.5207
```

Visualization of 2x3 Design

```r
library(ggplot2)

interaction_means <- d0 |>
  group_by(gender_feedback, base_condition) |>
  summarize(
    mean_female = mean(female_pick, na.rm = TRUE),
    se_female = sd(female_pick, na.rm = TRUE) / sqrt(n()),
    n = n()
  )

p_2x3 <- ggplot(interaction_means, aes(x = factor(base_condition, levels = c("low",
↪  "med", "high")),
                                       y = mean_female * 100,
                                       fill = factor(gender_feedback))) +
  geom_bar(stat = "identity", position = position_dodge(width = 0.8), width = 0.7) +
  # White text inside bars (when bar is tall enough)
  geom_text(aes(label = ifelse(mean_female * 100 > 15,
                                paste0(sprintf("%.1f", mean_female * 100), "%"), "")),
            position = position_dodge(width = 0.8), vjust = 1.5, size = 7, color =
            ↪  "white") +
  # Black text above bars (when bar is too small for white text)
  geom_text(aes(label = ifelse(mean_female * 100 <= 15,
                                paste0(sprintf("%.1f", mean_female * 100), "%"), "")),
            position = position_dodge(width = 0.8), vjust = -0.5, size = 7, color =
            ↪  "black") +
  geom_errorbar(aes(ymin = (mean_female - 1.96*se_female) * 100,
                    ymax = (mean_female + 1.96*se_female) * 100),
                width = 0.2, position = position_dodge(width = 0.8)) +
  scale_fill_manual(values = c("0" = "#011F5B", "1" = "#990000"),
                    labels = c("0" = "Control", "1" = "Gender Feedback")) +
  scale_y_continuous(labels = function(x) paste0(x, "%"), limits = c(0, 50),
                     breaks = seq(0, 50, 10)) +
  labs(x = "Base Condition (Category Size)",
       y = "% Selecting Female Author",
       title = "Gender Feedback x Base Condition",
       fill = "Treatment") +
  scale_x_discrete(labels = c("low" = "Low\n(3 authors)", "med" = "Medium\n(6 authors)",
                              "high" = "High\n(9 authors)")) +
  theme_bw() +
  theme(legend.position = "top",
        panel.grid.major = element_blank(),
        panel.grid.minor = element_blank())

print(p_2x3)
```




```
ggsave("Figure-Pilot-Overall.pdf", plot = p_2x3, width = 10, height = 8, units = "in",
↪   device = cairo_pdf, family = "Times New Roman")
```

Robustness Checks

Low Base Condition

```r
## Robust to demographic controls
r_low_demog <- lm(female_pick ~ gender_feedback + gender_code + race_code + age,
↪  data=d0_low)

cat("Low Base: With Demographic Controls\n")
```

```
## Low Base: With Demographic Controls
```

```r
robust_summary(r_low_demog)
```

```
##
## Call:
## lm(formula = female_pick ~ gender_feedback + gender_code + race_code +
##     age, data = d0_low)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.28416 -0.15489 -0.10171 -0.04308  0.93011
##
## Coefficients:
##                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)     -0.074496   0.106474  -0.700    0.485
## gender_feedback  0.028696   0.054497   0.527    0.599
## gender_code      0.085001   0.053098   1.601    0.112
## race_code       -0.016524   0.057377  -0.288    0.774
## age              0.003352   0.002503   1.339    0.183
##
## Residual standard error: 0.3253 on 144 degrees of freedom
## Multiple R-squared:  0.0373, Adjusted R-squared:  0.01055
## F-statistic: 1.395 on 4 and 144 DF,  p-value: 0.2387
```

```r
robust_confint(r_low_demog)
```

```
##                        2.5 %      97.5 %
## (Intercept)     -0.284948548 0.135957509
## gender_feedback -0.079020964 0.136413189
## gender_code     -0.019950769 0.189951798
## race_code       -0.129934421 0.096886181
## age             -0.001594832 0.008299582
```

```r
## Logistic regression
r_low_logit <- glm(female_pick ~ gender_feedback, family = binomial, data=d0_low)
cat("\nLow Base: Logistic Regression Model\n")
```

```
##
## Low Base: Logistic Regression Model
```

```r
summary(r_low_logit)
```

```
##
## Call:
## glm(formula = female_pick ~ gender_feedback, family = binomial,
##     data = d0_low)
##
## Coefficients:
##                 Estimate Std. Error z value Pr(>|z|)
## (Intercept)      -2.2588     0.3972  -5.687 1.29e-08 ***
## gender_feedback   0.4978     0.5141   0.968    0.333
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 109.82  on 148  degrees of freedom
## Residual deviance: 108.86  on 147  degrees of freedom
## AIC: 112.86
##
## Number of Fisher Scoring iterations: 4
```

```r
# Odds ratio
tidy_low_logit <- tidy(r_low_logit, exponentiate = TRUE, conf.int = T)
print(tidy_low_logit)
```

```
## # A tibble: 2 x 7
##   term            estimate std.error statistic      p.value conf.low conf.high
##   <chr>              <dbl>     <dbl>     <dbl>        <dbl>    <dbl>     <dbl>
## 1 (Intercept)        0.104     0.397    -5.69  0.0000000129   0.0436     0.212
## 2 gender_feedback    1.65      0.514     0.968 0.333          0.610      4.72
```

Medium Base Condition

```r
## Robust to demographic controls
r_med_demog <- lm(female_pick ~ gender_feedback + gender_code + race_code + age,
↪  data=d0_med)

cat("Medium Base: With Demographic Controls\n")
```

```
## Medium Base: With Demographic Controls
```

```r
robust_summary(r_med_demog)
```

```
##
## Call:
## lm(formula = female_pick ~ gender_feedback + gender_code + race_code +
##     age, data = d0_med)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -0.4527 -0.3639 -0.2866  0.5877  0.7960
##
## Coefficients:
##                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)      0.237304   0.152906   1.552   0.1228
## gender_feedback  0.068408   0.079821   0.857   0.3928
## gender_code     -0.077674   0.077134  -1.007   0.3156
## race_code        0.161014   0.092654   1.738   0.0843 .
## age             -0.000584   0.002842  -0.205   0.8375
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.4731 on 147 degrees of freedom
## Multiple R-squared:  0.02907,	Adjusted R-squared:  0.002655
## F-statistic:   1.1 on 4 and 147 DF,  p-value: 0.3586
```

```r
robust_confint(r_med_demog)
```

```
##                        2.5 %      97.5 %
## (Intercept)     -0.064874227 0.539481397
## gender_feedback -0.089336894 0.226153457
## gender_code     -0.230108740 0.074760978
## race_code       -0.022092447 0.344119350
## age             -0.006200546 0.005032487
```

```r
## Logistic regression
r_med_logit <- glm(female_pick ~ gender_feedback, family = binomial, data=d0_med)
cat("\nMedium Base: Logistic Regression Model\n")
```

```
##
## Medium Base: Logistic Regression Model
```

```r
summary(r_med_logit)
```

```
##
## Call:
## glm(formula = female_pick ~ gender_feedback, family = binomial,
##     data = d0_med)
##
## Coefficients:
##                 Estimate Std. Error z value Pr(>|z|)
## (Intercept)      -0.8348     0.2497  -3.343 0.000828 ***
## gender_feedback   0.2958     0.3448   0.858 0.390965
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 193.96  on 151  degrees of freedom
## Residual deviance: 193.22  on 150  degrees of freedom
## AIC: 197.22
##
## Number of Fisher Scoring iterations: 4
```

```r
# Odds ratio
tidy_med_logit <- tidy(r_med_logit, exponentiate = TRUE, conf.int = T)
print(tidy_med_logit)
```

```
## # A tibble: 2 x 7
##   term            estimate std.error statistic  p.value conf.low conf.high
##   <chr>              <dbl>     <dbl>     <dbl>    <dbl>    <dbl>     <dbl>
## 1 (Intercept)        0.434     0.250    -3.34  0.000828    0.261     0.699
## 2 gender_feedback    1.34      0.345     0.858 0.391       0.685     2.66
```

High Base Condition

```r
## Robust to demographic controls
r_high_demog <- lm(female_pick ~ gender_feedback + gender_code + race_code + age,
↪  data=d0_high)

cat("High Base: With Demographic Controls\n")
```

```
## High Base: With Demographic Controls
```

```r
robust_summary(r_high_demog)
```

```
##
## Call:
## lm(formula = female_pick ~ gender_feedback + gender_code + race_code +
##     age, data = d0_high)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -0.5052 -0.4110 -0.3294  0.5744  0.7071
##
## Coefficients:
##                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)      0.434890   0.164539   2.643  0.00911 **
## gender_feedback -0.041405   0.082218  -0.504  0.61530
## gender_code     -0.081306   0.084135  -0.966  0.33545
## race_code       -0.062947   0.093784  -0.671  0.50316
## age              0.001407   0.003599   0.391  0.69637
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.4947 on 146 degrees of freedom
## Multiple R-squared:  0.0118, Adjusted R-squared:  -0.01527
## F-statistic: 0.4359 on 4 and 146 DF,  p-value: 0.7825
```

```r
robust_confint(r_high_demog)
```

```
##                       2.5 %      97.5 %
## (Intercept)      0.109702805 0.760076253
## gender_feedback -0.203896637 0.121086089
## gender_code     -0.247586297 0.084973689
## race_code       -0.248297575 0.122402609
## age             -0.005705561 0.008519876
```

```r
## Logistic regression
r_high_logit <- glm(female_pick ~ gender_feedback, family = binomial, data=d0_high)
cat("\nHigh Base: Logistic Regression Model\n")
```

```
##
## High Base: Logistic Regression Model
```

```r
summary(r_high_logit)
```

```
##
## Call:
## glm(formula = female_pick ~ gender_feedback, family = binomial,
##     data = d0_high)
##
## Coefficients:
##                 Estimate Std. Error z value Pr(>|z|)
## (Intercept)      -0.3185     0.2323  -1.371    0.170
## gender_feedback  -0.1995     0.3331  -0.599    0.549
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 202.92  on 150  degrees of freedom
## Residual deviance: 202.56  on 149  degrees of freedom
## AIC: 206.56
##
## Number of Fisher Scoring iterations: 4
```

```r
# Odds ratio
tidy_high_logit <- tidy(r_high_logit, exponentiate = TRUE, conf.int = T)
print(tidy_high_logit)
```

```
## # A tibble: 2 x 7
##   term            estimate std.error statistic p.value conf.low conf.high
##   <chr>              <dbl>     <dbl>     <dbl>   <dbl>    <dbl>     <dbl>
## 1 (Intercept)        0.727     0.232    -1.37    0.170    0.458      1.14
## 2 gender_feedback    0.819     0.333    -0.599   0.549    0.425      1.57
```

Interaction Model with Controls

