Exposure to Zero-Sum Political Polarization on Social Media and Their Impact on Mental Health Among Undergraduates

Politically Polarizing Social Media Content and Mental Health

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This study examines how exposure to polarizing social media content, particularly content that engages with users' zero-sum beliefs, affects the mental health of undergraduate students. Zero-sum beliefs refer to the perception that one group's gain inherently results in another's loss. Gains have been linked to heightened political intergroup conflict and increased polarization. A mixed-methods survey assessed participants' engagements with politically polarizing zero-sum media and their corresponding emotional and psychological responses. It was hypothesized that viewing politically polarizing content that engages with zero-sum beliefs would decrease users' mental health. Participants were randomly shown either politically leaning video content or politically polarizing content. Quantitative analysis was performed using programs created with the R language, while the qualitative study was done via coding in NVivo. The sample's demographics contained 63.2% women and 29.9% men. Of these respondents, 75% leaned left politically, and 5.68% leaned right, with the remainder being moderate or not providing an answer. Results indicate that viewing politically polarizing content has no significant impact on zero-sum beliefs (p=0.0034), hope (p=0.114), or anxiety (p=0.82). Qualitative results imply connections between certain types of content and increased mental distress. These findings aim to clarify the psychological effects of exposure to zero-sum social media content and to inform future interventions that promote healthier online engagement and reduce the mental health burden associated with political polarization. The study aims to determine whether exposure to zero-sum messaging is related to measurable declines in the mental health of undergraduates.

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1 Introduction

1.1 Significance

The intensification of political polarization, often characterized by zero-sum beliefs, carries profound implications for mental health and warrants recognition as a critical public health concern. Mental health remains a pressing public issue, as it represents a fundamental component of overall well-being. Furthermore, concerns about the mental health consequences associated with political polarization have rendered it an increasingly prominent, though still insufficiently studied, topic of research. Studies show that political polarization in the United States is at an all-time high, and this polarization is associated with elevated levels of stress on college campuses, with politically polarized students reporting greater psychological distress on average (Reynolds et al., 2025). The digital environment places further strain on this issue as social media serves as a major social context for political engagement and exposure to divisiveness. This is reflected in findings which indicate that sixty-two percent of users get news from social media due to accessibility, improved technology, and the cost policy of creating an account on social media (Singh et al., 2024). Therefore, this serves as a universal problem for groups that mainly get their news and information from social media. Research also indicates that college students represent an at-risk population for political polarization, in part because their elevated levels of psychological distress increase susceptibility to polarizing beliefs and behaviors (Reynolds et al., 2025). This has the capability to further harm not just individuals but institutions at large. Studies exemplify that mental health and GPA are negatively correlated variables, which would impact both students and institutions. Depression was also found to be a significant predictor of not only GPA but also the likelihood of a student dropping out of college. Therefore, negative mental health is associated with academic outcomes, which in large part affects institutions (Eisenberg et al., 2009). Collectively, political polarization poses a substantial public health threat through its detrimental effects on mental health, affecting both individuals and institutions, and underscores the importance of investigating associated factors, including social isolation, that may exacerbate these outcomes.

Political polarization and zero-sum thinking foster social isolation by weakening trust and social cohesion, which not only increases individual vulnerability to mental health problems but also amplifies social isolation as a critical public health concern. This public health concern generates additional problems, as research has shown that insufficient social connection is associated with increased risk for anxiety, depression, and dementia (U.S. Department of Health and Human Services, 2023). The presence of zero-sum beliefs has the potential to cause a negative chain reaction, which contributes to social isolation. Social cohesion is eroded by zero-sum mindsets, leading to isolation and loneliness, which in turn weakens both community and mental health, ultimately contributing to an increase in social fragmentation. Gains have been linked to heightened political intergroup conflict and increased polarization (Roberts, 2022; Davidai, 2023). Additionally, research has shown that only 39% of adults in the United States said that they felt connected to others, and nearly half of United States adults report experiencing loneliness (U.S. Department of Health and Human Services, 2023). These statistics already raise concerns for public health, and as the digital environment expeditely expands alongside rising political polarization and zero-sum beliefs, the issue is likely to be exacerbated. Consequently, similar populations remain vulnerable to the impacts of political polarization and zero-sum beliefs identified within the mental health public health concern. The combined effects of political polarization and zero-sum beliefs on social isolation represent an escalating public health concern that threatens both mental health and societal stability.

1.2 Knowns and Unknowns

Political polarization has been growing in the United States in recent decades, mirroring the rise in social media as a primary source of news and information among adults in the 20th century (Pew Research Center, 2014; Pew Research Center, 2025). Affective polarization, defined as the extent to which people hold negative feelings toward opposing political parties, has increased as well, which suggests that political attitudes are becoming more emotionally charged (Konicki, 2025). Social media serves as an environment where exposure to politically polarizing content is amplified, which can be attributed to algorithmic recommendations that are congenial with an individual's beliefs.

Since political polarization is associated with more psychological distress among college students, this amplified exposure could cause detrimental effects to the overall wellness of students (Reynolds et al., 2025). Additionally, it is known that zero-sum beliefs have been linked to intergroup conflict, as shown through research finding a positive correlation between zero-sum beliefs and willingness to sacrifice democratic procedures for partisan benefit and support using violent means (Fearon et al., 2021). Together, these findings highlight how political polarization and zero-sum beliefs are not only socially consequential but also have significant public health risks.

However, some gaps in knowledge remain. First, the direct impact of exposure to politically polarizing zero-sum content on undergraduate mental health is poorly understood. While associations between political polarization and distress have been observed, few studies have measured emotional responses to the exposure of zero-sum content and beliefs. Second, the way in which social media algorithms contribute to the reinforcement of zero-sum beliefs remains an unanswered question. Because recommendation algorithms lack transparency, it's difficult to determine the extent to which social media content impacts zero-sum beliefs or political polarization among individuals. Finally, a majority of existing research relies on population-level surveys, which causes gaps in understanding immediate individual psychological effects. There is also limited research addressing qualitative experiences, such as participants' reasons for distress in response to particular ideas. These gaps prompt the need for an experimental mixed-methods research to examine the emotional impact on the engagement with zero-sum political content on social media among undergraduates.

1.3 Research Aims

The research question our team will be exploring is, "How does politically polarizing social media content impact the mental health of undergraduate students through engagement with zero-sum beliefs?" Previous literature has led our team to hypothesize that engagement with politically polarizing content that conveys zero-sum beliefs will be associated with negative mental health effects in undergraduate students. Our primary research will consist of comparing pretest and posttest data on reported hopefulness and mental distress of participants when they are exposed to politically leaning or polarizing social media content. We will be conducting a mixed-methods research study using an embedded concurrent design to collect qualitative and quantitative data in one survey. Quantitative data on respondents' emotions will be collected to obtain counts of individuals who experience each of the 5 emotional response options. Qualitative data will allow us to develop further understanding of why individuals exhibit each type of emotional response. This research will be done using an exploratory approach, as little is known about the relationship between political content and immediate mental health effects. The main goal of this study is to understand how politically polarizing social media content impacts the mental health of students through engagement with zero-sum beliefs. Our team will also take an exploratory approach to answer individual research questions regarding sociodemographic effects on media literacy, conspiracy theory support, prevention and promotion mindsets, and motivations for starting or stopping social media use. Understanding the role of sociodemographics on political polarization and mental distress will allow us to determine which individuals are most likely to be polarized. Some gaps in research include the lack of information about politically polarizing social media content and mental health, as well as a lack of information on how sociodemographics predict polarization. Other potential limits include a generalization problem, as our survey consists mostly of Binghamton University undergraduate students and may not have a large enough sample size.

2 Methods

2.1 Participants and Sampling

The study was approved by the Institutional Review Board of a public higher education institution in New York. The purpose of the study was to better understand how politically polarizing social media content impacts the mental health of individuals through engagement with zero-sum beliefs. All research procedures were conducted ethically to protect the rights, welfare, confidentiality, and privacy of participants. Participants were eligible to participate if they were at least 18 years of age, enrolled as undergraduate students, and active users of social media platforms. A convenient sample method was used. Interested individuals accessed the survey link through QR codes on flyers or social media posts. Participants were recruited through campus tabling, word of mouth, personal social media posts, and flyers distributed throughout the campus. Before participation, all individuals reviewed an informed consent form that outlined the study's purpose, procedures, potential risks, and confidentiality protections. Participation was voluntary, and no identifying information was collected. Participants who completed less than 50% of the survey were excluded from analysis. Data were collected through a self-administered online survey via Qualtrics during a 6-week recruitment process. All data were self-reported by participants. Demographic information will be collected to describe the characteristics of the sample and will be reported throughout the results section.

2.2 Data Analysis Plan

2.2.1 Measures

Political polarization was narrowed down for this study to mainly focus on affective polarization. Affective polarization was defined as "assess[ing] the extent to which people like (or feel warmth towards) their political allies and dislike (or feel lack of warmth towards) their political opponents" (Kubin & von Sikorski, 2021). Measures for political polarization spanned both quantitative and qualitative questions within the Qualtrics survey. Items included showing videos from TikTok with various levels of political leaning content in them and asking follow-up questions such as "How would you engage with this content?" (through `LEAN_IMM_ENGAGE`, `POL_IMM_ENGAGE`, and so on), "How much do you agree with what was mentioned in the video?" (through `LEAN_IMM_ALIGN`, `POL_IMM_ALIGN`, and so on) and "How does this content make you feel?" (through `LEAN_IMM_EMOTION`, `POL_IMM_EMOTION`, and so on). All participants were exposed to the same categories of videos (women's rights, economy, DEI, etc.), but approximately half of the participants were shown the same five politically polarizing TikTok videos, while the other half were shown the same five politically leaning TikTok videos. The politically polarizing videos were more aggressive and apparent in their disapproval of other opinions, while the politically leaning videos remained as calm, independent opinions. Zero-sum beliefs were defined as subjective beliefs relating to the concept of one group's gain leading to another group's loss (Davidai & Tepper, 2023). In the survey, participants were given the same nine prompts about their zero-sum beliefs both before (`PREZEROSUM`) and after (`POSTZEROSUM`) they were shown the political TikTok videos. There were: 1) When more resources go to undocumented immigrants, fewer are available for citizens (`ZSPRE_IMM`, `ZSPOST_IMM`), 2) Universal healthcare means worse healthcare for those who can afford private insurance (`ZSPRE_HEALTH`, `ZSPOST_HEALTH`), 3) Men lose societal advantages when women gain equal rights (ZSPRE_WOMEN1, ZSPOST_WOMEN2), 4) As women face less sexism, men end up facing more sexism (ZSPRE_WOMEN2, ZS_POST_WOMEN2), 5) When some people are getting poorer, it means that other people are getting richer (ZSPRE_ECONOMY, ZSPOST_ECONOMY), 6) Gains in opportunities for underrepresented groups come at the expense of majority-group members (ZSPRE_DEI1, ZSPOST_DEI1), 7) Less discrimination against minorities means more discrimination against whites (ZSPRE_DEI2, ZSPOST_DEI2), 8) Environmental protection measures often come at the expense of human prosperity (ZSPRE_ENVIRO1, ZSPOST_ENVIRO1), and 9) Economic advancement is traded for environmental degradation (ZSPRE_ENVIRO2, ZSPOST_ENVIRO2). Responses to each prompt were measured using a 6-point Likert scale with the following options: Strongly Disbelieve (1), Disbelieve (2), Somewhat Disbelieve (3), Somewhat Believe (4), Believe (5), Strongly Believe (6), along with options for "don't know" and "prefer not to say". The latter two options were coded with values of -50 and -99, respectively, and were screened out during analysis.

First, zero-sum belief measures were explored and a Wilcoxon Signed-Rank Test for each zero-sum belief variable (pre vs post intervention) was conducted. Histograms were used to check normality, and findings revealed a non-normal distribution for all PREZEROSUM and POSTZEROSUM variables. Following that, HOPE and ANXIETY was explored also using a Wilcoxon Signed-Rank Test, as both HOPE and ANXIETY possessed a non-normal distribution. Finally after those tests, Polarizing and Leaning video alignment (POLARALIGN, LEANALIGN) vs engagement (POLARENGAGEMENT, LEANENGAGEMENT) was explored using linear regression plots through a Spearman's Rank Correlation test.

2.2.2 Data Analysis - Quantitative

Quantitative data were analyzed using programs created with the R language. Data was coded to variables and values were transformed if needed. R, along with the markdown program Quarto, was used to visualize the quantitative data collected via graphs and tables. The data was screened to remove invalid responses. These included participants who did not answer questions, participants who were found to be ineligible, joke responses, and participants who created false responses (e.g., using generative artificial intelligence to create their responses for them). To handle the data that was collected, filtering was performed to remove "don't know" and "prefer not to say" responses, along with the aforementioned screening. For each variable analyzed quantitatively, statistical tests were performed to determine the normality of its distribution. Due to the non-normal distribution of the data for the variables (zero-sum beliefs, hope, and anxiety), Wilcoxon Signed-Rank tests were performed for their aggregate scores. Composites were created for comparisons of variables concerning participants' zero-sum beliefs before and after viewing political content.

2.2.2.1 Load

```r
library(readxl)
library(dplyr)
library(ggplot2)
library(stats)
library(tidyverse)
library(psych)
```

```r
library(knitr)
library(tibble)
library(tidyr)
library(scales)
library(english)
library(stringr)
library(patchwork)
library(corrplot)
library(RColorBrewer)
library(stats)

# source: The FRI Playbook (McCarty, 2025)
# explanation: loads different libraries to use for data analysis/cleaning
```

2.2.2.2 Import Data

```r
library(readxl)
alldata <- read_excel(
  "11.06.2025.Intervention.Team3.Clean.xlsx",
  col_names = TRUE)

alldata[alldata == -99] <- NA
alldata[alldata == -50] <- NA

# source: The FRI Playbook (McCarty, 2025)
# explanation: alldata with values as -99 or -50 will count as missing data and will therefore
```

Variable Selection

```r
library(dplyr)
selecteddata <- alldata %>%
  select(ZSPRE_IMM, ZSPRE_HEALTH, ZSPRE_WOMEN1, ZSPRE_WOMEN2, ZSPRE_ECONOMY, ZSPRE_DEI1, ZSPRE_

# source: R for Data Science - Data Transformation (Wickham et al., 2023)
# explanation: Selects variables to be used in the data analyses. Filter() cleans the data so
```

2.2.2.3 Transform

Zero Sum Belief Composites

```r
library(psych)
zerosum_keys <- list(
  PREZEROSUM = c("ZSPRE_IMM", "ZSPRE_HEALTH", "ZSPRE_WOMEN1", "ZSPRE_WOMEN2", "ZSPRE_ECONOMY",
  POSTZEROSUM = c("ZSPOST_IMMI", "ZSPOST_HEALTH", "ZSPOST_WOMEN1", "ZSPOST_WOMEN2", "ZSPOST_EC
)
```

```
# source: The FRI Playbook (McCarty, 2025)
# explanation: a list called zerosum_keys is created. This tells R which survey questions belor
```

```
zerosum_scores <- scoreItems(zerosum_keys, selecteddata)
composite_scores <- zerosum_scores$scores

selecteddata$PREZEROSUM <- composite_scores[, "PREZEROSUM"]
selecteddata$POSTZEROSUM <- composite_scores[, "POSTZEROSUM"]

# source: The FRI Playbook (McCarty, 2025)
# explanation: Extracts the scores from the PREZEROSUM and POSTZEROSUM lists and adds it to the
```

```
condition1_selecteddata <- selecteddata %>%
  filter(CONDITION == 1)

# source: The FRI Playbook (McCarty, 2025)
# expanation: creates a new dataset called condition1_selecteddata by taking the existing datas
```