```r
## Interaction model with demographic controls
r_factorial_demog <- lm(female_pick ~ gender_feedback*base_condition_factor + gender_code
↪  + race_code + age, data=d0)

cat("2x3 Factorial with Demographic Controls\n")
```

```
## 2x3 Factorial with Demographic Controls
```

```r
robust_summary(r_factorial_demog)
```

```
##
## Call:
## lm(formula = female_pick ~ gender_feedback * base_condition_factor +
##     gender_code + race_code + age, data = d0)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -0.4672 -0.3543 -0.1428  0.5803  0.9440
##
## Coefficients:
##                                        Estimate Std. Error t value Pr(>|t|)
## (Intercept)                            0.037384   0.080809   0.463  0.64387
## gender_feedback                        0.048172   0.054767   0.880  0.37956
## base_condition_factormed               0.197295   0.065098   3.031  0.00258
## base_condition_factorhigh              0.325171   0.067516   4.816 2.01e-06
## gender_code                           -0.018943   0.042014  -0.451  0.65230
## race_code                              0.017860   0.047974   0.372  0.70987
## age                                    0.001296   0.001713   0.757  0.44956
## gender_feedback:base_condition_factormed   0.024000   0.096174   0.250  0.80305
## gender_feedback:base_condition_factorhigh -0.099596   0.097672  -1.020  0.30843
##
## (Intercept)
## gender_feedback
## base_condition_factormed                 **
## base_condition_factorhigh                ***
## gender_code
## race_code
## age
## gender_feedback:base_condition_factormed
## gender_feedback:base_condition_factorhigh
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.4388 on 443 degrees of freedom
## Multiple R-squared:  0.0749, Adjusted R-squared:  0.0582
## F-statistic: 4.484 on 8 and 443 DF,  p-value: 3.005e-05
```

```r
robust_confint(r_factorial_demog)
```

```
##                                                   2.5 %      97.5 %
## (Intercept)                                -0.121433522 0.196201063
## gender_feedback                            -0.059464050 0.155808628
## base_condition_factormed                    0.069356238 0.325233037
## base_condition_factorhigh                   0.192479249 0.457862806
## gender_code                                -0.101513430 0.063627909
## race_code                                  -0.076426094 0.112145161
## age                                        -0.002069688 0.004661915
## gender_feedback:base_condition_factormed   -0.165013012 0.213013144
## gender_feedback:base_condition_factorhigh  -0.291553134 0.092361090
```

```r
## Logistic regression with interaction
r_factorial_logit <- glm(female_pick ~ gender_feedback*base_condition_factor, family =
↪  binomial, data=d0)
cat("\n2x3 Factorial: Logistic Regression Model\n")
```

```
##
## 2x3 Factorial: Logistic Regression Model
```

```r
summary(r_factorial_logit)
```

```
##
## Call:
## glm(formula = female_pick ~ gender_feedback * base_condition_factor,
##     family = binomial, data = d0)
##
## Coefficients:
##                                           Estimate Std. Error z value Pr(>|z|)
## (Intercept)                                -2.2588     0.3972  -5.687 1.29e-08
## gender_feedback                             0.4978     0.5141   0.968   0.3329
## base_condition_factormed                    1.4240     0.4691   3.035   0.0024
## base_condition_factorhigh                   1.9403     0.4601   4.217 2.48e-05
## gender_feedback:base_condition_factormed   -0.2020     0.6190  -0.326   0.7442
## gender_feedback:base_condition_factorhigh  -0.6973     0.6126  -1.138   0.2550
##
## (Intercept)                               ***
## gender_feedback
## base_condition_factormed                  **
## base_condition_factorhigh                 ***
## gender_feedback:base_condition_factormed
## gender_feedback:base_condition_factorhigh
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 540.57  on 451  degrees of freedom
## Residual deviance: 504.64  on 446  degrees of freedom
## AIC: 516.64
```

```
##
## Number of Fisher Scoring iterations: 4
```

```r
# Odds ratio
tidy_factorial_logit <- tidy(r_factorial_logit, exponentiate = TRUE, conf.int = T)
print(tidy_factorial_logit)
```

```
## # A tibble: 6 x 7
##   term                   estimate std.error statistic p.value conf.low conf.high
##   <chr>                     <dbl>     <dbl>     <dbl>   <dbl>    <dbl>     <dbl>
## 1 (Intercept)               0.104     0.397    -5.69  1.29e-8   0.0436     0.212
## 2 gender_feedback           1.65      0.514     0.968 3.33e-1   0.610      4.72
## 3 base_condition_factor~    4.15      0.469     3.04  2.40e-3   1.73      11.1
## 4 base_condition_factor~    6.96      0.460     4.22  2.48e-5   2.97      18.4
## 5 gender_feedback:base_~    0.817     0.619    -0.326 7.44e-1   0.236      2.72
## 6 gender_feedback:base_~    0.498     0.613    -1.14  2.55e-1   0.145      1.63
```

Interaction with Initial Base Selection

Low Base Condition

```
## Interaction with initial women selection in low base
r_interaction_low <- lm(female_pick ~ gender_feedback*base_gender, data=d0_low)

cat("Low Base: Interaction with Initial Women Selection\n")
```

```
## Low Base: Interaction with Initial Women Selection
```

```
robust_summary(r_interaction_low)
```

```
##
## Call:
## lm(formula = female_pick ~ gender_feedback * base_gender, data = d0_low)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.31935 -0.18009 -0.04284 -0.04083  0.95716
##
## Coefficients:
##                             Estimate Std. Error t value Pr(>|t|)
## (Intercept)                  0.22521    0.09438   2.386   0.0183 *
## gender_feedback              0.09414    0.13157   0.715   0.4755
## base_gender                 -0.09119    0.04819  -1.892   0.0604 .
## gender_feedback:base_gender -0.04807    0.06738  -0.714   0.4767
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.3155 on 145 degrees of freedom
## Multiple R-squared:  0.08802,    Adjusted R-squared:  0.06915
## F-statistic: 4.665 on 3 and 145 DF,  p-value: 0.003838
```

```
robust_confint(r_interaction_low)
```

```
##                                   2.5 %     97.5 %
## (Intercept)                  0.03866784 0.41176056
## gender_feedback             -0.16590809 0.35418216
## base_gender                 -0.18642817 0.00405363
## gender_feedback:base_gender -0.18123857 0.08508963
```

Medium Base Condition

```r
## Interaction with initial women selection in medium base
r_interaction_med <- lm(female_pick ~ gender_feedback*base_gender, data=d0_med)

cat("Medium Base: Interaction with Initial Women Selection\n")
```

```
## Medium Base: Interaction with Initial Women Selection
```

```r
robust_summary(r_interaction_med)
```

```
##
## Call:
## lm(formula = female_pick ~ gender_feedback * base_gender, data = d0_med)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -0.4963 -0.3594 -0.3026  0.5942  0.8091
##
## Coefficients:
##                              Estimate Std. Error t value Pr(>|t|)
## (Intercept)                   0.19091    0.12392   1.541   0.1256
## gender_feedback               0.28227    0.16169   1.746   0.0829 .
## base_gender                   0.06108    0.06196   0.986   0.3258
## gender_feedback:base_gender -0.11795    0.07612  -1.550   0.1234
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.473 on 148 degrees of freedom
## Multiple R-squared:  0.02311,    Adjusted R-squared:  0.003308
## F-statistic: 1.167 on 3 and 148 DF,  p-value: 0.3244
```

```r
robust_confint(r_interaction_med)
```

```
##                                    2.5 %     97.5 %
## (Intercept)                 -0.05397040 0.43579154
## gender_feedback             -0.03725907 0.60178986
## base_gender                 -0.06134992 0.18351965
## gender_feedback:base_gender -0.26837019 0.03246655
```

High Base Condition

```r
## Interaction with initial women selection in high base
r_interaction_high <- lm(female_pick ~ gender_feedback*base_gender, data=d0_high)

cat("High Base: Interaction with Initial Women Selection\n")
```

```
## High Base: Interaction with Initial Women Selection
```

```r
robust_summary(r_interaction_high)
```

```
##
## Call:
## lm(formula = female_pick ~ gender_feedback * base_gender, data = d0_high)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -0.5282 -0.4080 -0.3593  0.5906  0.7159
##
## Coefficients:
##                              Estimate Std. Error t value Pr(>|t|)
## (Intercept)                   0.34793    0.11835   2.940  0.00382 **
## gender_feedback               0.08655    0.17314   0.500  0.61792
## base_gender                   0.03004    0.04367   0.688  0.49269
## gender_feedback:base_gender -0.05510    0.06312  -0.873  0.38415
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.494 on 147 degrees of freedom
## Multiple R-squared:  0.008088,   Adjusted R-squared:  -0.01215
## F-statistic: 0.3996 on 3 and 147 DF,  p-value: 0.7535
```

```r
robust_confint(r_interaction_high)
```

```
##                                   2.5 %     97.5 %
## (Intercept)                  0.11403929 0.58183054
## gender_feedback             -0.25561411 0.42870562
## base_gender                 -0.05627397 0.11634906
## gender_feedback:base_gender -0.17984157 0.06964571
```

Full Model with Three-Way Interaction

```r
## Three-way interaction: gender_feedback x base_condition x base_gender
r_interaction_full <- lm(female_pick ~ gender_feedback*base_condition_factor*base_gender,
↪  data=d0)

cat("Three-Way Interaction: Gender Feedback x Base Condition x Initial Women
↪  Selection\n")
```

```
## Three-Way Interaction: Gender Feedback x Base Condition x Initial Women Selection
```

```r
robust_summary(r_interaction_full)
```

```
##
## Call:
## lm(formula = female_pick ~ gender_feedback * base_condition_factor *
##     base_gender, data = d0)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -0.5282 -0.3593 -0.1801  0.5619  0.9572
##
## Coefficients:
##                                                      Estimate Std. Error
## (Intercept)                                          0.225214   0.094384
## gender_feedback                                      0.094137   0.131571
## base_condition_factormed                            -0.034304   0.155771
## base_condition_factorhigh                            0.122721   0.151381
## base_gender                                         -0.091187   0.048188
## gender_feedback:base_condition_factormed             0.188128   0.208460
## gender_feedback:base_condition_factorhigh           -0.007591   0.217457
## gender_feedback:base_gender                         -0.048074   0.067375
## base_condition_factormed:base_gender                 0.152272   0.078490
## base_condition_factorhigh:base_gender                0.121225   0.065035
## gender_feedback:base_condition_factormed:base_gender  -0.069877   0.101653
## gender_feedback:base_condition_factorhigh:base_gender -0.007023   0.092324
##                                                     t value Pr(>|t|)
## (Intercept)                                           2.386   0.0174 *
## gender_feedback                                       0.715   0.4747
## base_condition_factormed                             -0.220   0.8258
## base_condition_factorhigh                             0.811   0.4180
## base_gender                                          -1.892   0.0591 .
## gender_feedback:base_condition_factormed              0.902   0.3673
## gender_feedback:base_condition_factorhigh            -0.035   0.9722
## gender_feedback:base_gender                          -0.714   0.4759
## base_condition_factormed:base_gender                  1.940   0.0530 .
## base_condition_factorhigh:base_gender                 1.864   0.0630 .
## gender_feedback:base_condition_factormed:base_gender   -0.687   0.4922
## gender_feedback:base_condition_factorhigh:base_gender  -0.076   0.9394
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## Residual standard error: 0.4354 on 440 degrees of freedom
## Multiple R-squared:  0.09524,    Adjusted R-squared:  0.07262
## F-statistic: 4.211 on 11 and 440 DF,  p-value: 5.98e-06
```

```r
robust_confint(r_interaction_full)
```

```
##                                                              2.5 %      97.5 %
## (Intercept)                                             0.03971450 0.410713893
## gender_feedback                                        -0.16444904 0.352723105
## base_condition_factormed                               -0.34045069 0.271843439
## base_condition_factorhigh                              -0.17479821 0.420239647
## base_gender                                            -0.18589380 0.003519256
## gender_feedback:base_condition_factormed               -0.22157229 0.597829013
## gender_feedback:base_condition_factorhigh              -0.43497469 0.419792139
## gender_feedback:base_gender                            -0.18049142 0.084342474
## base_condition_factormed:base_gender                   -0.00199036 0.306534636
## base_condition_factorhigh:base_gender                  -0.00659274 0.249042375
## gender_feedback:base_condition_factormed:base_gender  -0.26966319 0.129908504
## gender_feedback:base_condition_factorhigh:base_gender -0.18847488 0.174427966
```

Secondary Analysis - Other Attributes

Low Base Condition