Women's Rights Composites

```
library(psych)
women_keys <- list(
  PREZSWOMEN = c("ZSPRE_WOMEN1", "ZSPRE_WOMEN2"),
  POSTZSWOMEN = c("ZSPOST_WOMEN1", "ZSPOST_WOMEN2")
)

# source: The FRI Playbook (McCarty, 2025)
# explanation: a list called women_keys is created. This tells R which survey questions belong
```

```
women_scores <- scoreItems(women_keys, selecteddata)
composite_scores_women <- women_scores$scores

selecteddata$PREZSWOMEN <- composite_scores_women[, "PREZSWOMEN"]
selecteddata$POSTZSWOMEN <- composite_scores_women[, "POSTZSWOMEN"]

# source: The FRI Playbook (McCarty, 2025)
# explanation: Extracts the scores from the PREZSWOMEN and POSTZSWOMEN lists and adds it to the
```

```
condition2_selecteddata <- selecteddata %>%
  filter(CONDITION == 1)

# source: The FRI Playbook (McCarty, 2025)
# expanation: creates a new dataset called condition2_selecteddata by taking the existing datas
```

DEI Composites

```
library(psych)
DEI_keys <- list(
  PREZSDEI = c("ZSPRE_DEI1", "ZSPRE_DEI2"),
  POSTZSDEI = c("ZSPOST_DEI1", "ZSPOST_DEI1")
)

# source: The FRI Playbook (McCarty, 2025)
# explanation: a list called DEI_keys is created. This tells R which survey questions belong to
```

```
DEI_scores <- scoreItems(DEI_keys, selecteddata)
composite_scores_DEI <- DEI_scores$scores

selecteddata$PREZSDEI <- composite_scores_DEI[, "PREZSDEI"]
selecteddata$POSTZSDEI <- composite_scores_DEI[, "POSTZSDEI"]

# source: The FRI Playbook (McCarty, 2025)
# explanation: Extracts the scores from the PREZSDEI and POSTZSDEI lists and adds it to the dat
```

```
condition3_selecteddata <- selecteddata %>%
  filter(CONDITION == 1)

# source: The FRI Playbook (McCarty, 2025)
# expanation: creates a new dataset called condition3_selecteddata by taking the existing datas
```

Numeric Conversion

```
library(dplyr)

# Convert all ENGAGE columns to numeric using dplyr
selecteddata <- selecteddata %>%
 mutate(across(ends_with("_ENGAGE"), ~ as.numeric(as.character(.))))

# Verify conversion
cat("Checking ENGAGE column types:\n")
selecteddata %>%
  select(ends_with("_ENGAGE")) %>%
  sapply(class) %>%
  print()

# source: Team 2 code
# explanation: converts variables into numeric data
```

Environment Composites

```r
library(psych)
enviro_keys <- list(
  PREZSENVIRO = c("ZSPRE_ENVIRO1", "ZSPRE_ENVIRO2"),
  POSTZSENVIRO = c("ZSPOST_ENVIRO1", "ZSPOST_ENVIRO1")
)

# source: The FRI Playbook (McCarty, 2025)
# explanation: a list called enviro_keys is created. This tells R which survey questions belong
```

DEI Composites

```r
enviro_scores <- scoreItems(enviro_keys, selecteddata)
composite_scores_enviro <- enviro_scores$scores

selecteddata$PREZSENVIRO <- composite_scores_enviro[, "PREZSENVIRO"]
selecteddata$POSTZSENVIRO <- composite_scores_enviro[, "POSTZSENVIRO"]

# source: The FRI Playbook (McCarty, 2025)
# explanation: Extracts the scores from the PREZSENVIRO and POSTZSENVIRO lists and adds it to t
```

```r
condition5_selecteddata <- selecteddata %>%
  filter(CONDITION == 1)

# source: The FRI Playbook (McCarty, 2025)
# expanation: creates a new dataset called condition5_selecteddata by taking the existing datas
```

Alignment Composites

```r
library(psych)
ALIGN_keys <- list(
  POLARALIGN = c("POL_IMM_ALIGN", "POL_HEALTHC_ALIGN", "POL_WOMEN_ALIGN", "POL_ECONOMY_ALIGN",
  LEANALIGN = c("LEAN_IMM_ALIGN", "LEAN_HEALTHC_ALIGN", "LEAN_WOMEN_ALIGN", "LEAN_ECONOMY_ALIG
)

# source: The FRI Playbook (McCarty, 2025)
# explanation: a list called ALIGN_keys is created. This tells R which survey questions belong
```

```r
ALIGN_scores <- scoreItems(ALIGN_keys, selecteddata)
composite_scores_ALIGN <- ALIGN_scores$scores

selecteddata$POLARALIGN <- composite_scores_ALIGN[, "POLARALIGN"]
selecteddata$LEANALIGN <- composite_scores_ALIGN[, "LEANALIGN"]

ALIGN_vars <- c("POLARALIGN", "LEANALIGN")
# source: The FRI Playbook (McCarty, 2025)
# explanation: Extracts the scores from the POLARALIGN and LEANALIGN lists and adds it to the d
```

Engagement Composites

```
library(psych)
engagement_keys <- list(
  POLARENGAGEMENT = c("POL_IMM_ENGAGE", "POL_HEALTHC_ENGAGE", "POL_WOMEN_ENGAGE", "POL_ECONOMY_
  LEANENGAGEMENT = c("LEAN_IMM_ENGAGE", "LEAN_HEALTHC_ENGAGE", "LEAN_WOMEN_ENGAGE", "LEAN_ECON
)

# source: The FRI Playbook (McCarty, 2025)
# explanation: a list called engagement_keys is created. This tells R which survey questions be
```

```
library(psych)
engagement_scores <- psych::scoreItems(engagement_keys, selecteddata, missing = TRUE, impute =
composite_scores_engagement <- engagement_scores$scores

selecteddata$POLARENGAGEMENT <- composite_scores_engagement[, "POLARENGAGEMENT"]
selecteddata$LEANENGAGEMENT <- composite_scores_engagement[, "LEANENGAGEMENT"]

# The FRI Playbook (McCarty, 2025)
# explanation: Extracts the scores from the POLARENGAGEMENT and LEANENGAGEMENT lists and adds
```

Numeric Conversions

```
library(dplyr)

# Convert all POST ZERO SUM columns to numeric using dplyr
selecteddata <- selecteddata %>%
 mutate(across(starts_with("POST"), ~ as.numeric(as.character(.))))

# Verify conversion
cat("Checking POST ZERO SUM column types:\n")
selecteddata %>%
  select(starts_with("POST")) %>%
  sapply(class) %>%
  print()

# source: Team 2 code
# explanation: converts variables into numeric data
```

```
library(dplyr)

# Convert all PRE ZERO SUM columns to numeric using dplyr
selecteddata <- selecteddata %>%
 mutate(across(starts_with("PRE"), ~ as.numeric(as.character(.))))

# Verify conversion
```

```r
cat("Checking PRE ZERO SUM column types:\n")
selecteddata %>%
  select(starts_with("PRE")) %>%
  sapply(class) %>%
  print()

# source: Team 2 code
# explanation: converts variables into numeric data
```

```r
library(dplyr)

# Convert all ALIGN columns to numeric using dplyr
selecteddata <- selecteddata %>%
 mutate(across(ends_with("_ALIGN"), ~ as.numeric(as.character(.))))

# Verify conversion
cat("Checking ALIGN column types:\n")
selecteddata %>%
  select(ends_with("_ALIGN")) %>%
  sapply(class) %>%
  print()

# source: Team 2 code
# explanation: converts variables into numeric data
```

Reliability Analysis

```r
zerosum_scores

# source: The FRI Playbook (McCarty, 2025)
# explanation: Views reliability statistics to check consistency in measuring a construct. the
```

2.2.3 Data Analysis - Qualitative

The data were analyzed using the NVivo software to code qualitative data, and to aid in the generation of a visual representation of how specific engagement with zero-sum beliefs through polarizing content affects the prevalence of negative mental health. Data were screened for non-normal and normal distributions. Participants who did not consent, who did not answer the qualitative question, and who did not provide valid responses to the open-ended questions were deemed invalid respondents and removed. Both a directed and a conventional approach were employed while collecting and analyzing data. A directed approach is used when broadly adding to existing theories, which state that political polarization and engagement with zero-sum beliefs have negative implications for mental health. Additionally, this research also uses a conventional approach to coding, as the content is specific to the Qualtrics survey and produces responses from which codes emerge directly from the data. Data was first prepared by being exported to Excel from the Qualtrics survey. This data was then cleaned up in Excel based on the conventions of ineligibility explained above. The survey was then imported into the NVivo project, where analysis began. The following process was carried out twice: once for the polarizing content section of the survey and once for the leaning content section. Seven codes were created, which corresponded to each of the six videos within the section, and a seventh code was created for responses that did not specify a video. Open-ended responses were then sorted through, and different codes emerged. These emerging codes included reasons for distress given a specific video. Therefore, codes depicting reasons for distress were placed under the previous codes created for specific videos. Relevant information was then categorized within its respective code. Consequently, one participant had at least two different sets of code one that corresponds to a specific video and one that corresponds to a specific reason for distress. The resulting coded data indicated the number of files, representing both the participants and references that include the relevant content. Finally, a visual representation of this data was created into a bar plot to support findings. Additionally, various tables were created to exemplify quotes and define polarizing versus leaning content.

2.2.4 Mixed Methods

The study utilized a mixed methods design using a concurrent embedded design, where both quantitative and qualitative measures were collected at once. This is a commonly considered mixed-methods strategy (Bishop, 2015). The survey was designed using six blocks, where the first and second blocks asked participants questions regarding motivations to start and end social media sessions, promotion and prevention mindsets, self-esteem, and media literacy (although it is important to note that these measures were not explored in this particular study). The third block then questioned participants about their sociodemographics, political beliefs, feelings of hope and anxiety, and zero-sum beliefs. This was the first measure of participants' hope, anxiety, and zero-sum beliefs before the intervention. Following this questionnaire, the experimental intervention begins where participants are randomly placed into either the fourth block, where they are exposed to politically polarizing content, or the fifth block, where they are exposed to politically leaning content. The last block asks participants about their hope and anxiety feelings and zero-sum beliefs once again after the intervention.

Using a complementary approach, the qualitative data served to enhance the understanding of an individual's emotions after watching videos that exhibited zero-sum beliefs. For the experimental aspect of the survey, a well-being item allowed participants to choose from 5 emotions to explain how they felt after interacting with each content material. After the experiment, participants were asked the qualitative question of "If any of this content caused more distress for you, what specific videos and why?" This measure expands upon the quantitative wellness measure to allow participants to answer the question of why, which is vital for interpreting and understanding our results, as distress can be caused by many external factors. Understanding what specifically caused distress could enhance the results of our study and potentially introduce new information that could lead to future research regarding the interaction between zero-sum belief content and mental health. Quantitative data were analyzed using the R language and Quarto to visualize data for the frequencies with which different emotions were felt after interacting with each specific zero-sum belief. Qualitative data were analyzed using NVivo to code open-ended responses, employing both directed and conventional content analysis approaches to identify themes reflecting how engagement with zero-sum beliefs in polarizing content influences negative mental health outcomes. Visual representations such as word clouds, word trees, and frequency tables were generated to illustrate the prevalence and relationships among emergent codes.

3 Results

3.1 Descriptive Statistics

3.1.1 Sociodemographics

The final sample consisted of 80 undergraduate students aged 18–22 with a mean age of 18.97 and a standard deviation of 0.82, indicating that a majority of survey participants were on the younger side of being an undergraduate student. All other gender data (including nonbinary, other, don't know, and prefer not to say) was not included in testing. The sample's demographics contained 63.2% women (n=55) and 29.9% men (n=26). All other gender data (including nonbinary, other, don't know, and prefer not to say) was not included in testing. Of these respondents, 75% leaned left politically (n=66), and 5.68% leaned right (n=5), with 8 participants being moderate (n=8) and 9 not providing an affiliation (n=9). For political affiliation analysis purposes, only participants who identified as liberal or conservative were included.

Demographically speaking, this sample is not fully representative of undergraduate students in the United States. With gender, undergraduates are ~42.7% male, and ~57.3% female (Hanson, 2025). Politically, students are ~47% liberal, ~21% conservative, and ~16% moderate (Stevens, 2024). The sample collected by this study, thus, may underrepresent men and conservatives, while overrepresenting liberals.

3.1.2 Primary Variables

The main quantitative variables coded were related to zero-sum beliefs, hope, and anxiety. Scores for these were collected both before and after the content intervention. Zero-sum scores were composited, and pre-intervention (`PREZEROSUM`) had an value of 0.65, with an value of 0.59 after the intervention (`POSTZEROSUM`). Hope and anxiety scores, along with composite zero-sum scores, were not normally distributed. Thus, Wilcoxon Signed-Rank Tests were performed to find possible significant changes or correlations.

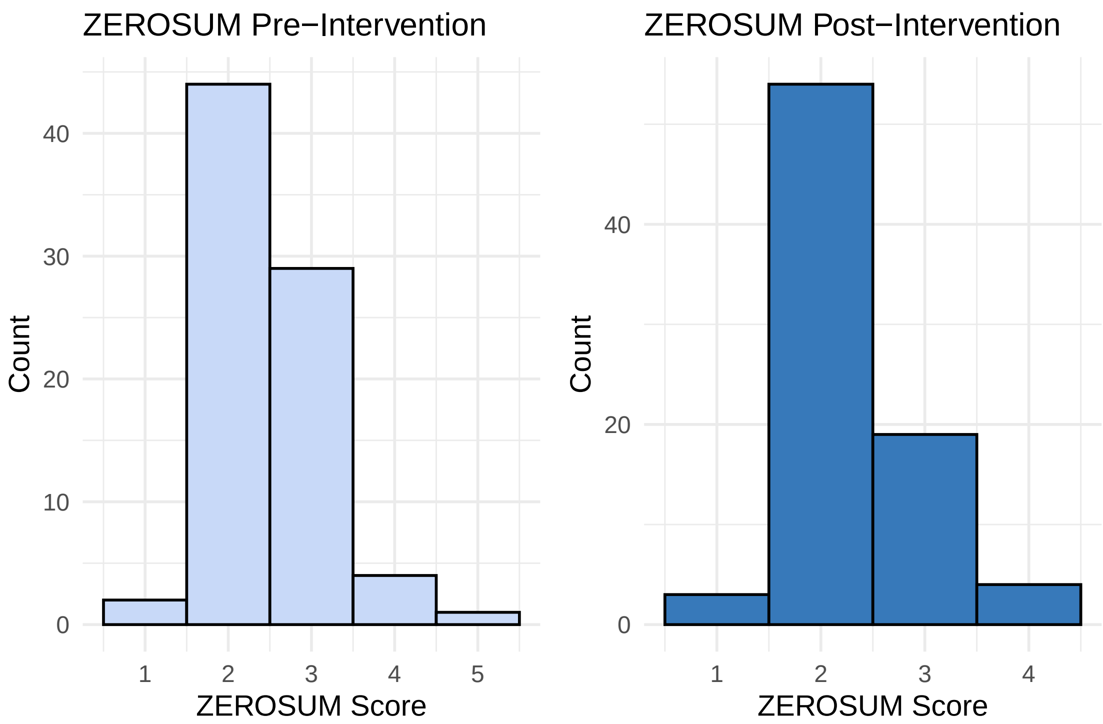
Zero-sum Beliefs Histogram

```
p1 <- ggplot(selecteddata, aes(x = PREZEROSUM)) +
  geom_histogram(binwidth = 1, fill = "#c8d9f8", color = "black") +
  labs(title = "ZEROSUM Pre-Intervention", x = "ZEROSUM Score", y = "Count") + theme_minimal()

p2 <- ggplot(selecteddata, aes(x = POSTZEROSUM)) +
  geom_histogram(binwidth = 1, fill = "#3779ba", color = "black") +
  labs(title = "ZEROSUM Post-Intervention", x = "ZEROSUM Score", y = "Count") + theme_minimal(

zshistogram <- p1 + p2

zshistogram
```




```
ggsave("Pre and Post Intervention Zero Sum Histogram.png", plot = zshistogram)

# source: R for Data Science - Data Visualization (Wickham et al., 2023)
# explanation: creates two histograms to display the distrubution of participants' zerosum sco
```

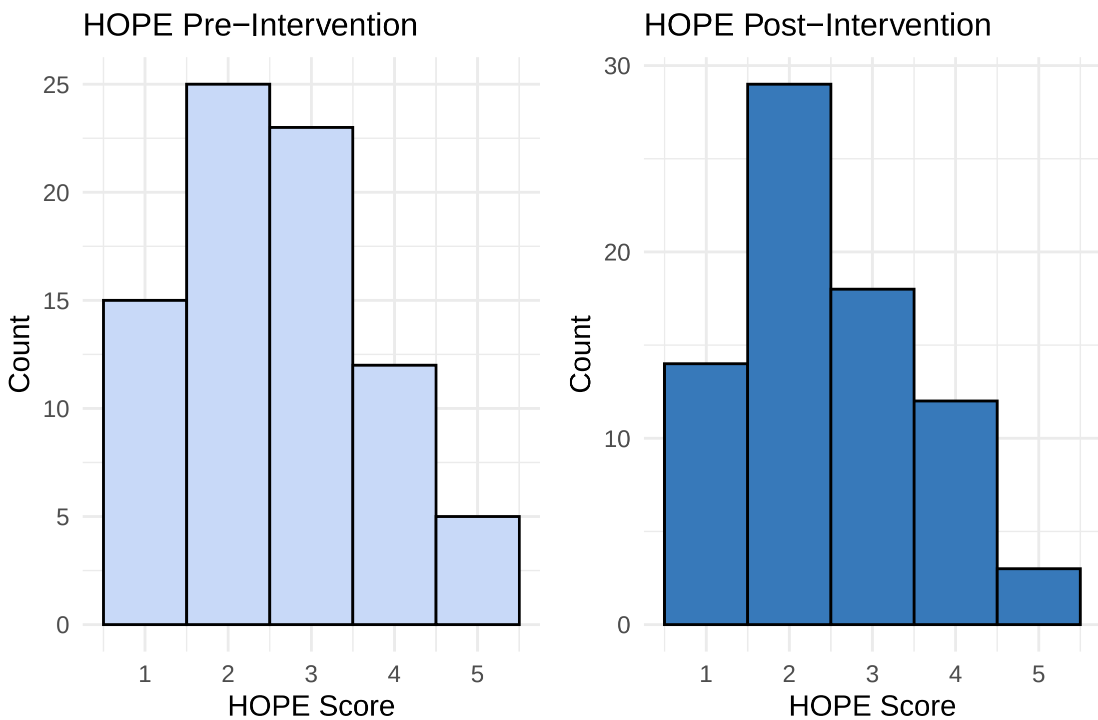
Hope Histogram

```
p3 <- ggplot(selecteddata, aes(x = PRE_HOPE)) +
  geom_histogram(binwidth = 1, fill = "#c8d9f8", color = "black") +
  labs(title = "HOPE Pre-Intervention", x = "HOPE Score", y = "Count") + theme_minimal() + ther

p4 <- ggplot(selecteddata, aes(x = POST_HOPE)) +
  geom_histogram(binwidth = 1, fill = "#3779ba", color = "black") +
  labs(title = "HOPE Post-Intervention", x = "HOPE Score", y = "Count") + theme_minimal() + the

hopehistogram <- p3 + p4

hopehistogram
```




```
ggsave("Pre and Post Intervention Hope Histogram.png", plot = hopehistogram)

# source: R for Data Science - Data Visualization (Wickham et al., 2023)
# explanation: creates two histograms to display the distrubution of participants' hope scores
```

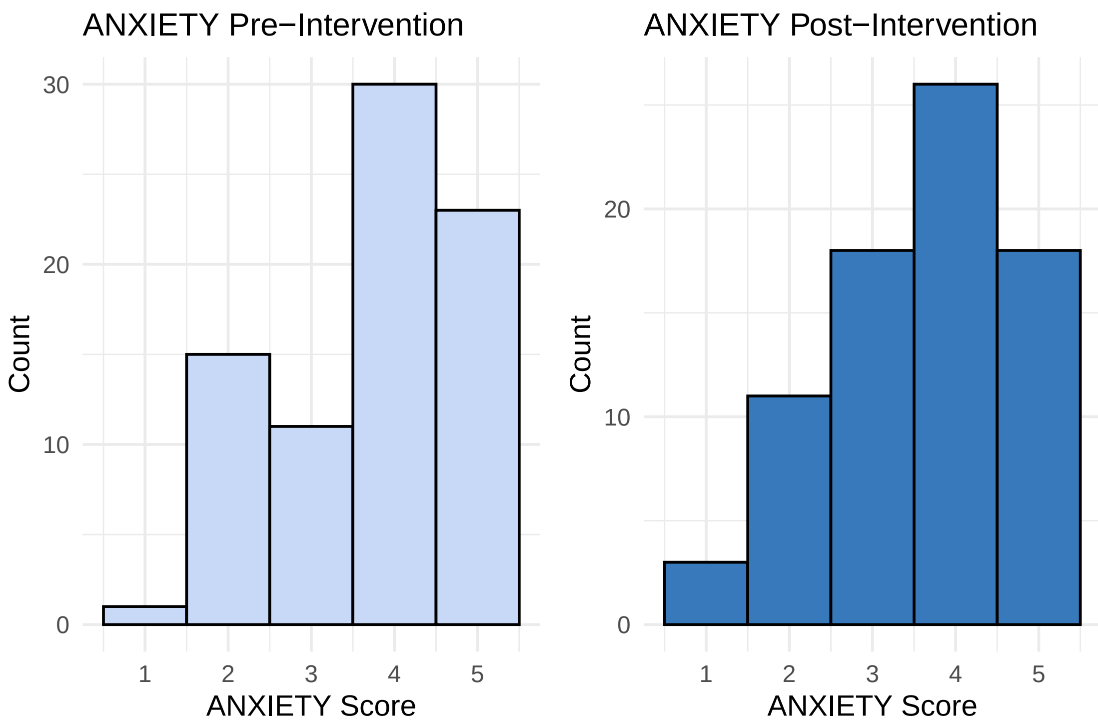
Anxiety Histogram

```
p5 <- ggplot(selecteddata, aes(x = PRE_ANXIETY)) +
  geom_histogram(binwidth = 1, fill = "#c8d9f8", color = "black") +
  labs(title = "ANXIETY Pre-Intervention", x = "ANXIETY Score", y = "Count") + theme_minimal()

p6 <- ggplot(selecteddata, aes(x = POST_ANXIETY)) +
  geom_histogram(binwidth = 1, fill = "#3779ba", color = "black") +
  labs(title = "ANXIETY Post-Intervention", x = "ANXIETY Score", y = "Count") + theme_minimal(

anxietyhistogram <- p5 + p6

anxietyhistogram
```




```
ggsave("Pre and Post Intervention Anxiety Histogram.png", plot = anxietyhistogram)
# source: R for Data Science - Data Visualization (Wickham et al., 2023)
# explanation: creates two histograms to display the distrubution of participants' anxiety sco
```

3.2 Quantitative Findings

3.2.1 Zero-sum Beliefs

Figure 1 depicts the overall composite of respondents' zero-sum beliefs, comparing how they rated their beliefs pre- and post-viewing of the selected social media videos. The histograms for pretest (PREZEROSUM) and posttest (POSTZEROSUM) zero-sum data were not normally distributed, so a Wilcoxon Signed-Rank Test was performed to examine differences in pre- and post-test scores. Pre-intervention and post-intervention scores were significantly different (V = 480, p =.0034).

Impact of zero-sum videos: pre- vs. post-intervention

```
# Create long data with participant ID
paired_data_long <- condition1_selecteddata %>%
  select(POSTZEROSUM, PREZEROSUM) %>%
  filter(!is.na(POSTZEROSUM) & !is.na(PREZEROSUM)) %>% # Remove missing pairs
  mutate(ID = row_number()) %>%
  pivot_longer(cols = c(PREZEROSUM, POSTZEROSUM),
               names_to = "Composite",
               values_to = "Score") %>%
  mutate(Composite = factor(Composite, levels = c("PREZEROSUM", "POSTZEROSUM"))) # changes the
```

```r
# Plot: boxplot + paired lines
zero_sum_figure <- ggplot(paired_data_long, aes(x = Composite, y = Score, group = ID)) +
  geom_boxplot(aes(group = Composite), width = 0.5, alpha = 0.3, fill = "white", outlier.shape
  geom_line(color = "gray70", alpha = 0.6) +
  geom_point(data = paired_data_long %>%
             filter(Composite == "POSTZEROSUM"),
             shape = 16, size = 3, color = "#3779ba") +
  geom_point(data = paired_data_long %>%
             filter(Composite == "PREZEROSUM"),
             shape = 17, size = 3, color = "#c8d9f8") +
  labs(title = "Pre vs. Post Intervention with Zero-sum Videos",
       x = "Intervention Period", y = "Score") +
  theme_minimal() + theme(plot.title = element_text(size = 12))

zero_sum_figure
```

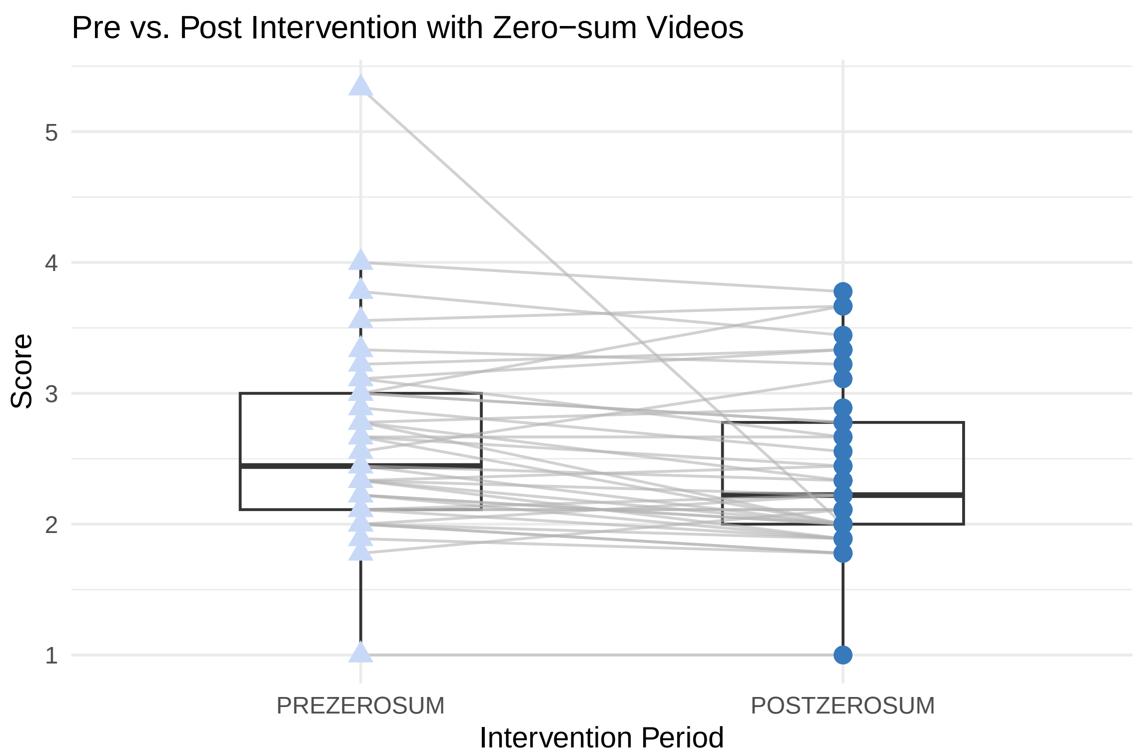


Figure 1: figure 1. Paired pre- and post-intervention zero-sum beliefs of participants. Boxplots show overall distributions with lines connecting participants scores before and after the intervention.

```r
ggsave("Paired Samples: Pre vs. Post Intervention with Zero-sum Videos.png", plot = zero_sum_fi

# source: Zero-sum social identity, not zero-sum economic beliefs, explain voting preference in
# explanation: Compares participants' zero-sum beliefs scores before and after watching interve
```

```r
wilcox.test(condition1_selecteddata$PREZEROSUM, condition1_selecteddata$POSTZEROSUM, paired = T
```

```
	Wilcoxon signed rank test with continuity correction

data:  condition1_selecteddata$PREZEROSUM and condition1_selecteddata$POSTZEROSUM
V = 480, p-value = 0.003359
alternative hypothesis: true location shift is greater than 0
```

```r
# source: Paired Samples Wilcoxon Test in R (STHDA, n.d.)
# explanation: Performs a Wilcoxon Signed-Rank Test to compare participants' zero-sum scores pr
```

Impact of zero-sum immigration videos: pre- vs. post-intervention

```r
# Create long data with participant ID
paired_data_long <- condition1_selecteddata %>%
  select(ZSPRE_IMM, ZSPOST_IMMI) %>%
  filter(!is.na(ZSPRE_IMM) & !is.na(ZSPOST_IMMI)) %>% # Remove missing pairs
  mutate(ID = row_number()) %>%
  pivot_longer(cols = c(ZSPOST_IMMI, ZSPRE_IMM),
               names_to = "Composite",
               values_to = "Score") %>%
  mutate(Composite = factor(Composite, levels = c("ZSPRE_IMM", "ZSPOST_IMMI"))) # changes the o

# Plot: boxplot + paired lines
immigration_figure <- ggplot(paired_data_long, aes(x = Composite, y = Score, group = ID)) +
  geom_boxplot(aes(group = Composite), width = 0.5, alpha = 0.3, fill = "white", outlier.shape
  geom_line(color = "gray70", alpha = 0.6) +
  geom_point(data = paired_data_long %>%
             filter(Composite == "ZSPRE_IMM"),
             shape = 16, size = 3, color = "#c8d9f8") +
  geom_point(data = paired_data_long %>%
             filter(Composite == "ZSPOST_IMMI"),
             shape = 17, size = 3, color = "#3779ba") +
  labs(title = "Pre vs. Post Intervention with Zero-sum Immigration Videos",
       x = "Intervention Period", y = "Score") +
  theme_minimal() + theme(plot.title = element_text(size = 12))

immigration_figure
```

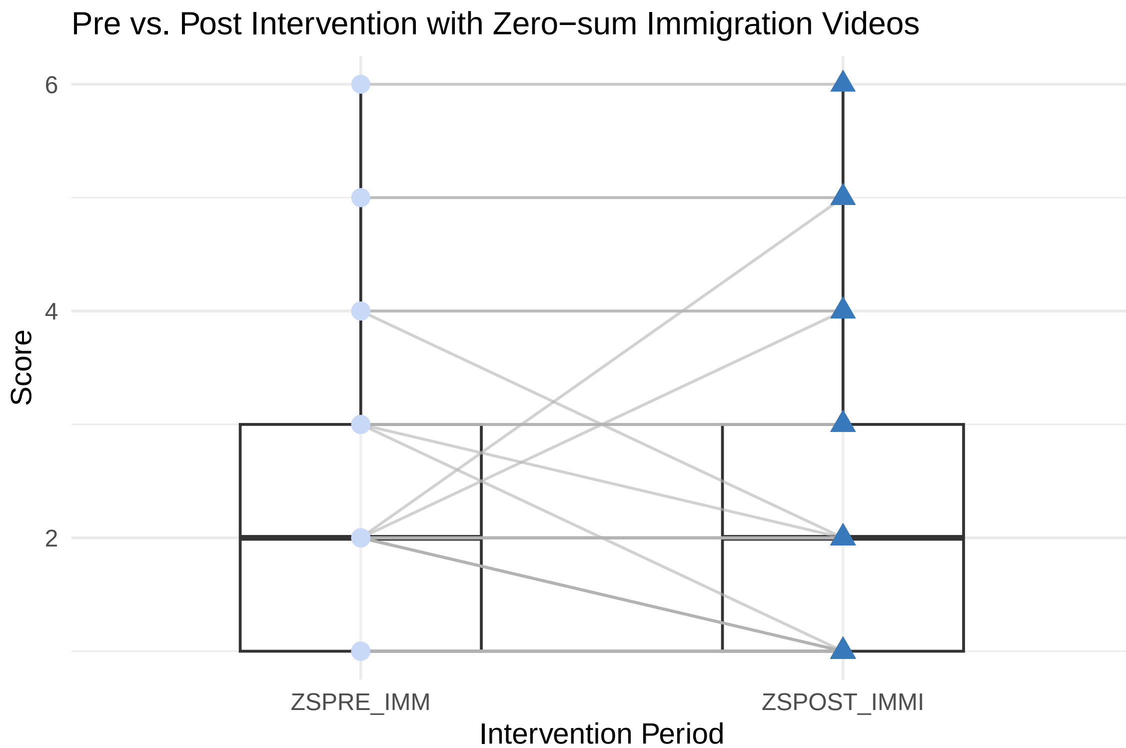


Figure 2: figure 2. Paired pre- and post-intervention immigration zero-sum beliefs of participants. Boxplots show overall distributions with lines connecting participants scores before and after the intervention.

```
ggsave("Pre vs. Post Intervention with Zero-sum Immigration Videos.png", plot = immigration_fi

# source: Zero-sum social identity, not zero-sum economic beliefs, explain voting preference i
# explanation: Compares participants' immigration zero-sum beliefs scores before and after wat
```

```
wilcox.test(condition1_selecteddata$ZSPRE_IMM, condition1_selecteddata$ZSPOST_IMMI, paired = T
```

```
	Wilcoxon signed rank test with continuity correction

data:  condition1_selecteddata$ZSPRE_IMM and condition1_selecteddata$ZSPOST_IMMI
V = 37, p-value = 0.1732
alternative hypothesis: true location shift is greater than 0
```

```
# source: Paired Samples Wilcoxon Test in R (STHDA, n.d.)
# explanation: Performs a Wilcoxon Signed-Rank Test to compare participants' zero-sum scores p
```