```
## Poets feedback - Low Base
r_poets_low <- lm(poets_pick ~ poets_shown, data=d0_low)
cat("Low Base: Effect of Poets Feedback on Poet Selection\n")
```

```
## Low Base: Effect of Poets Feedback on Poet Selection
```

```
robust_summary(r_poets_low)
```

```
##
## Call:
## lm(formula = poets_pick ~ poets_shown, data = d0_low)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.09091 -0.07087 -0.07087 -0.07087  0.92913
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.09091    0.06421   1.416    0.159
## poets_shown -0.02004    0.06819  -0.294    0.769
##
## Residual standard error: 0.2632 on 147 degrees of freedom
## Multiple R-squared:  0.0007394,  Adjusted R-squared:  -0.006058
## F-statistic: 0.1088 on 1 and 147 DF,  p-value: 0.742
```

```
robust_confint(r_poets_low)
```

```
##                   2.5 %    97.5 %
## (Intercept) -0.03598388 0.2178021
## poets_shown -0.15479802 0.1147121
```

```
## Oldies (1800s) feedback - Low Base
r_oldies_low <- lm(oldies_pick ~ oldies_shown, data=d0_low)
cat("\nLow Base: Effect of 1800s Feedback on 1800s Author Selection\n")
```

```
##
## Low Base: Effect of 1800s Feedback on 1800s Author Selection
```

```
robust_summary(r_oldies_low)
```

```
##
## Call:
## lm(formula = oldies_pick ~ oldies_shown, data = d0_low)
##
```

```
## Residuals:
##     Min      1Q  Median      3Q     Max
## -0.2362 -0.2362 -0.2362 -0.2273  0.7727
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.227273   0.093601   2.428   0.0164 *
## oldies_shown 0.008948   0.101017   0.089   0.9295
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.4268 on 147 degrees of freedom
## Multiple R-squared:  5.606e-05,  Adjusted R-squared:  -0.006746
## F-statistic: 0.008242 on 1 and 147 DF,  p-value: 0.9278
```

```
robust_confint(r_oldies_low)
```

```
##                    2.5 %    97.5 %
## (Intercept)   0.04229602 0.4122494
## oldies_shown -0.19068461 0.2085801
```

```
## Books (10+) feedback - Low Base
r_books_low <- lm(books_pick ~ books_shown, data=d0_low)
cat("\nLow Base: Effect of 10+ Books Feedback on 10+ Books Author Selection\n")
```

```
##
## Low Base: Effect of 10+ Books Feedback on 10+ Books Author Selection
```

```
robust_summary(r_books_low)
```

```
##
## Call:
## lm(formula = books_pick ~ books_shown, data = d0_low)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -0.1864 -0.1864 -0.1864 -0.1290  0.8710
##
## Coefficients:
##            Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.12903    0.06222   2.074   0.0398 *
## books_shown  0.05741    0.07196   0.798   0.4263
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.3814 on 147 degrees of freedom
## Multiple R-squared:  0.00377,   Adjusted R-squared:  -0.003007
## F-statistic: 0.5563 on 1 and 147 DF,  p-value: 0.457
```

```r
robust_confint(r_books_low)
```

```
##                    2.5 %    97.5 %
## (Intercept)  0.006076749 0.2519878
## books_shown -0.084804372 0.1996212
```

Medium Base Condition

```r
## Poets feedback - Medium Base
r_poets_med <- lm(poets_pick ~ poets_shown, data=d0_med)
cat("Medium Base: Effect of Poets Feedback on Poet Selection\n")
```

```
## Medium Base: Effect of Poets Feedback on Poet Selection
```

```r
robust_summary(r_poets_med)
```

```
##
## Call:
## lm(formula = poets_pick ~ poets_shown, data = d0_med)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -0.2059 -0.2059 -0.2059 -0.1875  0.8125
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.18750    0.10408   1.801   0.0736 .
## poets_shown  0.01838    0.10979   0.167   0.8673
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.4056 on 150 degrees of freedom
## Multiple R-squared:  0.000196,   Adjusted R-squared:  -0.006469
## F-statistic: 0.02941 on 1 and 150 DF,  p-value: 0.8641
```

```r
robust_confint(r_poets_med)
```

```
##                   2.5 %    97.5 %
## (Intercept) -0.01815875 0.3931587
## poets_shown -0.19854809 0.2353128
```

```r
## Oldies (1800s) feedback - Medium Base
r_oldies_med <- lm(oldies_pick ~ oldies_shown, data=d0_med)
cat("\nMedium Base: Effect of 1800s Feedback on 1800s Author Selection\n")
```

```
##
## Medium Base: Effect of 1800s Feedback on 1800s Author Selection
```

```r
robust_summary(r_oldies_med)
```

```
##
## Call:
## lm(formula = oldies_pick ~ oldies_shown, data = d0_med)
##
```

```
## Residuals:
##     Min      1Q  Median      3Q     Max
## -0.4286 -0.2971 -0.2971  0.7029  0.7029
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    0.4286     0.1424   3.009  0.00308 **
## oldies_shown  -0.1315     0.1477  -0.890  0.37491
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.4637 on 150 degrees of freedom
## Multiple R-squared:  0.006767,   Adjusted R-squared:  0.0001451
## F-statistic: 1.022 on 1 and 150 DF,  p-value: 0.3137
```

```r
robust_confint(r_oldies_med)
```

```
##                   2.5 %    97.5 %
## (Intercept)   0.1471356 0.7100073
## oldies_shown -0.4233618 0.1604218
```

```r
## Books (10+) feedback - Medium Base
r_books_med <- lm(books_pick ~ books_shown, data=d0_med)
cat("\nMedium Base: Effect of 10+ Books Feedback on 10+ Books Author Selection\n")
```

```
##
## Medium Base: Effect of 10+ Books Feedback on 10+ Books Author Selection
```

```r
robust_summary(r_books_med)
```

```
##
## Call:
## lm(formula = books_pick ~ books_shown, data = d0_med)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -0.3302 -0.3302 -0.3261  0.6698  0.6739
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 0.326087   0.070654   4.615 8.37e-06 ***
## books_shown 0.004102   0.084370   0.049    0.961
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.4729 on 150 degrees of freedom
## Multiple R-squared:  1.609e-05,  Adjusted R-squared:  -0.00665
## F-statistic: 0.002413 on 1 and 150 DF,  p-value: 0.9609
```

```r
robust_confint(r_books_med)
```

```
##                  2.5 %    97.5 %
## (Intercept)  0.1864819 0.4656920
## books_shown -0.1626058 0.1708093
```

High Base Condition

```r
## Poets feedback - High Base
r_poets_high <- lm(poets_pick ~ poets_shown, data=d0_high)
cat("High Base: Effect of Poets Feedback on Poet Selection\n")
```

```
## High Base: Effect of Poets Feedback on Poet Selection
```

```r
robust_summary(r_poets_high)
```

```
##
## Call:
## lm(formula = poets_pick ~ poets_shown, data = d0_high)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -0.4706 -0.3433 -0.3433  0.6567  0.6567
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   0.4706     0.1286   3.659 0.000351 ***
## poets_shown  -0.1273     0.1351  -0.942 0.347563
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.4808 on 149 degrees of freedom
## Multiple R-squared:  0.007048,   Adjusted R-squared:  0.0003841
## F-statistic: 1.058 on 1 and 149 DF,  p-value: 0.3054
```

```r
robust_confint(r_poets_high)
```

```
##                   2.5 %    97.5 %
## (Intercept)  0.2164256 0.7247508
## poets_shown -0.3942632 0.1396539
```

```r
## Oldies (1800s) feedback - High Base
r_oldies_high <- lm(oldies_pick ~ oldies_shown, data=d0_high)
cat("\nHigh Base: Effect of 1800s Feedback on 1800s Author Selection\n")
```

```
##
## High Base: Effect of 1800s Feedback on 1800s Author Selection
```

```r
robust_summary(r_oldies_high)
```

```
##
## Call:
## lm(formula = oldies_pick ~ oldies_shown, data = d0_high)
##
```

```
## Residuals:
##     Min      1Q  Median      3Q     Max
## -0.4348 -0.4141 -0.4141  0.5859  0.5859
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   0.43478    0.10807   4.023 9.09e-05 ***
## oldies_shown -0.02072    0.11663  -0.178    0.859
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.4963 on 149 degrees of freedom
## Multiple R-squared:  0.000228,   Adjusted R-squared:  -0.006482
## F-statistic: 0.03398 on 1 and 149 DF,  p-value: 0.854
```

```r
robust_confint(r_oldies_high)
```

```
##                   2.5 %    97.5 %
## (Intercept)   0.2212447 0.6483205
## oldies_shown -0.2511900 0.2097498
```

```r
## Books (10+) feedback - High Base
r_books_high <- lm(books_pick ~ books_shown, data=d0_high)
cat("\nHigh Base: Effect of 10+ Books Feedback on 10+ Books Author Selection\n")
```

```
##
## High Base: Effect of 10+ Books Feedback on 10+ Books Author Selection
```

```r
robust_summary(r_books_high)
```

```
##
## Call:
## lm(formula = books_pick ~ books_shown, data = d0_high)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -0.4224 -0.4224 -0.3429  0.5776  0.6571
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.34286    0.08259   4.151 5.54e-05 ***
## books_shown  0.07956    0.09467   0.840    0.402
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.4928 on 149 degrees of freedom
## Multiple R-squared:  0.004681,   Adjusted R-squared:  -0.001999
## F-statistic: 0.7007 on 1 and 149 DF,  p-value: 0.4039
```

```r
robust_confint(r_books_high)
```

```
##                   2.5 %    97.5 %
## (Intercept)  0.1796529 0.5060614
## books_shown -0.1075038 0.2666171
```

Interaction Models for Other Attributes

```r
## Test if attribute feedback effects differ by base condition
r_poets_interaction <- lm(poets_pick ~ poets_shown*base_condition_factor, data=d0)
cat("Poets x Base Condition Interaction\n")
```

```
## Poets x Base Condition Interaction
```

```r
robust_summary(r_poets_interaction)
```

```
##
## Call:
## lm(formula = poets_pick ~ poets_shown * base_condition_factor,
##     data = d0)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.47059 -0.20588 -0.09091 -0.07087  0.92913
##
## Coefficients:
##                                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)                            0.09091    0.06421   1.416  0.15753
## poets_shown                           -0.02004    0.06819  -0.294  0.76894
## base_condition_factormed               0.09659    0.12230   0.790  0.43006
## base_condition_factorhigh              0.37968    0.14376   2.641  0.00855 **
## poets_shown:base_condition_factormed   0.03843    0.12924   0.297  0.76636
## poets_shown:base_condition_factorhigh -0.10726    0.15133  -0.709  0.47883
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.3942 on 446 degrees of freedom
## Multiple R-squared:  0.0835, Adjusted R-squared:  0.07322
## F-statistic: 8.126 on 5 and 446 DF,  p-value: 2.357e-07
```

```r
robust_confint(r_poets_interaction)
```

```
##                                             2.5 %    97.5 %
## (Intercept)                           -0.03528168 0.2170999
## poets_shown                           -0.15405231 0.1139664
## base_condition_factormed              -0.14375614 0.3369380
## base_condition_factorhigh              0.09714774 0.6622106
## poets_shown:base_condition_factormed  -0.21556956 0.2924202
## poets_shown:base_condition_factorhigh -0.40467475 0.1901513
```

```r
r_oldies_interaction <- lm(oldies_pick ~ oldies_shown*base_condition_factor, data=d0)
cat("\nOldies x Base Condition Interaction\n")
```

```
##
## Oldies x Base Condition Interaction
```

```r
robust_summary(r_oldies_interaction)
```

```
##
## Call:
## lm(formula = oldies_pick ~ oldies_shown * base_condition_factor,
##     data = d0)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -0.4348 -0.2971 -0.2362  0.5859  0.7727
##
## Coefficients:
##                                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)                           0.227273   0.093601   2.428   0.0156 *
## oldies_shown                          0.008948   0.101017   0.089   0.9295
## base_condition_factormed              0.201299   0.170436   1.181   0.2382
## base_condition_factorhigh             0.207510   0.142965   1.451   0.1474
## oldies_shown:base_condition_factormed  -0.140418   0.178961  -0.785   0.4331
## oldies_shown:base_condition_factorhigh -0.029668   0.154298  -0.192   0.8476
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.4633 on 446 degrees of freedom
## Multiple R-squared:  0.02796,    Adjusted R-squared:  0.01706
## F-statistic: 2.565 on 5 and 446 DF,  p-value: 0.02648
```

```r
robust_confint(r_oldies_interaction)
```

```
##                                              2.5 %    97.5 %
## (Intercept)                             0.04331965 0.4112258
## oldies_shown                           -0.18957988 0.2074754
## base_condition_factormed               -0.13365901 0.5362564
## base_condition_factorhigh              -0.07345975 0.4884795
## oldies_shown:base_condition_factormed  -0.49213019 0.2112947
## oldies_shown:base_condition_factorhigh -0.33290877 0.2735731
```

```r
r_books_interaction <- lm(books_pick ~ books_shown*base_condition_factor, data=d0)
cat("\nBooks x Base Condition Interaction\n")
```

```
##
## Books x Base Condition Interaction
```

```r
robust_summary(r_books_interaction)
```

```
##
## Call:
## lm(formula = books_pick ~ books_shown * base_condition_factor,
##     data = d0)
##
## Residuals:
```

```
##     Min      1Q  Median      3Q     Max
## -0.4224 -0.3302 -0.1864  0.5776  0.8710
##
## Coefficients:
##                                        Estimate Std. Error t value Pr(>|t|)
## (Intercept)                             0.12903    0.06222   2.074   0.0387 *
## books_shown                             0.05741    0.07196   0.798   0.4254
## base_condition_factormed                0.19705    0.09414   2.093   0.0369 *
## base_condition_factorhigh               0.21382    0.10340   2.068   0.0392 *
## books_shown:base_condition_factormed   -0.05331    0.11089  -0.481   0.6310
## books_shown:base_condition_factorhigh   0.02215    0.11891   0.186   0.8523
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.452 on 446 degrees of freedom
## Multiple R-squared:  0.0456, Adjusted R-squared:  0.0349
## F-statistic: 4.262 on 5 and 446 DF,  p-value: 0.0008509
```

```r
robust_confint(r_books_interaction)
```

```
##                                              2.5 %    97.5 %
## (Intercept)                             0.006757163 0.2513074
## books_shown                            -0.084017392 0.1988342
## base_condition_factormed                0.012035602 0.3820738
## base_condition_factorhigh               0.010604033 0.4170457
## books_shown:base_condition_factormed   -0.271240317 0.1646269
## books_shown:base_condition_factorhigh  -0.211548930 0.2558454
```

Deep Dive: Base Rates and Selection Patterns

Actual Female Selection Rates in First 6 Choices

```
cat("=== ACTUAL FEMALE SELECTION RATES IN FIRST 6 CHOICES ===\n\n")
```

```
## === ACTUAL FEMALE SELECTION RATES IN FIRST 6 CHOICES ===
```

```
# Overall summary
cat("Overall Statistics:\n")
```

```
## Overall Statistics:
```

```
cat("Mean number of women selected (out of 6):", round(mean(d0$base_gender), 2), "\n")
```

```
## Mean number of women selected (out of 6): 1.87
```

```
cat("Mean percentage of women selected:", round(mean(d0$base_gender)/6 * 100, 2), "%\n")
```

```
## Mean percentage of women selected: 31.19 %
```

```
cat("SD:", round(sd(d0$base_gender), 2), "\n\n")
```

```
## SD: 1.18
```

```
# By base condition
cat("By Base Condition:\n")
```

```
## By Base Condition:
```

```
base_rates_summary <- d0 |>
  group_by(base_condition) |>
  summarise(
    n = n(),
    mean_count = round(mean(base_gender), 2),
    mean_pct = round(mean(base_gender)/6 * 100, 2),
    sd_count = round(sd(base_gender), 2),
    median_count = median(base_gender),
    min_count = min(base_gender),
    max_count = max(base_gender)
  )

print(base_rates_summary)
```

```
## # A tibble: 3 x 8
##   base_condition     n mean_count mean_pct sd_count median_count min_count
##   <chr>          <int>      <dbl>    <dbl>    <dbl>        <dbl>     <int>
## 1 high             151       2.44     40.6     1.34            2         0
## 2 low              149       1.34     22.3     0.79            1         0
## 3 med              152       1.84     30.6     1.09            2         0
## # i 1 more variable: max_count <int>
```

```r
# Check if high base leads to > 50% women
cat("\n--- Checking if High Base leads to >50% women selected ---\n")
```

```
##
## --- Checking if High Base leads to >50% women selected ---
```

```r
d0_high_summary <- d0 |>
  filter(base_condition == "high") |>
  summarise(
    pct_with_majority_women = round(mean(base_gender > 3) * 100, 2),
    pct_with_half_or_more = round(mean(base_gender >= 3) * 100, 2)
  )

cat("In HIGH base condition:\n")
```

```
## In HIGH base condition:
```

```r
cat("  % with >50% women (4+ out of 6):", d0_high_summary$pct_with_majority_women, "%\n")
```

```
##   % with >50% women (4+ out of 6): 17.88 %
```

```r
cat("  % with 50% or more women (3+ out of 6):", d0_high_summary$pct_with_half_or_more,
↪  "%\n")
```

```
##   % with 50% or more women (3+ out of 6): 49.01 %
```

```r
# Distribution of base_gender by base_condition
cat("\n--- Distribution of women selected in first 6 choices ---\n")
```

```
##
## --- Distribution of women selected in first 6 choices ---
```

```r
distribution <- d0 |>
  group_by(base_condition, base_gender) |>
  summarise(n = n(), .groups = "drop") |>
  group_by(base_condition) |>
  mutate(pct = round(n/sum(n) * 100, 1)) |>
  arrange(base_condition, base_gender)

print(distribution)
```

```
## # A tibble: 18 x 4
## # Groups:   base_condition [3]
##    base_condition base_gender     n   pct
##    <chr>                <int> <int> <dbl>
##  1 high                     0    12   7.9
##  2 high                     1    24  15.9
##  3 high                     2    41  27.2
##  4 high                     3    47  31.1
##  5 high                     4    17  11.3
##  6 high                     5     7   4.6
##  7 high                     6     3   2
##  8 low                      0    20  13.4
##  9 low                      1    69  46.3
## 10 low                      2    50  33.6
## 11 low                      3    10   6.7
## 12 med                      0    15   9.9
## 13 med                      1    42  27.6
## 14 med                      2    60  39.5
## 15 med                      3    27  17.8
## 16 med                      4     5   3.3
## 17 med                      5     2   1.3
## 18 med                      6     1   0.7
```

What Feedback is Being Shown

```
cat("=== FEEDBACK SHOWN TO PARTICIPANTS ===\n\n")
```

```
## === FEEDBACK SHOWN TO PARTICIPANTS ===
```

```
# Who gets what feedback
cat("Feedback Distribution:\n")
```

```
## Feedback Distribution:
```

```
feedback_summary <- d0 |>
  summarise(
    n_gender_feedback = sum(gender_feedback),
    n_poets_shown = sum(poets_shown),
    n_oldies_shown = sum(oldies_shown),
    n_books_shown = sum(books_shown),
    pct_gender = round(mean(gender_feedback) * 100, 1),
    pct_poets = round(mean(poets_shown) * 100, 1),
    pct_oldies = round(mean(oldies_shown) * 100, 1),
    pct_books = round(mean(books_shown) * 100, 1)
  )

cat("Gender feedback (treatment):", feedback_summary$n_gender_feedback,
    "(", feedback_summary$pct_gender, "%)\n")
```

```
## Gender feedback (treatment): 226 ( 50 %)
```

```
cat("Poets feedback shown:", feedback_summary$n_poets_shown,
    "(", feedback_summary$pct_poets, "%)\n")
```

```
## Poets feedback shown: 397 ( 87.8 %)
```

```
cat("Oldies feedback shown:", feedback_summary$n_oldies_shown,
    "(", feedback_summary$pct_oldies, "%)\n")
```

```
## Oldies feedback shown: 393 ( 86.9 %)
```

```
cat("Books feedback shown:", feedback_summary$n_books_shown,
    "(", feedback_summary$pct_books, "%)\n\n")
```

```
## Books feedback shown: 340 ( 75.2 %)
```

```
# By base condition
cat("Feedback by Base Condition:\n")
```

```
## Feedback by Base Condition:
```

```r
feedback_by_base <- d0 |>
  group_by(base_condition) |>
  summarise(
    n = n(),
    pct_gender = round(mean(gender_feedback) * 100, 1),
    pct_poets = round(mean(poets_shown) * 100, 1),
    pct_oldies = round(mean(oldies_shown) * 100, 1),
    pct_books = round(mean(books_shown) * 100, 1)
  )

print(feedback_by_base)
```

```
## # A tibble: 3 x 6
##   base_condition     n pct_gender pct_poets pct_oldies pct_books
##   <chr>          <int>      <dbl>     <dbl>      <dbl>     <dbl>
## 1 high             151       49.7      88.7       84.8      76.8
## 2 low              149       50.3      85.2       85.2      79.2
## 3 med              152       50        89.5       90.8      69.7
```

```r
# Crosstab: who gets gender feedback AND which other attribute feedback
cat("\n--- Among those with Gender Feedback, which other attribute? ---\n")
```

```
##
## --- Among those with Gender Feedback, which other attribute? ---
```

```r
gender_and_other <- d0 |>
  filter(gender_feedback == 1) |>
  summarise(
    n = n(),
    n_poets = sum(poets_shown),
    n_oldies = sum(oldies_shown),
    n_books = sum(books_shown),
    pct_poets = round(mean(poets_shown) * 100, 1),
    pct_oldies = round(mean(oldies_shown) * 100, 1),
    pct_books = round(mean(books_shown) * 100, 1)
  )

print(gender_and_other)
```

```
## # A tibble: 1 x 7
##       n n_poets n_oldies n_books pct_poets pct_oldies pct_books
##   <int>   <dbl>    <dbl>   <dbl>     <dbl>      <dbl>     <dbl>
## 1   226     171      167     114      75.7       73.9      50.4
```

Comparative Selection Rates Across All Attributes

```r
cat("=== BASE RATES OF ALL FOUR ATTRIBUTES IN FIRST 6 SELECTIONS ===\n\n")
```

```
## === BASE RATES OF ALL FOUR ATTRIBUTES IN FIRST 6 SELECTIONS ===
```

```r
# Overall across all conditions
cat("Overall Statistics (all base conditions combined):\n")
```