Impact of zero-sum healthcare videos: pre- vs. post-intervention

```
# Create long data with participant ID
paired_data_long <- condition1_selecteddata %>%
  select(ZSPRE_HEALTH, ZSPOST_HEALTH) %>%
  filter(!is.na(ZSPRE_HEALTH) & !is.na(ZSPOST_HEALTH)) %>% # Remove missing pairs
  mutate(ID = row_number()) %>%
  pivot_longer(cols = c(ZSPOST_HEALTH, ZSPRE_HEALTH),
               names_to = "Composite",
               values_to = "Score") %>%
  mutate(Composite = factor(Composite, levels = c("ZSPRE_HEALTH", "ZSPOST_HEALTH"))) # changes

# Plot: boxplot + paired lines
healthcare_figure <- ggplot(paired_data_long, aes(x = Composite, y = Score, group = ID)) +
  geom_boxplot(aes(group = Composite), width = 0.5, alpha = 0.3, fill = "white", outlier.shape
  geom_line(color = "gray70", alpha = 0.6) +
  geom_point(data = paired_data_long %>%
             filter(Composite == "ZSPRE_HEALTH"),
             shape = 16, size = 3, color = "#c8d9f8") +
  geom_point(data = paired_data_long %>%
             filter(Composite == "ZSPOST_HEALTH"),
             shape = 17, size = 3, color = "#3779ba") +
  labs(title = "Pre vs. Post Intervention with Zero-sum Healthcare Videos",
       x = "Intervention Period", y = "Score") +
  theme_minimal() + theme(plot.title = element_text(size = 12))

healthcare_figure
```

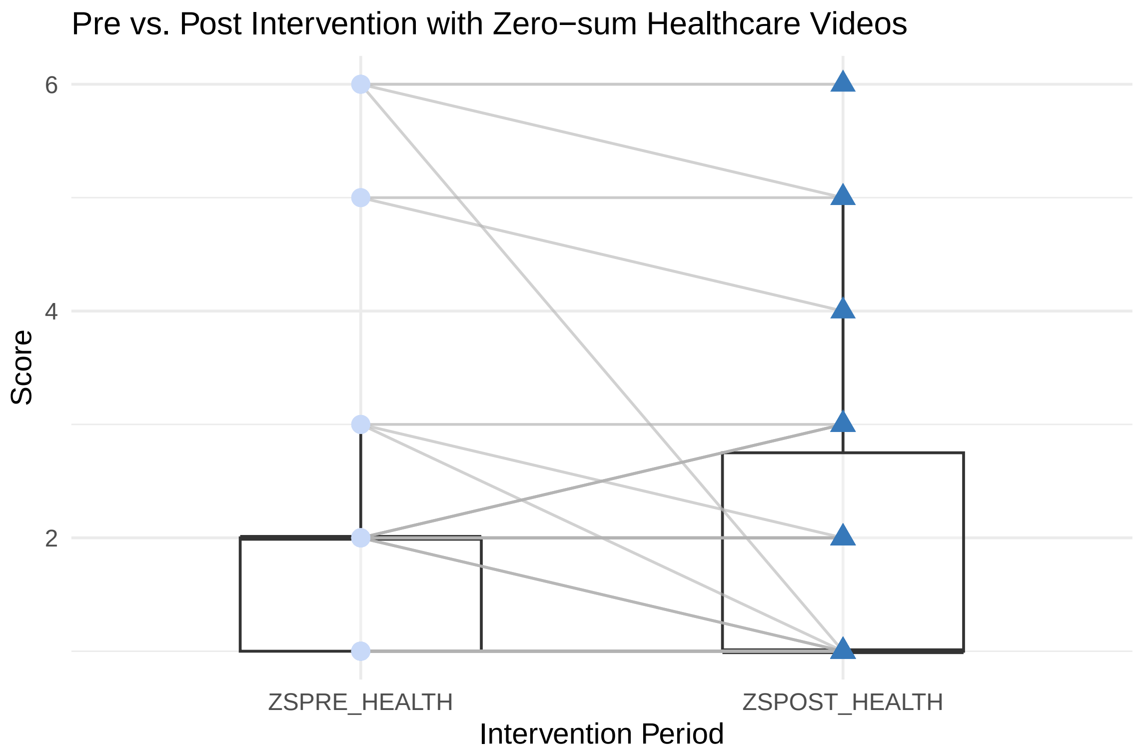


Figure 3: figure 3. Paired pre- and post-intervention healthcare zero-sum beliefs of participants. Boxplots show overall distributions with lines connecting participants scores before and after the intervention.

```
ggsave("Pre vs. Post Intervention with Zero-sum Healthcare Videos.png", plot = healthcare_figu

# source: Zero-sum social identity, not zero-sum economic beliefs, explain voting preference i
# explanation: Compares participants' healthcare zero-sum beliefs scores before and after watc
```

```
wilcox.test(condition1_selecteddata$ZSPRE_HEALTH, condition1_selecteddata$ZSPOST_HEALTH, paire
```

```
    Wilcoxon signed rank test with continuity correction

data:  condition1_selecteddata$ZSPRE_HEALTH and condition1_selecteddata$ZSPOST_HEALTH
V = 56, p-value = 0.08299
alternative hypothesis: true location shift is greater than 0
```

```
# source: Paired Samples Wilcoxon Test in R (STHDA, n.d.)
# explanation: Performs a Wilcoxon Signed-Rank Test to compare participants' zero-sum scores p
```

Impact of zero-sum women's rights videos: pre- vs. post-intervention

```
# Create long data with participant ID
paired_data_long <- condition1_selecteddata %>%
  select(ZSPRE_WOMEN1, ZSPOST_WOMEN1) %>%
  filter(!is.na(ZSPRE_WOMEN1) & !is.na(ZSPOST_WOMEN1)) %>% # Remove missing pairs
  mutate(ID = row_number()) %>%
  pivot_longer(cols = c(ZSPRE_WOMEN1, ZSPOST_WOMEN1),
               names_to = "Composite",
               values_to = "Score") %>%
  mutate(Composite = factor(Composite, levels = c("ZSPRE_WOMEN1", "ZSPOST_WOMEN1"))) # changes

# Plot: boxplot + paired lines
women_figure <- ggplot(paired_data_long, aes(x = Composite, y = Score, group = ID)) +
  geom_boxplot(aes(group = Composite), width = 0.5, alpha = 0.3, fill = "white", outlier.shape
  geom_line(color = "gray70", alpha = 0.6) +
  geom_point(data = paired_data_long %>%
             filter(Composite == "ZSPRE_WOMEN1"),
             shape = 16, size = 3, color = "#c8d9f8") +
  geom_point(data = paired_data_long %>%
             filter(Composite == "ZSPOST_WOMEN1"),
             shape = 17, size = 3, color = "#3779ba") +
  labs(title = "Pre vs. Post Intervention with Zero-sum Women's Rights Videos 1",
       x = "Intervention Period", y = "Score") +
  theme_minimal() + theme(plot.title = element_text(size = 12))

women_figure
```

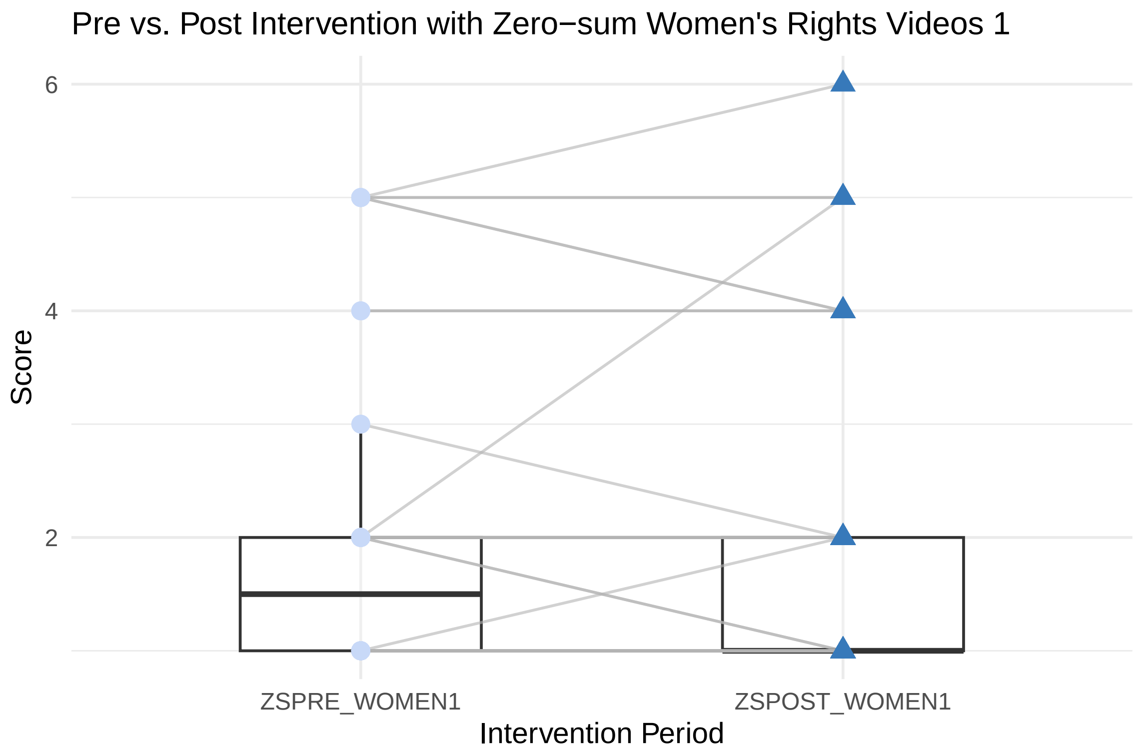


Figure 4: figure 4. Paired pre- and post-intervention women's rights zero-sum beliefs of participants. Boxplots show overall distributions with lines connecting participants scores before and after the intervention.

```
ggsave("Pre vs. Post Intervention with Zero-sum Women's Rights Videos.png", plot = women_figure

# source: Zero-sum social identity, not zero-sum economic beliefs, explain voting preference i
# explanation: Compares participants' women's rights zero-sum beliefs scores before and after
```

```
wilcox.test(condition1_selecteddata$ZSPRE_WOMEN1, condition1_selecteddata$ZSPOST_WOMEN1, paire
```

```
	Wilcoxon signed rank test with continuity correction

data:  condition1_selecteddata$ZSPRE_WOMEN1 and condition1_selecteddata$ZSPOST_WOMEN1
V = 20, p-value = 0.4105
alternative hypothesis: true location shift is greater than 0
```

```
# source: Paired Samples Wilcoxon Test in R (STHDA, n.d.)
# explanation: Performs a Wilcoxon Signed-Rank Test to compare participants' zero-sum scores p
```

```
# Create long data with participant ID
paired_data_long <- condition1_selecteddata %>%
  select(ZSPRE_WOMEN2, ZSPOST_WOMEN2) %>%
```

```r
  filter(!is.na(ZSPRE_WOMEN2) & !is.na(ZSPOST_WOMEN2)) %>% # Remove missing pairs
  mutate(ID = row_number()) %>%
  pivot_longer(cols = c(ZSPRE_WOMEN2, ZSPOST_WOMEN2),
               names_to = "Composite",
               values_to = "Score") %>%
  mutate(Composite = factor(Composite, levels = c("ZSPRE_WOMEN2", "ZSPOST_WOMEN2"))) # changes

# Plot: boxplot + paired lines
women_figure <- ggplot(paired_data_long, aes(x = Composite, y = Score, group = ID)) +
  geom_boxplot(aes(group = Composite), width = 0.5, alpha = 0.3, fill = "white", outlier.shape
  geom_line(color = "gray70", alpha = 0.6) +
  geom_point(data = paired_data_long %>%
             filter(Composite == "ZSPRE_WOMEN2"),
             shape = 16, size = 3, color = "#c8d9f8") +
  geom_point(data = paired_data_long %>%
             filter(Composite == "ZSPOST_WOMEN2"),
             shape = 17, size = 3, color = "#3779ba") +
  labs(title = "Pre vs. Post Intervention with Zero-sum Women's Rights Videos 2",
       x = "Intervention Period", y = "Score") +
  theme_minimal() + theme(plot.title = element_text(size = 12))

women_figure
```

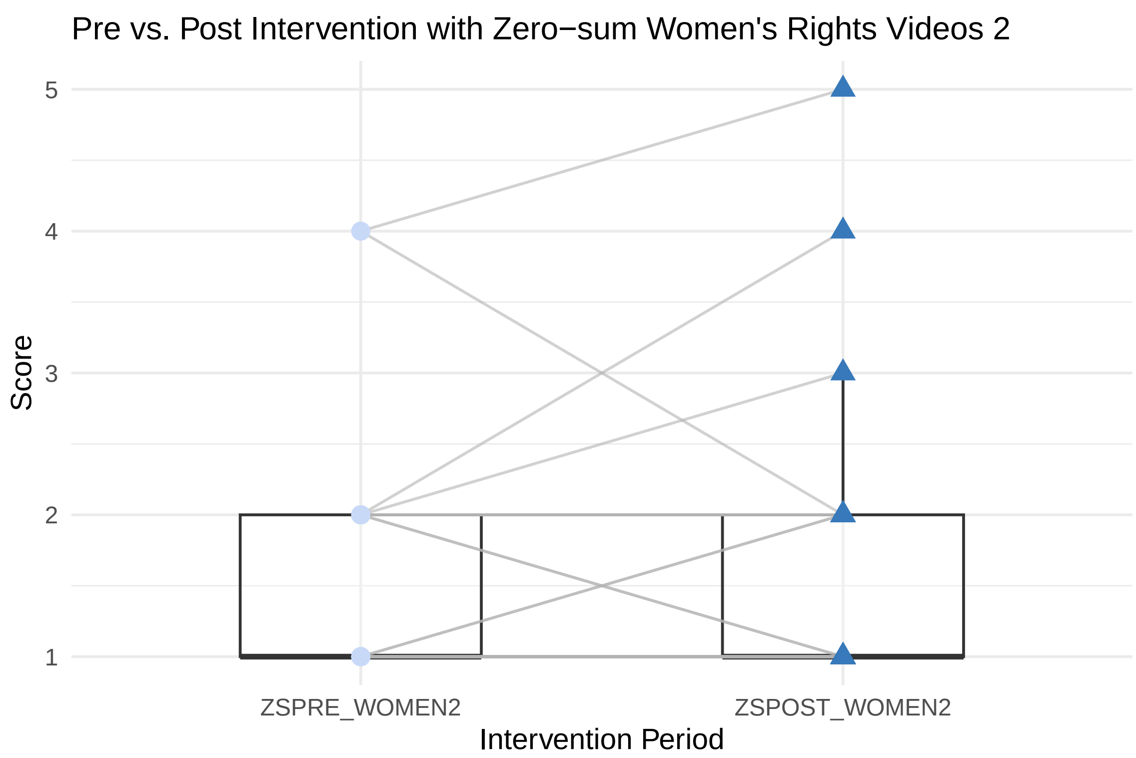


Figure 5: figure 5. Paired pre- and post-intervention women's rights zero-sum beliefs of participants. Boxplots show overall distributions with lines connecting participants scores before and after the intervention.

```
ggsave("Pre vs. Post Intervention with Zero-sum Women's Rights Videos 2.png", plot = women_figu

# source: Zero-sum social identity, not zero-sum economic beliefs, explain voting preference in
# explanation: Compares participants' women's rights zero-sum beliefs scores before and after w
```

```
wilcox.test(condition1_selecteddata$ZSPRE_WOMEN2, condition1_selecteddata$ZSPOST_WOMEN2, paired
```

```

    Wilcoxon signed rank test with continuity correction

data:  condition1_selecteddata$ZSPRE_WOMEN2 and condition1_selecteddata$ZSPOST_WOMEN2
V = 14.5, p-value = 0.7213
alternative hypothesis: true location shift is greater than 0
```

```
# source: Paired Samples Wilcoxon Test in R (STHDA, n.d.)
# explanation: Performs a Wilcoxon Signed-Rank Test to compare participants' zero-sum scores pr
```