```
## Overall Statistics (all base conditions combined):
```

```r
overall_attrs <- d0 |>
  summarise(
    mean_women = round(mean(base_gender), 2),
    mean_poets = round(mean(base_poets), 2),
    mean_oldies = round(mean(base_oldies), 2),
    mean_books = round(mean(base_books), 2),
    pct_women = round(mean(base_gender)/6 * 100, 1),
    pct_poets = round(mean(base_poets)/6 * 100, 1),
    pct_oldies = round(mean(base_oldies)/6 * 100, 1),
    pct_books = round(mean(base_books)/6 * 100, 1)
  )

print(overall_attrs)
```

```
## # A tibble: 1 x 8
##   mean_women mean_poets mean_oldies mean_books pct_women pct_poets pct_oldies
##        <dbl>      <dbl>       <dbl>      <dbl>     <dbl>     <dbl>      <dbl>
## 1       1.87       1.47        1.72       1.77      31.2      24.6       28.7
## # i 1 more variable: pct_books <dbl>
```

```r
cat("\n--- By Base Condition ---\n")
```

```
##
## --- By Base Condition ---
```

```r
by_base <- d0 |>
  group_by(base_condition) |>
  summarise(
    n = n(),
    women_pct = round(mean(base_gender)/6 * 100, 1),
    poets_pct = round(mean(base_poets)/6 * 100, 1),
    oldies_pct = round(mean(base_oldies)/6 * 100, 1),
    books_pct = round(mean(base_books)/6 * 100, 1)
  )

print(by_base)
```

```
## # A tibble: 3 x 6
##   base_condition     n women_pct poets_pct oldies_pct books_pct
##   <chr>          <int>     <dbl>     <dbl>      <dbl>     <dbl>
## 1 high             151      40.6      35.2       36.8      35.7
## 2 low              149      22.3      12.6       18.6      18.8
## 3 med              152      30.6      25.7       30.5      33.9
```

```
cat("\n--- 7th Selection Rates by Attribute and Base Condition ---\n")
```

```
##
## --- 7th Selection Rates by Attribute and Base Condition ---
```

```
seventh_selection <- d0 |>
  group_by(base_condition) |>
  summarise(
    n = n(),
    pct_select_woman = round(mean(female_pick) * 100, 1),
    pct_select_poet = round(mean(poets_pick) * 100, 1),
    pct_select_oldies = round(mean(oldies_pick) * 100, 1),
    pct_select_books = round(mean(books_pick) * 100, 1)
  )

print(seventh_selection)
```

```
## # A tibble: 3 x 6
##   base_condition     n pct_select_woman pct_select_poet pct_select_oldies
##   <chr>          <int>            <dbl>           <dbl>             <dbl>
## 1 high             151             39.7            35.8              41.7
## 2 low              149             12.1             7.4              23.5
## 3 med              152             33.6            20.4              30.9
## # i 1 more variable: pct_select_books <dbl>
```

Which Attribute Wins When Multiple are Underrepresented?

```r
cat("=== ATTRIBUTE PRIORITIZATION ANALYSIS ===\n\n")
```

```
## === ATTRIBUTE PRIORITIZATION ANALYSIS ===
```

```r
cat("When multiple attributes are underrepresented, which gets selected for 7th
↪  pick?\n\n")
```

```
## When multiple attributes are underrepresented, which gets selected for 7th pick?
```

```r
# Create underrepresentation indicators (below 50%)
d0 <- d0 |>
  mutate(
    women_underrep = as.numeric(base_gender < 3),
    poets_underrep = as.numeric(base_poets < 3),
    oldies_underrep = as.numeric(base_oldies < 3),
    books_underrep = as.numeric(base_books < 3),
    num_underrep = women_underrep + poets_underrep + oldies_underrep + books_underrep
  )

# Summary of underrepresentation
cat("Distribution of number of underrepresented attributes:\n")
```

```
## Distribution of number of underrepresented attributes:
```

```r
underrep_dist <- d0 |>
  group_by(num_underrep) |>
  summarise(n = n(), pct = round(n/nrow(d0) * 100, 1))

print(underrep_dist)
```

```
## # A tibble: 5 x 3
##   num_underrep     n   pct
##          <dbl> <int> <dbl>
## 1            0     1   0.2
## 2            1    13   2.9
## 3            2    95  21
## 4            3   159  35.2
## 5            4   184  40.7
```

```r
# When women are underrepresented vs not
cat("\n--- 7th Selection when Women ARE underrepresented (<50%) ---\n")
```

```
##
## --- 7th Selection when Women ARE underrepresented (<50%) ---
```

```
when_women_underrep <- d0 |>
  filter(women_underrep == 1) |>
  summarise(
    n = n(),
    pct_select_woman = round(mean(female_pick) * 100, 1),
    pct_select_poet = round(mean(poets_pick) * 100, 1),
    pct_select_oldies = round(mean(oldies_pick) * 100, 1),
    pct_select_books = round(mean(books_pick) * 100, 1)
  )

print(when_women_underrep)
```

```
## # A tibble: 1 x 5
##       n pct_select_woman pct_select_poet pct_select_oldies pct_select_books
##   <int>            <dbl>           <dbl>             <dbl>            <dbl>
## 1   333             26.4            17.7                30             28.2
```

```
cat("\n--- 7th Selection when Women are NOT underrepresented (>=50%) ---\n")
```

```
##
## --- 7th Selection when Women are NOT underrepresented (>=50%) ---
```

```
when_women_not_underrep <- d0 |>
  filter(women_underrep == 0) |>
  summarise(
    n = n(),
    pct_select_woman = round(mean(female_pick) * 100, 1),
    pct_select_poet = round(mean(poets_pick) * 100, 1),
    pct_select_oldies = round(mean(oldies_pick) * 100, 1),
    pct_select_books = round(mean(books_pick) * 100, 1)
  )

print(when_women_not_underrep)
```

```
## # A tibble: 1 x 5
##       n pct_select_woman pct_select_poet pct_select_oldies pct_select_books
##   <int>            <dbl>           <dbl>             <dbl>            <dbl>
## 1   119             34.5            31.1              37.8             36.1
```

```
# Most underrepresented attribute analysis
cat("\n--- Which attribute is MOST underrepresented? ---\n")
```

```
##
## --- Which attribute is MOST underrepresented? ---
```

```
d0 <- d0 |>
  mutate(
    most_underrep = case_when(
      base_gender < pmin(base_poets, base_oldies, base_books) ~ "women",
      base_poets < pmin(base_gender, base_oldies, base_books) ~ "poets",
```

```r
      base_oldies < pmin(base_gender, base_poets, base_books) ~ "oldies",
      base_books < pmin(base_gender, base_poets, base_oldies) ~ "books",
      TRUE ~ "tie"
    )
  )

most_underrep_dist <- d0 |>
  group_by(most_underrep) |>
  summarise(n = n(), pct = round(n/nrow(d0) * 100, 1))

cat("Distribution of which attribute is most underrepresented:\n")
```

```
## Distribution of which attribute is most underrepresented:
```

```r
print(most_underrep_dist)
```

```
## # A tibble: 5 x 3
##   most_underrep     n   pct
##   <chr>         <int> <dbl>
## 1 books            58  12.8
## 2 oldies           70  15.5
## 3 poets            80  17.7
## 4 tie             183  40.5
## 5 women            61  13.5
```

```r
# When each attribute is most underrepresented, what gets selected?
cat("\n--- When WOMEN are most underrepresented, 7th selection: ---\n")
```

```
##
## --- When WOMEN are most underrepresented, 7th selection: ---
```

```r
d0 |> filter(most_underrep == "women") |>
  summarise(
    n = n(),
    pct_woman = round(mean(female_pick) * 100, 1),
    pct_poet = round(mean(poets_pick) * 100, 1),
    pct_oldies = round(mean(oldies_pick) * 100, 1),
    pct_books = round(mean(books_pick) * 100, 1)
  ) |> print()
```

```
## # A tibble: 1 x 5
##       n pct_woman pct_poet pct_oldies pct_books
##   <int>     <dbl>    <dbl>      <dbl>     <dbl>
## 1    61      32.8     24.6       29.5      24.6
```

```r
cat("\n--- When POETS are most underrepresented, 7th selection: ---\n")
```

```
##
## --- When POETS are most underrepresented, 7th selection: ---
```

```r
d0 |> filter(most_underrep == "poets") |>
  summarise(
    n = n(),
    pct_woman = round(mean(female_pick) * 100, 1),
    pct_poet = round(mean(poets_pick) * 100, 1),
    pct_oldies = round(mean(oldies_pick) * 100, 1),
    pct_books = round(mean(books_pick) * 100, 1)
  ) |> print()
```

```
## # A tibble: 1 x 5
##       n pct_woman pct_poet pct_oldies pct_books
##   <int>     <dbl>    <dbl>      <dbl>     <dbl>
## 1    80      23.8     33.8       23.8      36.2
```

```r
cat("\n--- When OLDIES are most underrepresented, 7th selection: ---\n")
```

```
##
## --- When OLDIES are most underrepresented, 7th selection: ---
```

```r
d0 |> filter(most_underrep == "oldies") |>
  summarise(
    n = n(),
    pct_woman = round(mean(female_pick) * 100, 1),
    pct_poet = round(mean(poets_pick) * 100, 1),
    pct_oldies = round(mean(oldies_pick) * 100, 1),
    pct_books = round(mean(books_pick) * 100, 1)
  ) |> print()
```

```
## # A tibble: 1 x 5
##       n pct_woman pct_poet pct_oldies pct_books
##   <int>     <dbl>    <dbl>      <dbl>     <dbl>
## 1    70      32.9     14.3       44.3      28.6
```

```r
cat("\n--- When BOOKS are most underrepresented, 7th selection: ---\n")
```

```
##
## --- When BOOKS are most underrepresented, 7th selection: ---
```

```r
d0 |> filter(most_underrep == "books") |>
  summarise(
    n = n(),
    pct_woman = round(mean(female_pick) * 100, 1),
    pct_poet = round(mean(poets_pick) * 100, 1),
    pct_oldies = round(mean(oldies_pick) * 100, 1),
    pct_books = round(mean(books_pick) * 100, 1)
  ) |> print()
```

```
## # A tibble: 1 x 5
##       n pct_woman pct_poet pct_oldies pct_books
##   <int>     <dbl>    <dbl>      <dbl>     <dbl>
## 1    58      29.3     20.7       44.8      29.3
```

Treatment Effect by Level of Underrepresentation

```r
cat("=== TREATMENT EFFECT CONDITIONAL ON UNDERREPRESENTATION ===\n\n")
```

```
## === TREATMENT EFFECT CONDITIONAL ON UNDERREPRESENTATION ===
```

```r
# Among those who received GENDER feedback
cat("--- Among those who received GENDER feedback ---\n\n")
```

```
## --- Among those who received GENDER feedback ---
```

```r
cat("When women ARE underrepresented (<50%):\n")
```

```
## When women ARE underrepresented (<50%):
```

```r
r_gender_underrep <- d0 |>
  filter(women_underrep == 1) |>
  lm(female_pick ~ gender_feedback, data = _)

robust_summary(r_gender_underrep)
```

```
##
## Call:
## lm(formula = female_pick ~ gender_feedback, data = filter(d0,
##     women_underrep == 1))
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -0.3091 -0.3091 -0.2202  0.6909  0.7798
##
## Coefficients:
##                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)      0.22024    0.03216   6.847 3.67e-11 ***
## gender_feedback  0.08885    0.04842   1.835   0.0674 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.44 on 331 degrees of freedom
## Multiple R-squared:  0.01015,    Adjusted R-squared:  0.00716
## F-statistic: 3.394 on 1 and 331 DF,  p-value: 0.06632
```