Impact of zero-sum economy videos: pre- vs. post-intervention

```r
# Create long data with participant ID
paired_data_long <- condition1_selecteddata %>%
  select(ZSPRE_ECONOMY, ZSPOST_ECONOMY) %>%
  filter(!is.na(ZSPRE_ECONOMY) & !is.na(ZSPOST_ECONOMY)) %>% # Remove missing pairs
  mutate(ID = row_number()) %>%
  pivot_longer(cols = c(ZSPRE_ECONOMY, ZSPOST_ECONOMY),
               names_to = "Composite",
               values_to = "Score") %>%
  mutate(Composite = factor(Composite, levels = c("ZSPRE_ECONOMY", "ZSPOST_ECONOMY"))) # chang

# Plot: boxplot + paired lines
economy_figure <- ggplot(paired_data_long, aes(x = Composite, y = Score, group = ID)) +
  geom_boxplot(aes(group = Composite), width = 0.5, alpha = 0.3, fill = "white", outlier.shape
  geom_line(color = "gray70", alpha = 0.6) +
  geom_point(data = paired_data_long %>%
             filter(Composite == "ZSPRE_ECONOMY"),
             shape = 16, size = 3, color = "#c8d9f8") +
  geom_point(data = paired_data_long %>%
             filter(Composite == "ZSPOST_ECONOMY"),
             shape = 17, size = 3, color = "#3779ba") +
  labs(title = "Pre vs. Post Intervention with Zero-sum Economy Videos",
       x = "Intervention Period", y = "Score") +
  theme_minimal() + theme(plot.title = element_text(size = 12))

economy_figure
```

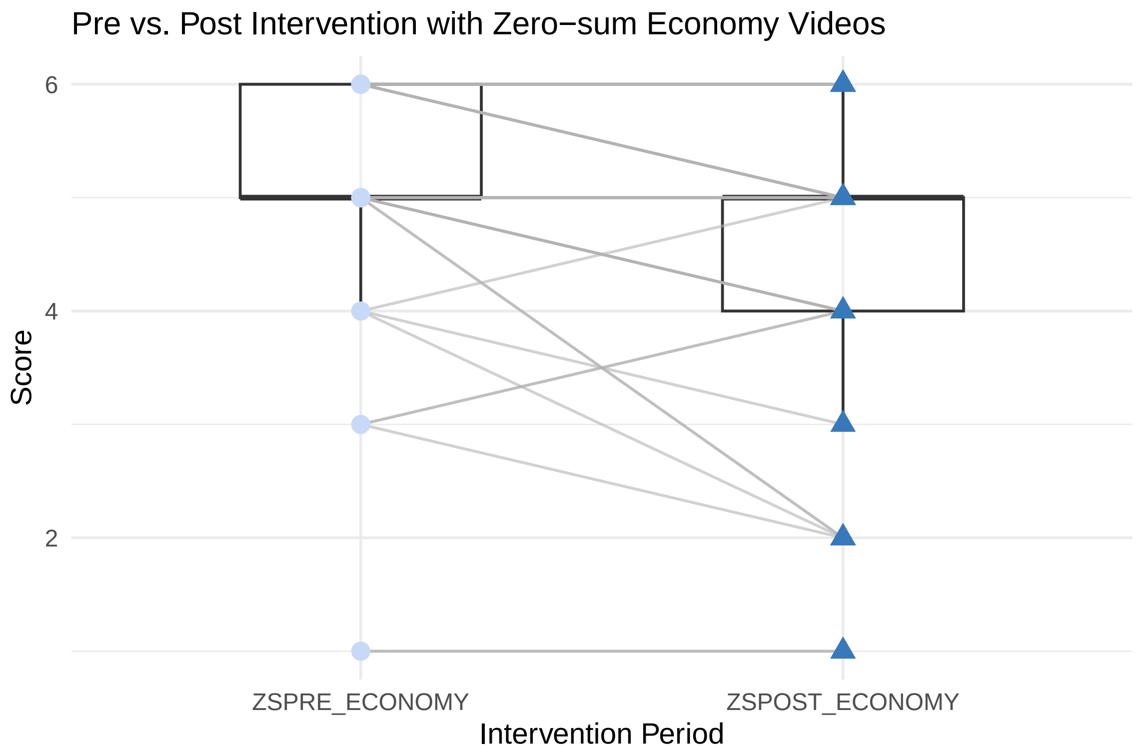


Figure 6: figure 6. Paired pre- and post-intervention economy zero-sum beliefs of participants. Boxplots show overall distributions with lines connecting participants scores before and after the intervention.

```
ggsave("Pre vs. Post Intervention with Zero-sum Economy Videos.png", plot = economy_figure)

# source: Zero-sum social identity, not zero-sum economic beliefs, explain voting preference in
# explanation: Compares participants' economy zero-sum beliefs scores before and after watching
```

```
wilcox.test(condition1_selecteddata$ZSPRE_ECONOMY, condition1_selecteddata$ZSPOST_ECONOMY, pai
```

```

	Wilcoxon signed rank test with continuity correction

data:  condition1_selecteddata$ZSPRE_ECONOMY and condition1_selecteddata$ZSPOST_ECONOMY
V = 164.5, p-value = 0.001393
alternative hypothesis: true location shift is greater than 0
```

```
# source: Paired Samples Wilcoxon Test in R (STHDA, n.d.)
# explanation: Performs a Wilcoxon Signed-Rank Test to compare participants' zero-sum scores pr
```

Impact of zero-sum DEI videos: pre- vs. post-intervention

```
# Create long data with participant ID
paired_data_long <- condition1_selecteddata %>%
  select(ZSPRE_DEI1, ZSPOST_DEI1) %>%
  filter(!is.na(ZSPRE_DEI1) & !is.na(ZSPOST_DEI1)) %>% # Remove missing pairs
  mutate(ID = row_number()) %>%
  pivot_longer(cols = c(ZSPRE_DEI1, ZSPOST_DEI1),
               names_to = "Composite",
               values_to = "Score") %>%
  mutate(Composite = factor(Composite, levels = c("ZSPRE_DEI1", "ZSPOST_DEI1"))) # changes the

# Plot: boxplot + paired lines
dei_figure <- ggplot(paired_data_long, aes(x = Composite, y = Score, group = ID)) +
  geom_boxplot(aes(group = Composite), width = 0.5, alpha = 0.3, fill = "white", outlier.shape
  geom_line(color = "gray70", alpha = 0.6) +
  geom_point(data = paired_data_long %>%
             filter(Composite == "ZSPRE_DEI1"),
             shape = 16, size = 3, color = "#c8d9f8") +
  geom_point(data = paired_data_long %>%
             filter(Composite == "ZSPOST_DEI1"),
             shape = 17, size = 3, color = "#3779ba") +
  labs(title = "Pre vs. Post Intervention with Zero-sum DEI Videos 1",
       x = "Intervention Period", y = "Score") +
  theme_minimal() + theme(plot.title = element_text(size = 12))

dei_figure
```

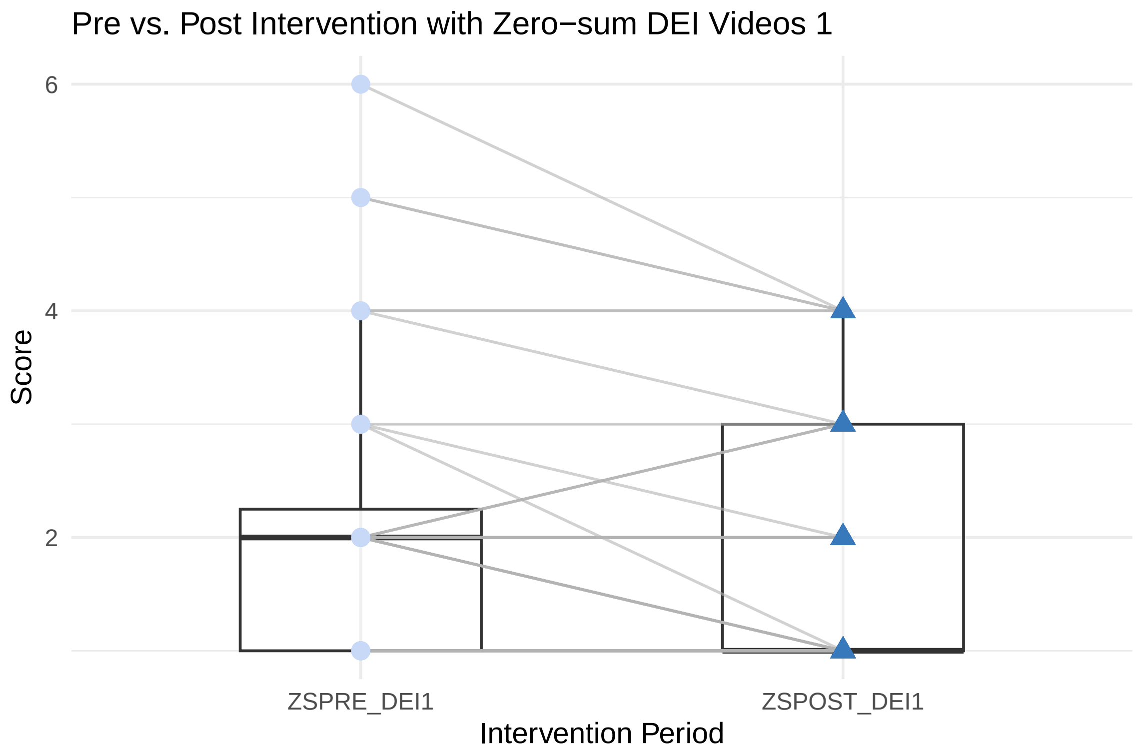


Figure 7: figure 7. Paired pre- and post-intervention DEI zero-sum beliefs of participants. Boxplots show overall distributions with lines connecting participants scores before and after the intervention.

```
ggsave("Pre vs. Post Intervention with Zero-sum DEI Videos.png", plot = dei_figure)

# source: Zero-sum social identity, not zero-sum economic beliefs, explain voting preference i
# explanation: Compares participants' economy zero-sum beliefs scores before and after watchin
```

```
wilcox.test(condition1_selecteddata$ZSPRE_DEI1, condition1_selecteddata$ZSPOST_DEI1, paired =
```

```

	Wilcoxon signed rank test with continuity correction

data:  condition1_selecteddata$ZSPRE_DEI1 and condition1_selecteddata$ZSPOST_DEI1
V = 85.5, p-value = 0.01384
alternative hypothesis: true location shift is greater than 0
```

```
# source: Paired Samples Wilcoxon Test in R (STHDA, n.d.)
# explanation: Performs a Wilcoxon Signed-Rank Test to compare participants' zero-sum scores p
```

```
# Create long data with participant ID
paired_data_long <- condition1_selecteddata %>%
  select(ZSPRE_DEI2, ZSPOST_DEI2) %>%
```

```r
  filter(!is.na(ZSPRE_DEI2) & !is.na(ZSPOST_DEI2)) %>% # Remove missing pairs
  mutate(ID = row_number()) %>%
  pivot_longer(cols = c(ZSPRE_DEI2, ZSPOST_DEI2),
               names_to = "Composite",
               values_to = "Score") %>%
  mutate(Composite = factor(Composite, levels = c("ZSPRE_DEI2", "ZSPOST_DEI2"))) # changes the

# Plot: boxplot + paired lines
dei_figure <- ggplot(paired_data_long, aes(x = Composite, y = Score, group = ID)) +
  geom_boxplot(aes(group = Composite), width = 0.5, alpha = 0.3, fill = "white", outlier.shape
  geom_line(color = "gray70", alpha = 0.6) +
  geom_point(data = paired_data_long %>%
             filter(Composite == "ZSPRE_DEI2"),
             shape = 16, size = 3, color = "#c8d9f8") +
  geom_point(data = paired_data_long %>%
             filter(Composite == "ZSPOST_DEI2"),
             shape = 17, size = 3, color = "#3779ba") +
  labs(title = "Pre vs. Post Intervention with Zero-sum DEI Videos 2",
       x = "Intervention Period", y = "Score") +
  theme_minimal() + theme(plot.title = element_text(size = 12))

dei_figure
```

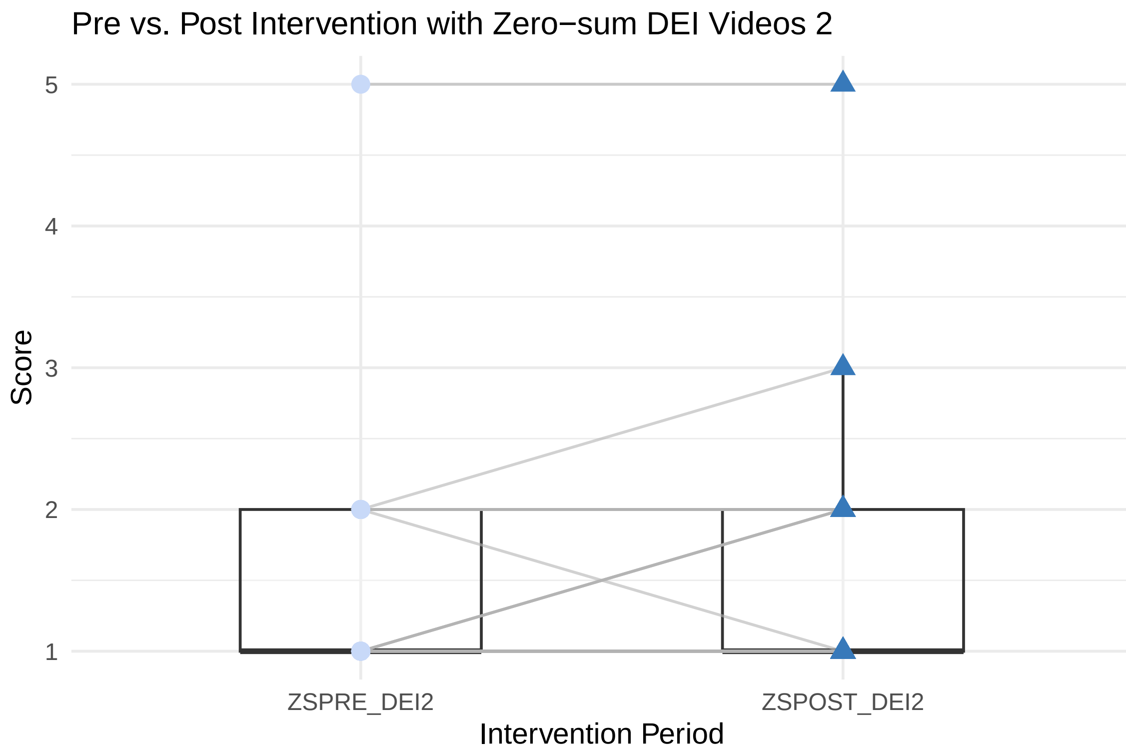


Figure 8: figure 8. Paired pre- and post-intervention DEI zero-sum beliefs of participants. Boxplots show overall distributions with lines connecting participants scores before and after the intervention.

```
ggsave("Pre vs. Post Intervention with Zero-sum DEI Videos 2.png", plot = dei_figure)

# source: Zero-sum social identity, not zero-sum economic beliefs, explain voting preference in
# explanation: Compares participants' economy zero-sum beliefs scores before and after watching
```

```
wilcox.test(condition1_selecteddata$ZSPRE_DEI2, condition1_selecteddata$ZSPOST_DEI2, paired = T
```

```

	Wilcoxon signed rank test with continuity correction

data:  condition1_selecteddata$ZSPRE_DEI2 and condition1_selecteddata$ZSPOST_DEI2
V = 3.5, p-value = 0.9599
alternative hypothesis: true location shift is greater than 0
```

```
# source: Paired Samples Wilcoxon Test in R (STHDA, n.d.)
# explanation: Performs a Wilcoxon Signed-Rank Test to compare participants' zero-sum scores pr
```

Impact of zero-sum environment videos: pre- vs. post-intervention

```
# Create long data with participant ID
paired_data_long<- condition1_selecteddata %>%
  select(ZSPRE_ENVIRO1, ZSPOST_ENVIRO1) %>%
  filter(!is.na(ZSPRE_ENVIRO1) & !is.na(ZSPOST_ENVIRO1)) %>% # Remove missing pairs
  mutate(ID = row_number()) %>%
  pivot_longer(cols = c(ZSPRE_ENVIRO1, ZSPOST_ENVIRO1),
               names_to = "Composite",
               values_to = "Score") %>%
  mutate(Composite = factor(Composite, levels = c("ZSPRE_ENVIRO1", "ZSPOST_ENVIRO1"))) # change

# Plot: boxplot + paired lines
environment_figure <- ggplot(paired_data_long, aes(x = Composite, y = Score, group = ID)) +
  geom_boxplot(aes(group = Composite), width = 0.5, alpha = 0.3, fill = "white", outlier.shape
  geom_line(color = "gray70", alpha = 0.6) +
  geom_point(data = paired_data_long %>%
             filter(Composite == "ZSPRE_ENVIRO1"),
             shape = 16, size = 3, color = "#c8d9f8") +
  geom_point(data = paired_data_long %>%
             filter(Composite == "ZSPOST_ENVIRO1"),
             shape = 17, size = 3, color = "#3779ba") +
  labs(title = "Pre vs. Post Intervention with Zero-sum Environment Videos 1",
       x = "Intervention Period", y = "Score") +
  theme_minimal() + theme(plot.title = element_text(size = 12))

environment_figure
```

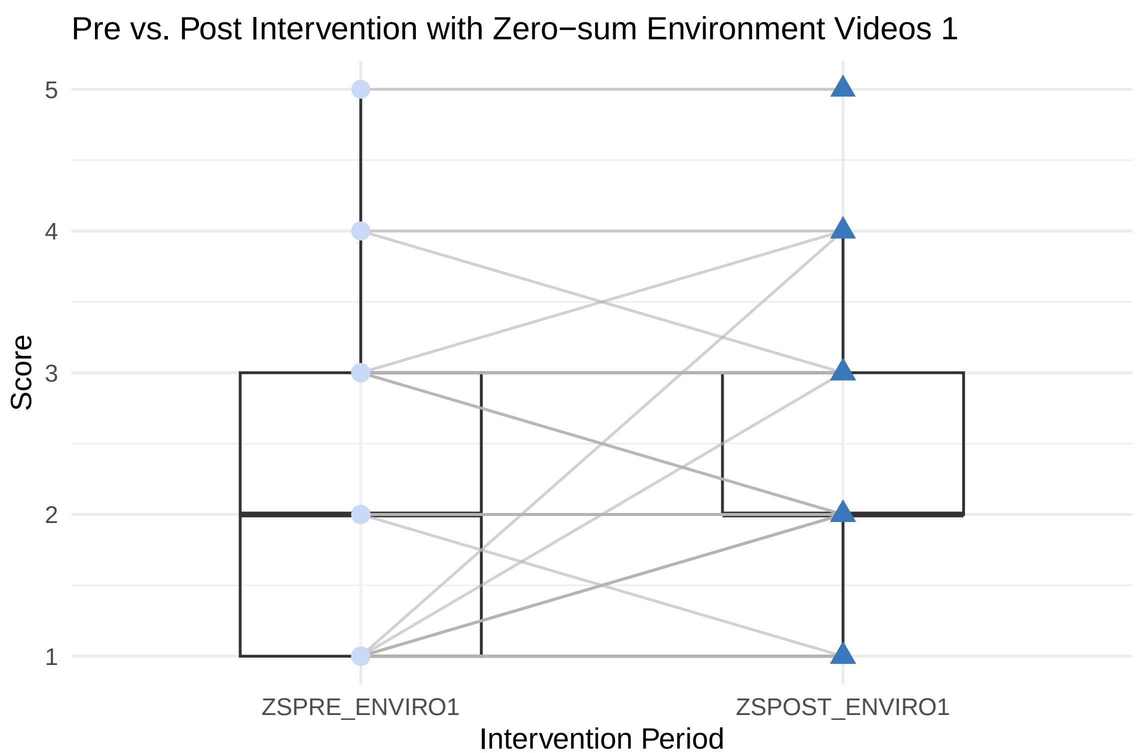


Figure 9: figure 9. Paired pre- and post-intervention environment zero-sum beliefs of participants. Boxplots show overall distributions with lines connecting participants scores before and after the intervention.

```
ggsave("Pre vs. Post Intervention with Zero-sum Environment Videos.png", plot = environment_fi

# source: Zero-sum social identity, not zero-sum economic beliefs, explain voting preference i
# explanation: Compares participants' environment zero-sum beliefs scores before and after wat
```

```
wilcox.test(condition1_selecteddata$ZSPRE_ENVIRO1, condition1_selecteddata$ZSPOST_ENVIRO1, pai
```

```
	Wilcoxon signed rank test with continuity correction

data:  condition1_selecteddata$ZSPRE_ENVIRO1 and condition1_selecteddata$ZSPOST_ENVIRO1
V = 27.5, p-value = 0.8431
alternative hypothesis: true location shift is greater than 0
```

```
# source: Paired Samples Wilcoxon Test in R (STHDA, n.d.)
# explanation: Performs a Wilcoxon Signed-Rank Test to compare participants' zero-sum scores p
```

```
# Create long data with participant ID
paired_data_long<- condition1_selecteddata %>%
  select(ZSPRE_ENVIRO2, ZSPOST_ENVIRO2) %>%
```

```r
  filter(!is.na(ZSPRE_ENVIRO2) & !is.na(ZSPOST_ENVIRO2)) %>% # Remove missing pairs
  mutate(ID = row_number()) %>%
  pivot_longer(cols = c(ZSPRE_ENVIRO2, ZSPOST_ENVIRO2),
               names_to = "Composite",
               values_to = "Score") %>%
  mutate(Composite = factor(Composite, levels = c("ZSPRE_ENVIRO2", "ZSPOST_ENVIRO2"))) # change

# Plot: boxplot + paired lines
environment_figure <- ggplot(paired_data_long, aes(x = Composite, y = Score, group = ID)) +
  geom_boxplot(aes(group = Composite), width = 0.5, alpha = 0.3, fill = "white", outlier.shape
  geom_line(color = "gray70", alpha = 0.6) +
  geom_point(data = paired_data_long %>%
             filter(Composite == "ZSPRE_ENVIRO2"),
             shape = 16, size = 3, color = "#c8d9f8") +
  geom_point(data = paired_data_long %>%
             filter(Composite == "ZSPOST_ENVIRO2"),
             shape = 17, size = 3, color = "#3779ba") +
  labs(title = "Pre vs. Post Intervention with Zero-sum Environment Videos 2",
       x = "Intervention Period", y = "Score") +
  theme_minimal() + theme(plot.title = element_text(size = 12))

environment_figure
```

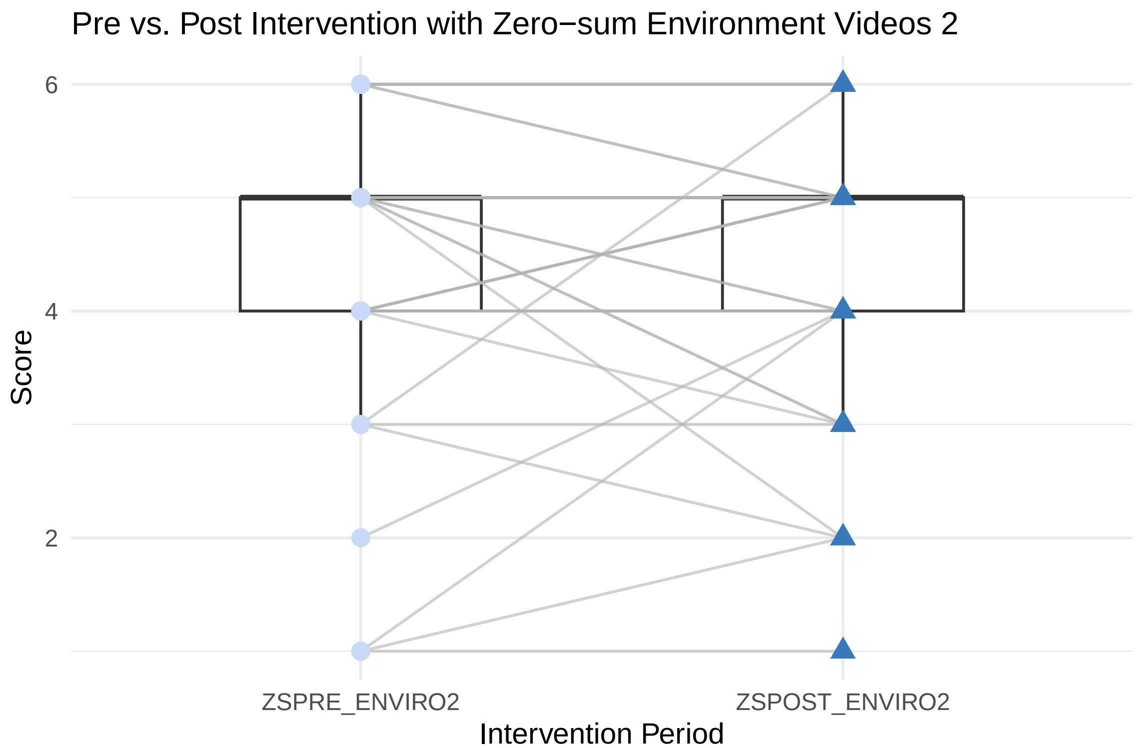


Figure 10: figure 10. Paired pre- and post-intervention environment zero-sum beliefs of participants. Boxplots show overall distributions with lines connecting participants scores before and after the intervention.

```
ggsave("Pre vs. Post Intervention with Zero-sum Environment Videos 2.png", plot = environment_i

# source: Zero-sum social identity, not zero-sum economic beliefs, explain voting preference in
# explanation: Compares participants' environment zero-sum beliefs scores before and after wat

wilcox.test(condition1_selecteddata$ZSPRE_ENVIRO2, condition1_selecteddata$ZSPOST_ENVIRO2, pai
```

```
	Wilcoxon signed rank test with continuity correction

data:  condition1_selecteddata$ZSPRE_ENVIRO2 and condition1_selecteddata$ZSPOST_ENVIRO2
V = 78, p-value = 0.4805
alternative hypothesis: true location shift is greater than 0
```

```
# source: Paired Samples Wilcoxon Test in R (STHDA, n.d.)
# explanation: Performs a Wilcoxon Signed-Rank Test to compare participants' zero-sum scores pr
```

3.2.2 Hope and Anxiety

Data was collected concerning participants' levels of hope and anxiety about the political landscape, before and after they were shown political content. As with zero-sum beliefs, histogram distributions for hope at pretest (`PRE_HOPE`) and hope at posttest (`POST_HOPE`) scores were not normally distributed, so a Wilcoxon Signed-Rank Test was performed to find the level of significance. Pre-intervention and post-intervention scores were not significantly different ($V = 38.5$, $p = 0.114$). Figure 11 illustrates the comparison between the two variables via boxplots, with a higher Hope Score reflecting a higher level of hope for the political landscape.

Histogram distributions of variables for anxiety (`PRE_ANXIETY` and `POST_ANXIETY`) were not normally distributed, so another Wilcoxon Signed-Rank Test was performed to find significance. This found a V-value of 7 and a p-value of 0.82. Figure 12 uses boxplots to show a comparison of anxiety variables, with a higher Anxiety Score indicating a higher amount of anxiety concerning the future of the political environment in the United States.

Hope scores: pre- vs. post-intervention

```
long_data <- condition1_selecteddata %>%
  select(PRE_HOPE, POST_HOPE) %>%
  pivot_longer(cols = c(PRE_HOPE, POST_HOPE),
               names_to = "Intervention_Period",
               values_to = "Hope_Score") %>%
  mutate(Intervention_Period = factor(Intervention_Period, levels = c("PRE_HOPE", "POST_HOPE")

# creates boxplots
hope_figure <- ggplot(long_data, aes(x = Intervention_Period, y = Hope_Score, fill = Interventi
  geom_boxplot(width = 0.5, alpha = 0.7) +
  labs(title = "Pre vs Post Intervention Hope Levels",
       x = "Intervention Period",
       y = "Hope Score") +
  scale_y_continuous(limits = c(1, 7), breaks = 1:7) +
  scale_fill_manual(values = c("PRE_HOPE" = "#c8d9f8", "POST_HOPE" = "#3779ba")) +
  theme_minimal() +
  theme(legend.position = "none") + theme(plot.title = element_text(size = 12))

hope_figure
```

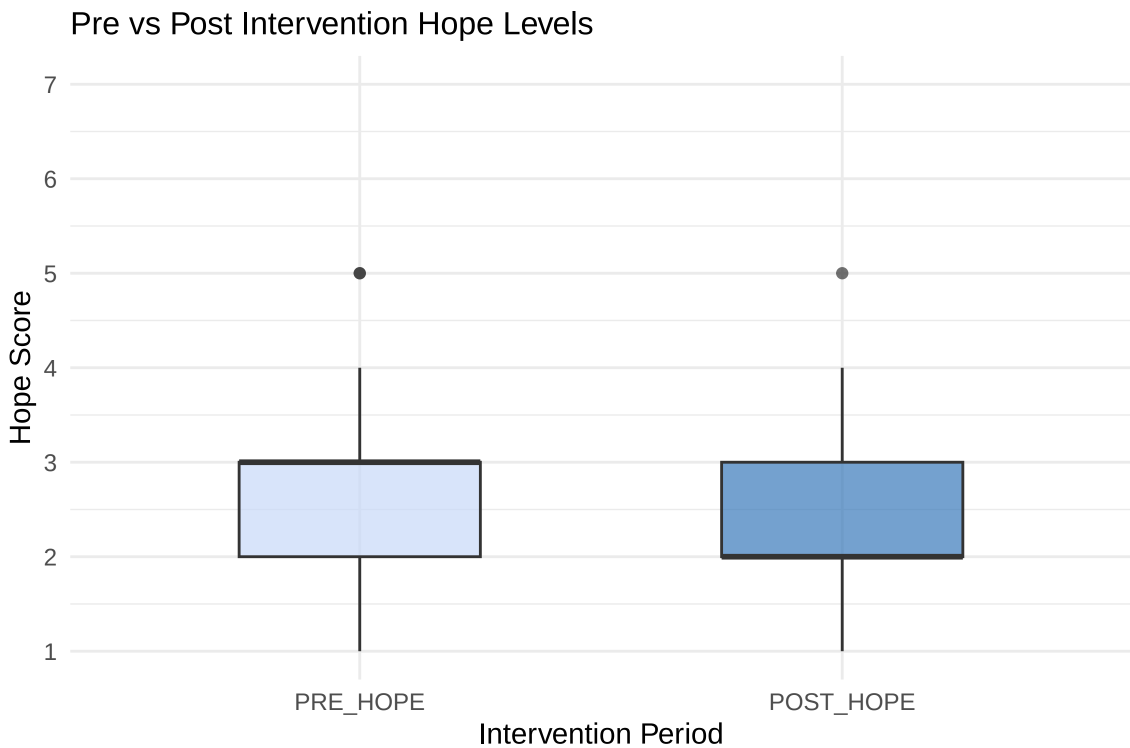


Figure 11: figure 11. Paired pre- and post-intervention hope scores of participants. Boxplots show overall distributions.

```
ggsave("Pre vs Post Intervention Hope Levels.png", plot = hope_figure)

# source: Zero-sum social identity, not zero-sum economic beliefs, explain voting preference in
# explanation: Compares participants' hope scores before and after watching intervention videos
```

```
wilcox.test(condition1_selecteddata$PRE_HOPE, condition1_selecteddata$POST_HOPE, paired = TRUE
```

```
    Wilcoxon signed rank test with continuity correction

data:  condition1_selecteddata$PRE_HOPE and condition1_selecteddata$POST_HOPE
V = 38.5, p-value = 0.1136
alternative hypothesis: true location shift is greater than 0
```

```
# source: Paired Samples Wilcoxon Test in R (STHDA, n.d.)
# explanation: Performs a Wilcoxon Signed-rank test to compare participants' hope scores pre- a
```