```r
cat("\nWhen women are NOT underrepresented (>=50%):\n")
```

```
##
## When women are NOT underrepresented (>=50%):
```

```r
r_gender_not_underrep <- d0 |>
  filter(women_underrep == 0) |>
  lm(female_pick ~ gender_feedback, data = _)

robust_summary(r_gender_not_underrep)
```

```
##
## Call:
## lm(formula = female_pick ~ gender_feedback, data = filter(d0,
##     women_underrep == 0))
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -0.4310 -0.4310 -0.2623  0.5690  0.7377
##
## Coefficients:
##                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)      0.43103    0.06617   6.514 1.91e-09 ***
## gender_feedback -0.16874    0.08750  -1.928   0.0562 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.4717 on 117 degrees of freedom
## Multiple R-squared:  0.0315, Adjusted R-squared:  0.02322
## F-statistic: 3.805 on 1 and 117 DF,  p-value: 0.05348
```

```r
# Compare means
cat("\n--- Mean selection rates ---\n")
```

```
##
## --- Mean selection rates ---
```

```r
d0 |>
  group_by(women_underrep, gender_feedback) |>
  summarise(
    n = n(),
    pct_select_woman = round(mean(female_pick) * 100, 1)
  ) |>
  print()
```

```
## # A tibble: 4 x 4
## # Groups:   women_underrep [2]
##   women_underrep gender_feedback     n pct_select_woman
##            <dbl>           <dbl> <int>            <dbl>
## 1              0               0    58             43.1
## 2              0               1    61             26.2
## 3              1               0   168             22
## 4              1               1   165             30.9
```

```r
# Interaction model
cat("\n--- Interaction: Gender Feedback x Women Underrepresented ---\n")
```

```
##
## --- Interaction: Gender Feedback x Women Underrepresented ---
```

```r
r_interaction_underrep <- lm(female_pick ~ gender_feedback * women_underrep, data = d0)
robust_summary(r_interaction_underrep)
```

```
##
## Call:
## lm(formula = female_pick ~ gender_feedback * women_underrep,
##     data = d0)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -0.4310 -0.3091 -0.2202  0.5690  0.7798
##
## Coefficients:
##                                Estimate Std. Error t value Pr(>|t|)
## (Intercept)                     0.43103    0.06617   6.514 1.97e-10 ***
## gender_feedback                -0.16874    0.08750  -1.928  0.05444 .
## women_underrep                 -0.21080    0.07357  -2.865  0.00436 **
## gender_feedback:women_underrep  0.25759    0.10001   2.576  0.01032 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.4485 on 448 degrees of freedom
## Multiple R-squared:  0.02244,    Adjusted R-squared:  0.01589
## F-statistic: 3.428 on 3 and 448 DF,  p-value: 0.0171
```

```r
robust_confint(r_interaction_underrep)
```

```
##                                     2.5 %       97.5 %
## (Intercept)                     0.3009992  0.561069728
## gender_feedback                -0.3407058  0.003226995
## women_underrep                 -0.3553810 -0.066211754
## gender_feedback:women_underrep  0.0610522  0.454132232
```

Figure - Simple Effects by Base Condition

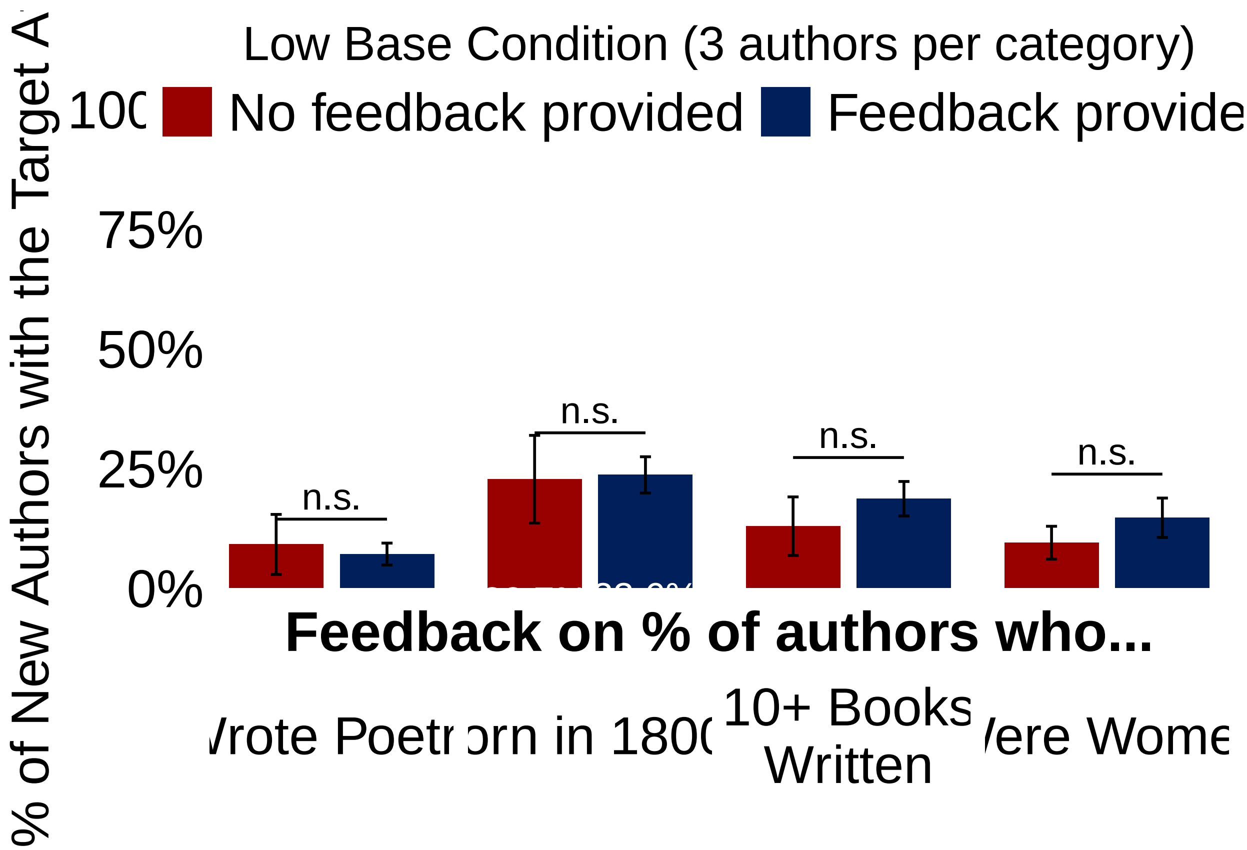
Low Base Condition Figure (3 authors)

```r
# Get p-values from regression models for LOW base condition
p_gender_low <- robust_summary(r_low)$coefficients["gender_feedback", "Pr(>|t|)"]
p_poets_low <- robust_summary(r_poets_low)$coefficients["poets_shown", "Pr(>|t|)"]
p_oldies_low <- robust_summary(r_oldies_low)$coefficients["oldies_shown", "Pr(>|t|)"]
p_books_low <- robust_summary(r_books_low)$coefficients["books_shown", "Pr(>|t|)"]
```

```r
# Function to convert p-value to significance stars
get_sig_stars <- function(p) {
  if (p < 0.001) return("***")
  else if (p < 0.01) return("**")
  else if (p < 0.05) return("*")
  else return("n.s.")
}

# Get significance labels for LOW base
sig_gender_low <- get_sig_stars(p_gender_low)
sig_poets_low <- get_sig_stars(p_poets_low)
sig_oldies_low <- get_sig_stars(p_oldies_low)
sig_books_low <- get_sig_stars(p_books_low)

dfemale_plot_low <- d0_low |>
  dplyr::select(gender_feedback, female_pick) |>
  dplyr::group_by(gender_feedback) |>
  dplyr::summarise(
    n = n(),
    freq = mean(female_pick),
    sd = sd(female_pick) * 100,
    se = (sd(female_pick) / sqrt(n())) * 100
  ) |>
  dplyr::mutate(
    gender_feedback = case_when(
      gender_feedback == 1 ~ "\"Treatment\"",
      TRUE ~ "\"Control\""
    )
  ) |>
  dplyr::rename(Condition = gender_feedback)

dpoets_plot_low <- d0_low |>
  dplyr::select(poets_shown, poets_pick) |>
  dplyr::group_by(poets_shown) |>
  dplyr::summarise(
    n = n(),
    freq = mean(poets_pick),
    sd = sd(poets_pick) * 100,
    se = (sd(poets_pick) / sqrt(n())) * 100
  )|>
  mutate(poets_shown = case_when(poets_shown==1 ~ "\"Treatment\"",
                                 TRUE ~ "\"Control\"")) |>
  rename(Condition = poets_shown)

doldies_plot_low <- d0_low |>
  dplyr::select(oldies_shown, oldies_pick) |>
  dplyr::group_by(oldies_shown) |>
  dplyr::summarise(
    n = n(),
    freq = mean(oldies_pick),
    sd = sd(oldies_pick) * 100,
    se = (sd(oldies_pick) / sqrt(n())) * 100
  )|>
  mutate(oldies_shown = case_when(oldies_shown==1 ~ "\"Treatment\"",
```

```
                        TRUE ~ "\"Control\"")) |>
  rename(Condition = oldies_shown)

dbooks_plot_low <- d0_low |>
  dplyr::select(books_shown, books_pick) |>
  dplyr::group_by(books_shown) |>
  dplyr::summarise(
    n = n(),
    freq = mean(books_pick),
    sd = sd(books_pick) * 100,
    se = (sd(books_pick) / sqrt(n())) * 100
  )|>
  mutate(books_shown = case_when(books_shown==1 ~ "\"Treatment\"",
                        TRUE ~ "\"Control\"")) |>
  rename(Condition = books_shown)

## Combine plots for LOW base
df_combined_low <- bind_rows(
  dpoets_plot_low %>% mutate(Category = "\nWrote Poetry", sig_label = sig_poets_low),
  doldies_plot_low %>% mutate(Category = "\nBorn in 1800s", sig_label = sig_oldies_low),
  dbooks_plot_low %>% mutate(Category = "\n10+ Books\nWritten", sig_label =
↪  sig_books_low),
  dfemale_plot_low %>% mutate(Category = "\nWere Women", sig_label = sig_gender_low)
, .id = "id") %>%
  mutate(Category = factor(Category, levels = c('\nWrote Poetry', '\nBorn in 1800s',
  ↪  '\n10+ Books\nWritten', '\nWere Women')))

p_combined_low <- ggplot(df_combined_low, aes(x = Condition, y = freq*100, fill =
↪  Condition)) +
  geom_bar(stat="identity", width = 0.85, position = position_dodge(width = 0.7)) +
  geom_text(aes(label=paste0(sprintf("%.1f", freq*100),"%")),
          position=position_dodge(width=0.7), vjust=5, size = 5, color = "white") +
  geom_errorbar(aes(ymin=freq*100-se, ymax=freq*100+se), width = .1, position =
  ↪  position_dodge(width = 0.7)) +
  facet_wrap(~factor(Category, c('\nWrote Poetry', '\nBorn in 1800s', '\n10+
  ↪  Books\nWritten', '\nWere Women')), nrow = 1, strip.position = "bottom") +
   geom_segment(data = df_combined_low %>% filter(Condition == "\"Treatment\""),
              aes(x = 1, xend = 2, y = freq*100 + se + 5, yend = freq*100 + se + 5),
              inherit.aes = FALSE) +
   geom_text(data = df_combined_low %>% filter(Condition == "\"Treatment\""),
           aes(x = 1.5, y = freq*100 + se + 7, label = sig_label),
           inherit.aes = FALSE, vjust = 0, size = 5) +
  theme_bw() +
  scale_fill_manual(values = c("#990000", "#011F5B"), labels = c("No feedback provided",
  ↪  "Feedback provided"), "Feedback") +
  scale_y_continuous(labels = function(x) paste0(x,"%"), limits = c(0,100)) +
  scale_x_discrete(labels = c("\"Control\"" = "Not\nShown", "\"Treatment\"" = "Shown")) +
  labs(x = "Feedback on % of authors who...", y = "% of New Authors with the Target
  ↪  Attribute",
      title = "Low Base Condition (3 authors per category)") +
  theme(plot.caption = element_text(face = "italic"),
       legend.position = c(0.5, 0.95),
       legend.title = element_blank(),
       legend.direction = "horizontal",
```

```
        legend.text = element_text(size = 20),
        legend.key.size = unit(7, 'mm'),
        legend.background = element_rect(fill = "white"),
        panel.grid.minor = element_blank(),
        panel.grid = element_blank(),
        panel.border = element_rect(fill= NA, color = "white"),
        plot.background = element_rect(fill = "white"),
        panel.background = element_rect(fill = "white"),
        axis.title.x = element_text(face="bold", size = 21, vjust = 17),
        plot.title = element_text(size = 18, hjust = 0.5),
        axis.title.y = element_text(size = 20, color = "black"),
        axis.text.x = element_blank(),
        axis.ticks = element_blank(),
        axis.text.y = element_text(size = 20, color = "black"),
        strip.text = element_text(size = 20, color = "black"),
        strip.background = element_rect(colour = "white", fill = "white"))

print(p_combined_low)
```



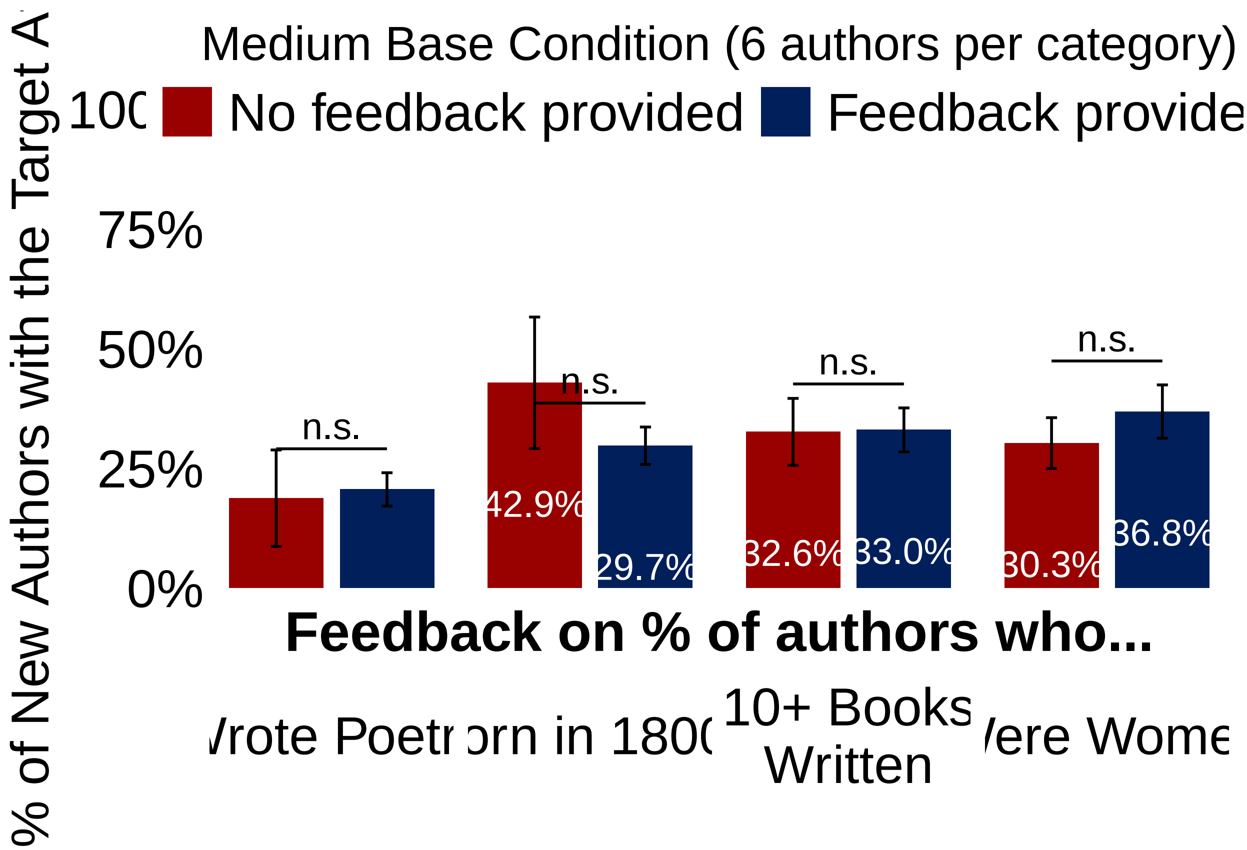

```
ggsave("Figure-Pilot-Low.pdf", plot = p_combined_low, width = 10, height = 8, units =
↪  "in", device = cairo_pdf, family = "Times New Roman")
```

Medium Base Condition Figure (6 authors)

```
# Get p-values from regression models for MEDIUM base condition
p_gender_med <- robust_summary(r_med)$coefficients["gender_feedback", "Pr(>|t|)"]
p_poets_med <- robust_summary(r_poets_med)$coefficients["poets_shown", "Pr(>|t|)"]
p_oldies_med <- robust_summary(r_oldies_med)$coefficients["oldies_shown", "Pr(>|t|)"]
p_books_med <- robust_summary(r_books_med)$coefficients["books_shown", "Pr(>|t|)"]

# Get significance labels for MEDIUM base
sig_gender_med <- get_sig_stars(p_gender_med)
sig_poets_med <- get_sig_stars(p_poets_med)
sig_oldies_med <- get_sig_stars(p_oldies_med)
sig_books_med <- get_sig_stars(p_books_med)

dfemale_plot_med <- d0_med |>
  dplyr::select(gender_feedback, female_pick) |>
  dplyr::group_by(gender_feedback) |>
  dplyr::summarise(
    n = n(),
    freq = mean(female_pick),
    sd = sd(female_pick) * 100,
    se = (sd(female_pick) / sqrt(n())) * 100
  ) |>
  dplyr::mutate(
    gender_feedback = case_when(
      gender_feedback == 1 ~ "\"Treatment\"",
      TRUE ~ "\"Control\""
    )
  ) |>
  dplyr::rename(Condition = gender_feedback)

dpoets_plot_med <- d0_med |>
  dplyr::select(poets_shown, poets_pick) |>
  dplyr::group_by(poets_shown) |>
  dplyr::summarise(
    n = n(),
    freq = mean(poets_pick),
    sd = sd(poets_pick) * 100,
    se = (sd(poets_pick) / sqrt(n())) * 100
  )|>
  mutate(poets_shown = case_when(poets_shown==1 ~ "\"Treatment\"",
                                 TRUE ~ "\"Control\"")) |>
  rename(Condition = poets_shown)

doldies_plot_med <- d0_med |>
  dplyr::select(oldies_shown, oldies_pick) |>
  dplyr::group_by(oldies_shown) |>
  dplyr::summarise(
    n = n(),
    freq = mean(oldies_pick),
    sd = sd(oldies_pick) * 100,
    se = (sd(oldies_pick) / sqrt(n())) * 100
  )|>
  mutate(oldies_shown = case_when(oldies_shown==1 ~ "\"Treatment\"",
```

```r
                        TRUE ~ "\"Control\"")) |>
  rename(Condition = oldies_shown)

dbooks_plot_med <- d0_med |>
  dplyr::select(books_shown, books_pick) |>
  dplyr::group_by(books_shown) |>
  dplyr::summarise(
    n = n(),
    freq = mean(books_pick),
    sd = sd(books_pick) * 100,
    se = (sd(books_pick) / sqrt(n())) * 100
  )|>
  mutate(books_shown = case_when(books_shown==1 ~ "\"Treatment\"",
                        TRUE ~ "\"Control\"")) |>
  rename(Condition = books_shown)

## Combine plots for MEDIUM base
df_combined_med <- bind_rows(
  dpoets_plot_med %>% mutate(Category = "\nWrote Poetry", sig_label = sig_poets_med),
  doldies_plot_med %>% mutate(Category = "\nBorn in 1800s", sig_label = sig_oldies_med),
  dbooks_plot_med %>% mutate(Category = "\n10+ Books\nWritten", sig_label =
↪  sig_books_med),
  dfemale_plot_med %>% mutate(Category = "\nWere Women", sig_label = sig_gender_med)
, .id = "id") %>%
  mutate(Category = factor(Category, levels = c('\nWrote Poetry', '\nBorn in 1800s',
   ↪  '\n10+ Books\nWritten', '\nWere Women')))

p_combined_med <- ggplot(df_combined_med, aes(x = Condition, y = freq*100, fill =
↪  Condition)) +
  geom_bar(stat="identity", width = 0.85, position = position_dodge(width = 0.7)) +
  geom_text(aes(label=paste0(sprintf("%.1f", freq*100),"%")),
            position=position_dodge(width=0.7), vjust=5, size = 5, color = "white") +
  geom_errorbar(aes(ymin=freq*100-se, ymax=freq*100+se), width = .1, position =
   ↪  position_dodge(width = 0.7)) +
  facet_wrap(~factor(Category, c('\nWrote Poetry', '\nBorn in 1800s', '\n10+
   ↪  Books\nWritten', '\nWere Women')), nrow = 1, strip.position = "bottom") +
   geom_segment(data = df_combined_med %>% filter(Condition == "\"Treatment\""),
                aes(x = 1, xend = 2, y = freq*100 + se + 5, yend = freq*100 + se + 5),
                inherit.aes = FALSE) +
   geom_text(data = df_combined_med %>% filter(Condition == "\"Treatment\""),
             aes(x = 1.5, y = freq*100 + se + 7, label = sig_label),
             inherit.aes = FALSE, vjust = 0, size = 5) +
  theme_bw() +
  scale_fill_manual(values = c("#990000", "#011F5B"), labels = c("No feedback provided",
   ↪  "Feedback provided"), "Feedback") +
  scale_y_continuous(labels = function(x) paste0(x,"%"), limits = c(0,100)) +
  scale_x_discrete(labels = c("\"Control\"" = "Not\nShown", "\"Treatment\"" = "Shown")) +
  labs(x = "Feedback on % of authors who...", y = "% of New Authors with the Target
   ↪  Attribute",
       title = "Medium Base Condition (6 authors per category)") +
  theme(plot.caption = element_text(face = "italic"),
        legend.position = c(0.5, 0.95),
        legend.title = element_blank(),
        legend.direction = "horizontal",
```