Anxiety scores: pre- vs. post-intervention

```
long_data <- condition1_selecteddata %>%
  select(PRE_ANXIETY, POST_ANXIETY) %>%
```

```
  pivot_longer(cols = c(PRE_ANXIETY, POST_ANXIETY),
               names_to = "Intervention_Period",
               values_to = "Anxiety_Score") %>%
  mutate(Intervention_Period = factor(Intervention_Period, levels = c("PRE_ANXIETY", "POST_ANXI

# creates boxplots
anxiety_figure <- ggplot(long_data, aes(x = Intervention_Period, y = Anxiety_Score, fill = Inte
  geom_boxplot(width = 0.5, alpha = 0.7) +
  labs(title = "Pre vs Post Intervention Anxiety Levels",
       x = "Intervention Period",
       y = "Anxiety Score") +
  scale_y_continuous(limits = c(1, 7), breaks = 1:7) +
   scale_fill_manual(values = c("PRE_ANXIETY" = "#c8d9f8", "POST_ANXIETY" = "#3779ba")) +
  theme_minimal() +
  theme(legend.position = "none") + theme(plot.title = element_text(size = 12))

anxiety_figure
```

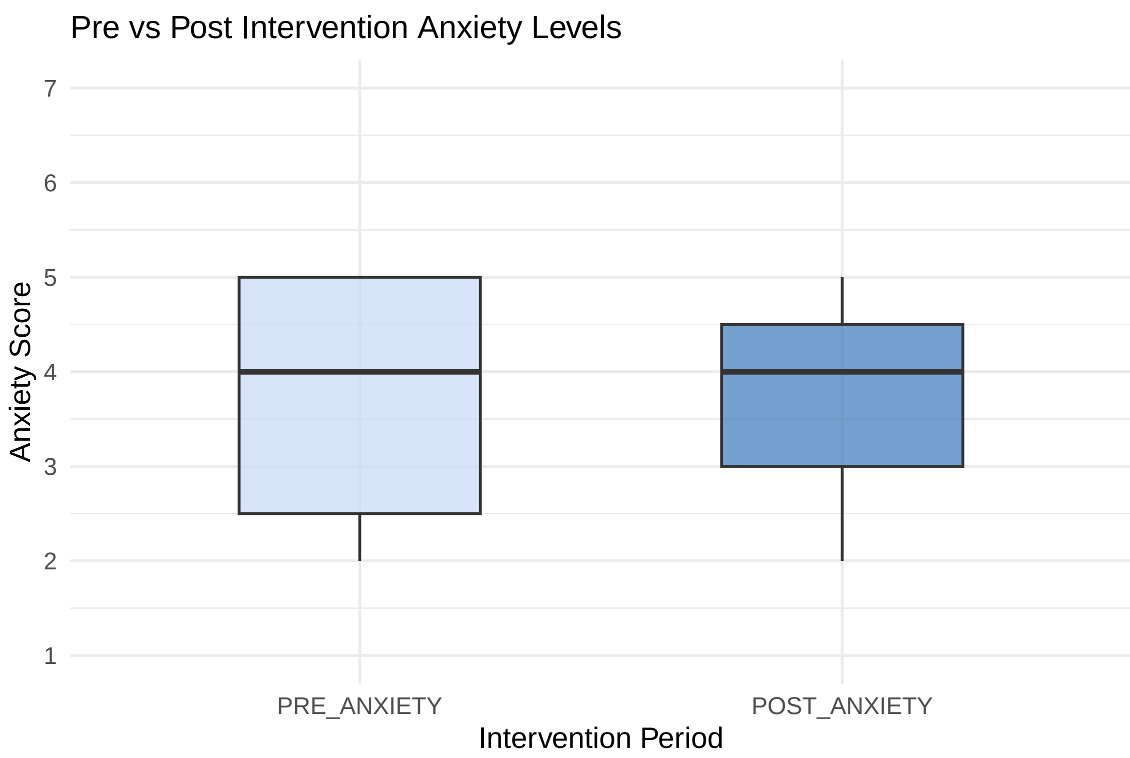


Figure 12: figure 12. Paired pre- and post-intervention anxiety scores of participants. Boxplots show overall distributions.

```
ggsave("Pre vs Post Intervention Anxiety Levels.png", plot = anxiety_figure)

# source: Zero-sum social identity, not zero-sum economic beliefs, explain voting preference in
# explanation: Compares participants' hope scores before and after watching intervention videos
```

```r
wilcox.test(condition1_selecteddata$PRE_ANXIETY, condition1_selecteddata$POST_ANXIETY, paired =
```

```
	Wilcoxon signed rank test with continuity correction

data:  condition1_selecteddata$PRE_ANXIETY and condition1_selecteddata$POST_ANXIETY
V = 7, p-value = 0.8246
alternative hypothesis: true location shift is greater than 0
```

```r
# source: Paired Samples Wilcoxon Test in R (STHDA, n.d.)
# explanation: Performs a Wilcoxon Signed-Rank test to compare participants' anxiety scores pre
```

3.2.3 Alignment versus Engagement

Polarizing content: alignment vs engagement

```r
polar_align_engage <- ggplot(selecteddata, aes(x = POLARALIGN, y = POLARENGAGEMENT)) +
  geom_point(alpha = 0.6, color = "red") +
  geom_smooth(method = "lm", color = "darkred", se = TRUE) +
  labs(title = "Polarizing Video Engagement vs Alignment",
       x = "Alignment", y = "Engagement") +
  theme_minimal() + theme(plot.title = element_text(size = 12))

polar_align_engage
```

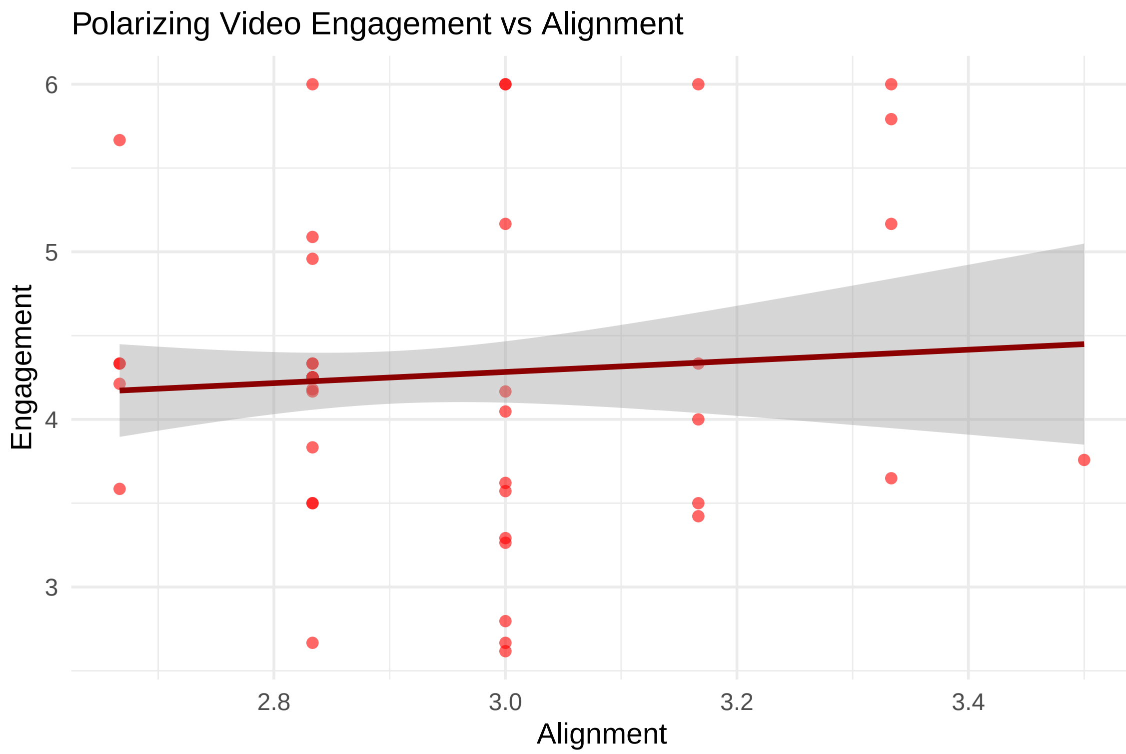


Figure 13: figure 13. Relationship between polarization alignment and engagement. Fitted with a regression line to show the association between participant's alignment with polarizing videos and their engagement levels.

```
ggsave("Polarizing Video Engagement vs alignment.png", plot = polar_align_engage)

# source: R for Data Science - Data Visualization (Wickham et al., 2023)
# explanation:Linear regression showing the relationship between a person's alignment with the
```

```
cor.test(selecteddata$POLARALIGN, selecteddata$POLARENGAGEMENT, method = "spearman")
```

```

	Spearman's rank correlation rho

data:  selecteddata$POLARALIGN and selecteddata$POLARENGAGEMENT
S = 99786, p-value = 0.1327
alternative hypothesis: true rho is not equal to 0
sample estimates:
      rho 
-0.169555 
```

```
# source: Correlation Test Between Two Variables in R (STHDA, n.d.)
# explanation: performs a correlation test. Spearman is used because of nonnormality.
```

Leaning content: engagement vs alignment

```r
lean_align_engage <- ggplot(selecteddata, aes(x = LEANALIGN, y = LEANENGAGEMENT)) +
  geom_point(alpha = 0.6, color = "blue") +
  geom_smooth(method = "lm", color = "darkblue", se = TRUE) +
  labs(title = "Leaning Video Engagement vs Alignment",
       x = "Alignment", y = "Engagement") +
  theme_minimal() + theme(plot.title = element_text(size = 12))

lean_align_engage
```

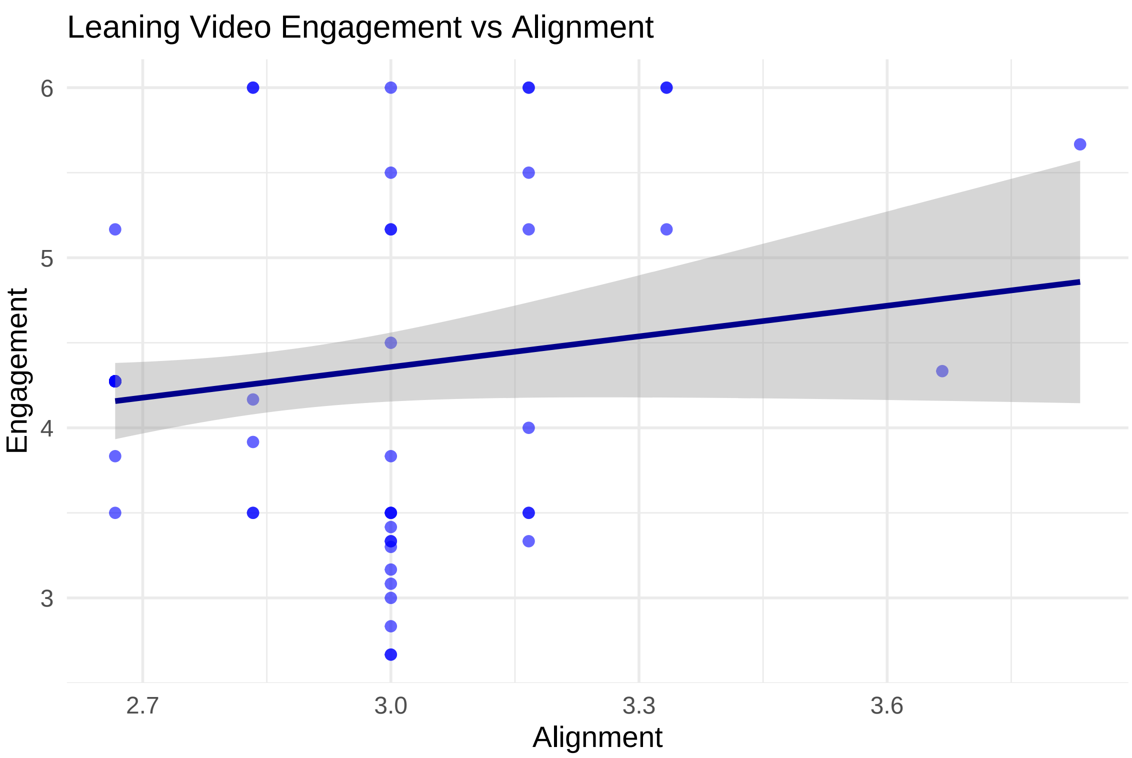


Figure 14: figure 14. Relationship between leaning alignment and engagement. Fitted with a regression line to show the association between participant's alignment with leaning videos and their engagement levels.

```r
ggsave("Leaning Video Engagement vs alignment.png", plot = lean_align_engage)

# source: R for Data Science - Data Visualization (Wickham et al., 2023)
# explanation: Linear regression showing the relationship between a person's alignment with the
```

```r
cor.test(selecteddata$LEANENGAGEMENT, selecteddata$LEANALIGN, method = "spearman")
```

```
    Spearman's rank correlation rho

data:  selecteddata$LEANENGAGEMENT and selecteddata$LEANALIGN
```

```
S = 86799, p-value = 0.8787
alternative hypothesis: true rho is not equal to 0
sample estimates:
       rho
-0.0173329
```

```
# source: correlation Test Between Two Variables in R (STHDA, n.d.)
# explanation: performs a correlation test. Spearman is used because of nonnormality.
```

3.3 Qualitative Findings

3.3.1 Overview of Coding and Data Structure

Two general codes, Leaning Content and Polarizing Content, were firstly created to coincide with the Qualtrics survey and corresponding qualitative question. Under these codes six new codes were created for each video displayed on the Qualtrics survey plus an additional code for No Video Specified and or Multiple Videos. For Leaning Content the only codes that remained were No Video Specified and or Multiple Videos, DEI Video 5, and Women Video 3. Additionally, for Polarizing Content the only codes that remained were No Video Specified and or Multiple Videos, DEI Video 5, Women Video 3, and Immigration Video 1. Responses that referenced specific videos were placed into their relative codes. The videos that were not referenced in any responses had their corresponding code removed for clarity.