```
        legend.text = element_text(size = 20),
        legend.key.size = unit(7, 'mm'),
        legend.background = element_rect(fill = "white"),
        panel.grid.minor = element_blank(),
        panel.grid = element_blank(),
        panel.border = element_rect(fill= NA, color = "white"),
        plot.background = element_rect(fill = "white"),
        panel.background = element_rect(fill = "white"),
        axis.title.x = element_text(face="bold", size = 21, vjust = 17),
        plot.title = element_text(size = 18, hjust = 0.5),
        axis.title.y = element_text(size = 20, color = "black"),
        axis.text.x = element_blank(),
        axis.ticks = element_blank(),
        axis.text.y = element_text(size = 20, color = "black"),
        strip.text = element_text(size = 20, color = "black"),
        strip.background = element_rect(colour = "white", fill = "white"))

print(p_combined_med)
```



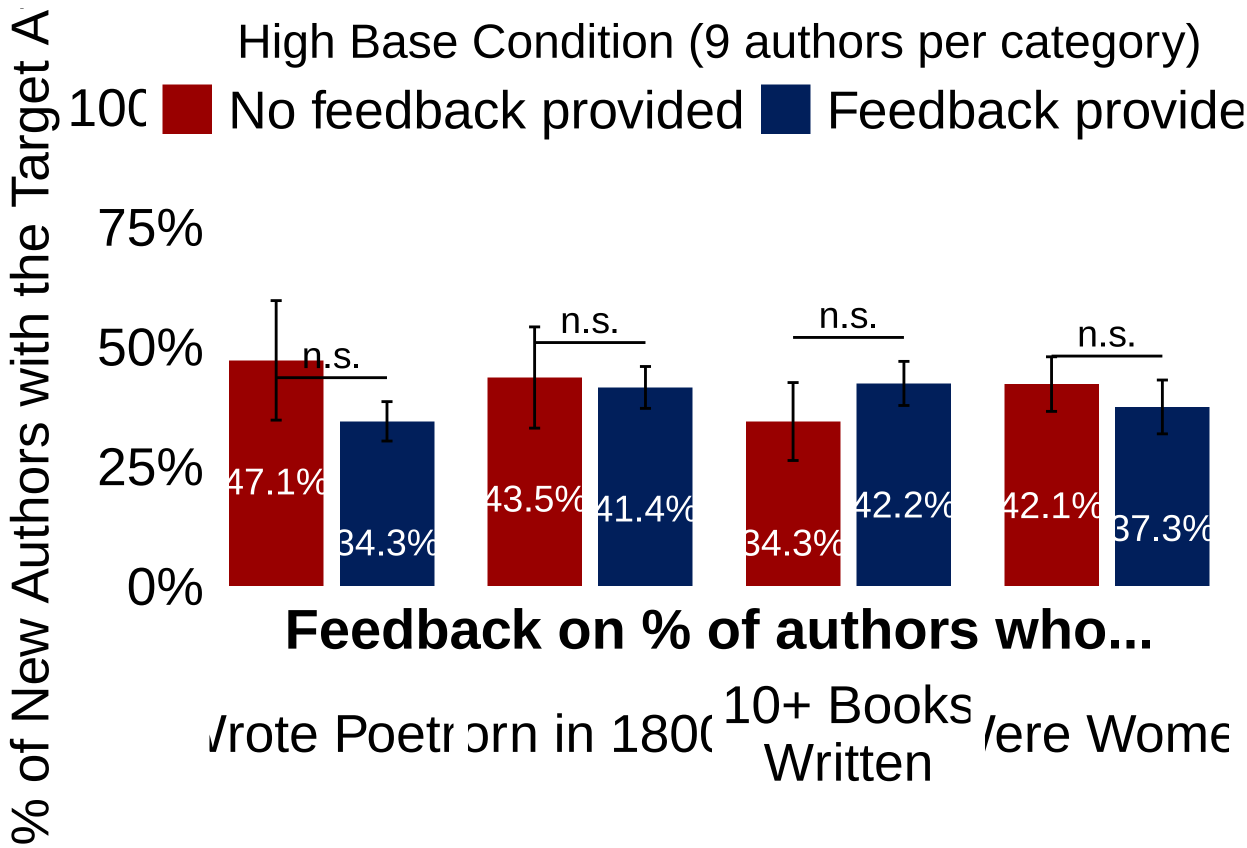

```
ggsave("Figure-Pilot-Med.pdf", plot = p_combined_med, width = 10, height = 8, units =
↪  "in", device = cairo_pdf, family = "Times New Roman")
```

High Base Condition Figure (9 authors)

```r
# Get p-values from regression models for HIGH base condition
p_gender_high <- robust_summary(r_high)$coefficients["gender_feedback", "Pr(>|t|)"]
p_poets_high <- robust_summary(r_poets_high)$coefficients["poets_shown", "Pr(>|t|)"]
p_oldies_high <- robust_summary(r_oldies_high)$coefficients["oldies_shown", "Pr(>|t|)"]
p_books_high <- robust_summary(r_books_high)$coefficients["books_shown", "Pr(>|t|)"]

# Get significance labels for HIGH base
sig_gender_high <- get_sig_stars(p_gender_high)
sig_poets_high <- get_sig_stars(p_poets_high)
sig_oldies_high <- get_sig_stars(p_oldies_high)
sig_books_high <- get_sig_stars(p_books_high)

dfemale_plot_high <- d0_high |>
  dplyr::select(gender_feedback, female_pick) |>
  dplyr::group_by(gender_feedback) |>
  dplyr::summarise(
    n = n(),
    freq = mean(female_pick),
    sd = sd(female_pick) * 100,
    se = (sd(female_pick) / sqrt(n())) * 100
  ) |>
  dplyr::mutate(
    gender_feedback = case_when(
      gender_feedback == 1 ~ "\"Treatment\"",
      TRUE ~ "\"Control\""
    )
  ) |>
  dplyr::rename(Condition = gender_feedback)

dpoets_plot_high <- d0_high |>
  dplyr::select(poets_shown, poets_pick) |>
  dplyr::group_by(poets_shown) |>
  dplyr::summarise(
    n = n(),
    freq = mean(poets_pick),
    sd = sd(poets_pick) * 100,
    se = (sd(poets_pick) / sqrt(n())) * 100
  )|>
  mutate(poets_shown = case_when(poets_shown==1 ~ "\"Treatment\"",
                                 TRUE ~ "\"Control\"")) |>
  rename(Condition = poets_shown)

doldies_plot_high <- d0_high |>
  dplyr::select(oldies_shown, oldies_pick) |>
  dplyr::group_by(oldies_shown) |>
  dplyr::summarise(
    n = n(),
    freq = mean(oldies_pick),
    sd = sd(oldies_pick) * 100,
    se = (sd(oldies_pick) / sqrt(n())) * 100
  )|>
  mutate(oldies_shown = case_when(oldies_shown==1 ~ "\"Treatment\"",
```

```
                          TRUE ~ "\"Control\"")) |>
  rename(Condition = oldies_shown)

dbooks_plot_high <- d0_high |>
  dplyr::select(books_shown, books_pick) |>
  dplyr::group_by(books_shown) |>
  dplyr::summarise(
    n = n(),
    freq = mean(books_pick),
    sd = sd(books_pick) * 100,
    se = (sd(books_pick) / sqrt(n())) * 100
  )|>
  mutate(books_shown = case_when(books_shown==1 ~ "\"Treatment\"",
                          TRUE ~ "\"Control\"")) |>
  rename(Condition = books_shown)

## Combine plots for HIGH base
df_combined_high <- bind_rows(
  dpoets_plot_high %>% mutate(Category = "\nWrote Poetry", sig_label = sig_poets_high),
  doldies_plot_high %>% mutate(Category = "\nBorn in 1800s", sig_label =
↪  sig_oldies_high),
  dbooks_plot_high %>% mutate(Category = "\n10+ Books\nWritten", sig_label =
↪  sig_books_high),
  dfemale_plot_high %>% mutate(Category = "\nWere Women", sig_label = sig_gender_high)
, .id = "id") %>%
  mutate(Category = factor(Category, levels = c('\nWrote Poetry', '\nBorn in 1800s',
   ↪  '\n10+ Books\nWritten', '\nWere Women')))

p_combined_high <- ggplot(df_combined_high, aes(x = Condition, y = freq*100, fill =
↪  Condition)) +
  geom_bar(stat="identity", width = 0.85, position = position_dodge(width = 0.7)) +
  geom_text(aes(label=paste0(sprintf("%.1f", freq*100),"%")),
            position=position_dodge(width=0.7), vjust=5, size = 5, color = "white") +
  geom_errorbar(aes(ymin=freq*100-se, ymax=freq*100+se), width = .1, position =
   ↪  position_dodge(width = 0.7)) +
  facet_wrap(~factor(Category, c('\nWrote Poetry', '\nBorn in 1800s', '\n10+
   ↪  Books\nWritten', '\nWere Women')), nrow = 1, strip.position = "bottom") +
   geom_segment(data = df_combined_high %>% filter(Condition == "\"Treatment\""),
                aes(x = 1, xend = 2, y = freq*100 + se + 5, yend = freq*100 + se + 5),
                inherit.aes = FALSE) +
   geom_text(data = df_combined_high %>% filter(Condition == "\"Treatment\""),
             aes(x = 1.5, y = freq*100 + se + 7, label = sig_label),
             inherit.aes = FALSE, vjust = 0, size = 5) +
  theme_bw() +
  scale_fill_manual(values = c("#990000", "#011F5B"), labels = c("No feedback provided",
   ↪  "Feedback provided"), "Feedback") +
  scale_y_continuous(labels = function(x) paste0(x,"%"), limits = c(0,100)) +
  scale_x_discrete(labels = c("\"Control\"" = "Not\nShown", "\"Treatment\"" = "Shown")) +
  labs(x = "Feedback on % of authors who...", y = "% of New Authors with the Target
   ↪  Attribute",
       title = "High Base Condition (9 authors per category)") +
  theme(plot.caption = element_text(face = "italic"),
        legend.position = c(0.5, 0.95),
        legend.title = element_blank(),
```

```
        legend.direction = "horizontal",
        legend.text = element_text(size = 20),
        legend.key.size = unit(7, 'mm'),
        legend.background = element_rect(fill = "white"),
        panel.grid.minor = element_blank(),
        panel.grid = element_blank(),
        panel.border = element_rect(fill= NA, color = "white"),
        plot.background = element_rect(fill = "white"),
        panel.background = element_rect(fill = "white"),
        axis.title.x = element_text(face="bold", size = 21, vjust = 17),
        plot.title = element_text(size = 18, hjust = 0.5),
        axis.title.y = element_text(size = 20, color = "black"),
        axis.text.x = element_blank(),
        axis.ticks = element_blank(),
        axis.text.y = element_text(size = 20, color = "black"),
        strip.text = element_text(size = 20, color = "black"),
        strip.background = element_rect(colour = "white", fill = "white"))

print(p_combined_high)
```




```
ggsave("Figure-Pilot-High.pdf", plot = p_combined_high, width = 10, height = 8, units =
↪  "in", device = cairo_pdf, family = "Times New Roman")
```

System of Simultaneous Equations

Low Base Condition

```
## LOW BASE CONDITION: Testing equality of attribute feedback effects

##                                    Wald.Coefficient      P_Value
## Gender Feedback - Poets Feedback      23.663869581 1.884867e-06
## Gender Feedback - Oldies Feedback      0.441134878 5.071029e-01
## Gender Feedback - Books Feedback       0.003401544 9.535317e-01
```

Medium Base Condition

```
## MEDIUM BASE CONDITION: Testing equality of attribute feedback effects

##                                   Wald.Coefficient    P_Value
## Gender Feedback - Poets Feedback          5.162594 0.02379566
## Gender Feedback - Oldies Feedback         5.731426 0.01728623
## Gender Feedback - Books Feedback          2.263582 0.13351365
```

High Base Condition

```
## HIGH BASE CONDITION: Testing equality of attribute feedback effects

##                                   Wald.Coefficient    P_Value
## Gender Feedback - Poets Feedback        0.03317574 0.85559674
## Gender Feedback - Oldies Feedback       3.36857895 0.06746107
## Gender Feedback - Books Feedback        1.47593205 0.22538687
```