3.3.2 Leaning Content Analysis

The codes within the Leaning Content qualitative data were first explored. More specifically, 66.7% of the sample was placed into the No Video Specified and or Multiple Videos, 20% was placed into DEI Video 5, and the remaining 13.3% was placed into Women Video 3 (see Figure A). These codes were then further analyzed and more concise codes emerged from the responses to create four new sets of categorical codes: Annoyance and or Anger with No Mental Distress, Mental Distress due to Disagreement, Mental Distress due to Personal Relevance, and No Mental Distress. The first responses explored were those placed within the Annoyance and or Anger with No Mental Distress code. Open-ended responses within the section consisted of statements like, "Some videos ticked me off," "I feel that there should have been an option for 'anger'," and "If anger counts, yeah. Plus some concern that people genuinely believe the stuff they say." This code made up 40% of the collected data (n = 6). The next code explored was Mental Distress due to Disagreement. Open-ended responses within the section consisted of statements like, "[T]he videos containing conservative viewpoints do cause me mental distress because many of those views and opinions come off to me as just a real lack of empathy for other humans and nothing but concern for self preservation," "Yes, some of these videos were encouraging topics that I highly disagree with, like the one about abortion. I think abortion does not kill and everyone should have the choice to do whatever they want with this body and people coming on the internet trying to make others seem like horrible people or in some cases murders for doing what they think is best for their lives is wrong and manipulative," and "The abortion video. I am done with the argument at this point- it is a woman's body, therefore it should be her choice. I'm not saying there can't be regulations, but everyone should have the right to an abortion." This code had 26.7% of coded responses (n =

4). The subsequent code examined was Mental Distress due to Personal Relevance. Qualitative comments within the section contained examples such as, “The DEI one did because I am Latino I understand that it’s harder for us to get that high of a score due to lack of resources,” “[Y]es, about the current atmosphere of hate in our country,” and “I would say the one about mcat score. Not only did I find the statistic confusing, but it also made me question the reality of their claims. If what they say is true then I worry about my future and the likelihood of me succeeding.” This code consisted of 20% of the coded responses (n = 3). The final code explored was No Mental Distress which made up 13.3% of the data (n = 2). Examples of responses from this section include, “None of the videos caused distress” and “Not really, I’m used to this rhetoric, I know what I believe and why I believe it. Arguing or being overly distressed with the same rhetoric will make you lose hope for humanity and overall depressed.I’ve been there before and now I know how to be numb and understand that some people are uneducated but MANY people just choose hatred regardless of the impact it has on others or themselves” (see Figure B).

Leaning Content Type	**Frequency (N=15)**	**Example Quote**
No Video Specified and or Multiple Videos	10 (66.7%)	“I found myself trying to scroll away from some of the videos in disgust or disinterest.”
DEI Video 5	3 (20%)	“Not really mental distress, I just found some of them annoying. The DEI video especially because of the high pitched voice.”
Women Video 3	2 (13.3%)	“The abortion video. I am done with the argument at this point- it is a woman's body, therefore it should be her choice. I'm not saying there can't be regulations, but everyone should have the right to an abortion.”

Figure 15: **Figure A.** Frequency and example quotes of leaning content specificity

Leaning Content Code	**Definition**	**Frequency (N=15)**
Annoyance and or Anger with No Mental Distress	This code captures participants who reported feelings of irritation or anger towards the content or its viewpoints but did not describe lingering discomfort. The reactions reflected frustration rather than genuine psychological discomfort.	6 (40%)
Mental Distress due to Disagreement	This code represents participants who experienced emotional discomfort when confronted with opinions that directly opposed their moral or personal values. The distress arose from perceived injustice, insensitivity, and/or lack of empathy within the opposing perspective.	4 (26.7%)
Mental Distress due to Personal Relevance	This code applies to participants who reported distress because the content felt personally significant or identity-related. The emotional reaction stemmed from connections between the content and their lived experiences or perceived inequalities.	3 (20%)
No Mental Distress	This code includes participants who explicitly stated they did not feel any emotional or psychological distress. They described being desensitized or emotionally resilient, often recognizing the existence of hateful rhetoric, but refusing to internalize it.	2 (13.3%)

Figure 16: **Figure B**. Leaning content codes and definitions across the dataset

3.3.3 Polarizing Content Analysis

The codes within the Polarizing Content were then explored following a similar structure to the Leaning Content analysis. Of the respondents, 40% were placed into No Video Specified and or Multiple Videos, 30% were placed into DEI Video 5, 20% in Women Video 3, and 10% in Immigration Video 1 (see Figure C). These codes were then further analyzed and more concise codes emerged from the responses to create four new sets of categorical codes: Mental Distress due to Disagreement, Mental Distress due to Misinformation, No Mental Distress, and Mental Distress due to Polarization. The first responses explored were those placed within the Mental Distress due to Disagreement code. Participant responses in this section included statements such as, "The one with Ben Shapiro because I genuinely could not tell if what he was saying was agreeable and I do NOT want to be agreeing with him," "Ben shapiro because of his affiliations," and "[T]he videos about people being [blatantly] ignorant and uneducated." This code made up 70% of the responses (n = 7). The next code explored was Mental Distress due to Misinformation. Open-ended responses within the section consisted of statements like, "The first one about immigration as he doesn't provide reasoning for any of the many claims he makes." This code made up 10% of the responses (n = 1). The following code analyzed was No Mental Distress which made up 10% of the responses as well (n = 1). In this code, respondents expressed ideas such as, "Not really distress, since I am not easily triggered by opinions." The final code explored was Mental Distress due to Polarization which made up the remaining 10% (n = 1). This code consisted of responses such as, "The 'pro choice' video, because it frustrates me that people don't see that generalizing is unhealthy, and that both groups can be unfair and aggressive at times" (see Figure D).

Polarizing Content Type	Frequency (N=10)	Example Quote
No Video Specified/Multiple Videos	4 (40%)	"The videos that were left leaning were always attacking the right side, but the right leaning videos were normal."
DEI Video 5	3 (30%)	"The ben shapiro one, he has a point about individuals being individuals but also he and the person speaking don't seem to know what DEI is. It's not giving a job to a POC just bc [they're] a POC they also still qualified - Shapiro seems to think unqualified people are getting an advantage over white qualified people."
Women Video 3	2 (20%)	"[T]he video about pro-choice/pro-life because it is a right that is actively being taken away for so many people."
Immigration Video 1	1 (10%)	"The first one about immigration as he doesn't provide reasoning for any of the many claims he makes."

Figure 17: **Figure C.** Frequency and example quotes of polarizing content specificity

Polarizing Content Code	Definition	Frequency (N=10)
Mental Distress due to Disagreement	This code represents participants who experienced emotional discomfort when confronted with opinions that directly opposed their moral or personal values. The distress arose from perceived injustice, insensitivity, and/or lack of empathy within the opposing perspective.	7 (70%)
Mental Distress due to Misinformation	This code captures participants who reported distress due to perceived factual inaccuracies, unsupported claims, or misleading narratives. Emotional discomfort was tied to frustration with the spread of misinformation or poor argumentation.	1 (10%)
No Mental Distress	This code includes participants who explicitly stated they did not feel any emotional or psychological distress. They described being desensitized or emotionally resilient, often recognizing the existence of hateful rhetoric, but refusing to internalize it.	1 (10%)
Mental Distress due to Polarization	This code encompasses participants who express frustration or fatigue towards the divisive and hostile nature of polarized discourse itself. The distress emerged from the perceived toxicity of polarization rather than a single viewpoint.	1 (10%)

Figure 18: **Figure D.** Polarizing content codes and definitions across the dataset

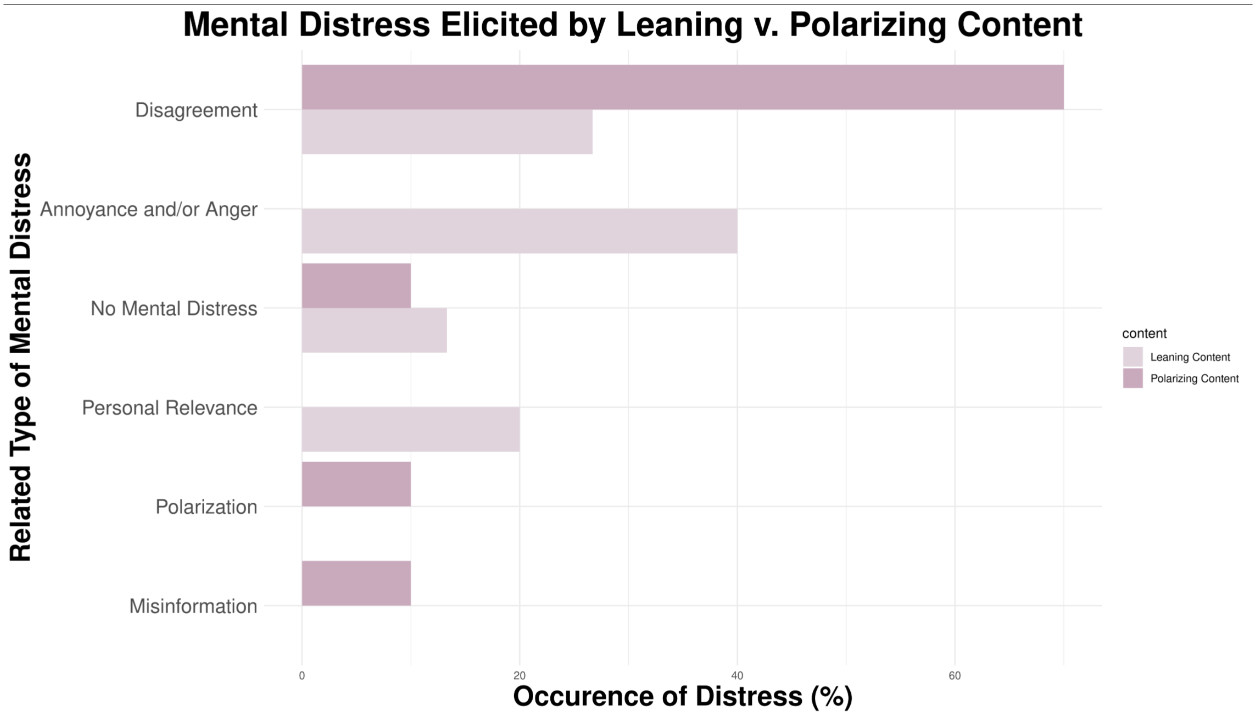


Figure 19: **Figure E.** Mental Distress Elicited by Leaning v. Polarizing Content

4 Discussion

The current study provides contrasting evidence for zero-sum beliefs influence on mental distress. The quantitative findings show no change in zero sum beliefs, hope, or anxiety from before the intervention to after. The qualitative findings suggest that specific types of videos may be causing mental distress. Together, these findings point to specific types of content as potentially causing mental distress, rather than all theorized zero-sum content.

4.1 Quantitative Findings

4.1.1 Polarizing Content's Impact on Zero-sum Beliefs

When it came to zero-sum beliefs, it was found that no one type of zero-sum belief is significantly impacted via the short-term intervention of political content created within the survey. However, there may be a slight impact overall, with total zero-sum scores being significantly lower after the intervention than before. This indicates that viewing politically polarizing content may have made participants less likely to hold zero-sum beliefs. This aligned with the alternative hypothesis, being that viewing politically polarizing content on social media has an impact on a user's zero-sum beliefs. However, it did not align fully with the hypothesis, as the impact was found to be negative, rather than reinforcing existing beliefs.

4.1.2 Polarizing Content's Impact on Hope and Anxiety

In terms of hope, the survey found that the political content intervention did not have a significant impact on respondents' hope for the future. The statistical test performed implied that viewing the content did not cause significant decreases or increases in the viewer's hope ($p=0.114$). This result was the same for anxiety. Tests performed in data analysis found no significant difference in one's anxiety for the future before and after the intervention ($p=0.82$). This meant that the hope result rejected the null hypothesis, instead aligning with the alternative hypothesis and demonstrating a negative impact that politically polarizing content has on social media users' hope. Anxiety scores failed to reject the null hypothesis.

4.1.3 Strengths and Limitations of the Quantitative Analysis

Limitations of this analysis should be taken into consideration. Firstly, results of statistical tests may be biased or skewed due to any outliers in the data, which would have an impact on significant differences found (or not found). Further, limitations may exist relating to the scope of the survey, since zero-sum beliefs can encompass many more topics, as can politically polarizing content.

The quantitative aspects of the study were strengthened by the consistency of the questions, such as the way that each variable tested pre- and post-intervention had questions in the survey that were asked and answered in the same way both before and after the content was viewed. The study is also reinforced through the data "cleaning," as the nature of the quantitative structure made it simple to remove incomplete or joke responses from the final dataset.

4.2 Qualitative Findings

4.2.1 Comparison of Leaning and Polarizing Content Codes

In terms of Leaning Content, the majority of participants did not indicate that they experienced mental distress. For instance, 40% indicated Annoyance and or Anger with No Mental Distress and 13.3% indicated No Mental Distress. However, the rest of the sample indicated some form of mental distress with 26.7% of responses indicating Mental Distress due to Disagreement and the remaining 20% indicating Mental Distress due to Personal Relevance.

When the codes within Leaning Content are compared to the codes within Polarizing Content, there is both overlap and the emergence of new code. A total of 70% of participants within the Polarizing Content code indicated Mental Distress due to Disagreement and 10% indicated No Mental Distress. These two codes are present in both Leaning Content and Polarizing Content. The other two codes in this category, Mental Distress due to Misinformation and Mental Distress due to Polarization are both unique and had 10% of the responses. These refined codes emerged by following a data-based approach and using conventional content analysis (Hsieh & Shannon, 2005).

4.2.2 Differences in Mental Distress Across Content Types

When the prevalence of categorized mental distress in Leaning Content and Polarizing Content are compared it is clear that mental distress was substantially higher within the Polarizing Content group. Specifically, 90% of respondents within Polarizing Content experienced some form of mental distress, while only 46.7% of respondents within Leaning Content experienced mental distress. It was more common for those within the Leaning Content to experience anger and/or annoyance without accompanying mental distress. Furthermore, comparing the two overlapping codes reveals that Mental Distress due to Disagreement made up only 26.7% of responses in Leaning Content but 70% of the responses in the Polarizing Content. Conversely, No Mental Distress, which is another overlapping code, was more prevalent in Leaning Content with 13.3% and 10% in Polarizing Content (see Figure E).

4.2.3 Support for Hypothesis and Alignment with Previous Research

These findings support the original hypothesis that engagement with politically polarizing content that conveys zero-sum beliefs will be associated with negative mental health effects in undergraduate students. These results also align with previous models and are consistent with previous research done which stated that politically polarized students reported greater psychological distress on average (Reynolds et al., 2025). Specifically, the results directly exemplify that participants exposed to the Polarizing Content demonstrated higher rates of reported mental distress than those in the Leaning Content group, directly reinforcing the hypothesized relationship and research.

4.2.4 Strenghts and Limitations of Qualitative Analysis

Several limitations should be noted when interpreting these findings. The Leaning Content only had a sample size of 15, and the Polarizing Content only had a sample size of 10. This sample size may not be representative of the entire undergraduate population. Furthermore, convenience sampling may have introduced selection bias, as most participants came from a single university. Additionally, research bias could have also affected qualitative coding despite efforts to use a consistent criteria to the basis of the placement of codes.

The basis of these findings should also be interpreted based on several methodological strengths. First, both the Leaning Content and Polarizing Content were clearly defined prior to analysis, ensuring consistent application of criteria across all responses. These predefined definitions were used universally while placing responses within respective codes, allowing for systematic and unbiased placement. This coding process was applied identically for the Leaning Content code and Polarizing Content code which consisted of different types of mental distress elicited. This ensures that all data analysis remained consistent throughout the entirety of the analytical process. Additionally, all coded responses were reviewed by multiple researchers, ensuring consensus and reducing the likelihood of individual coder bias. This collaborative review process strengthened the reliability of code assignments and analysis.

4.3 Implications for Public Health Theory and Practice

These findings are significant when applied to a broader context by highlighting the link between engagement with politically polarizing content that conveys zero-sum beliefs and negative mental health effects. Political engagement online has been seen to increase over time and these findings indicate that such engagement can cause mental distress (Singh et al., 2024). Moreover, both theoretical and practical implications can be made for the field of mental health.

Theoretically, the results contribute to a growing understanding of how digital environments and exposure to politically polarizing, zero-sum narratives can influence psychological well-being among undergraduate students. Practically, the findings suggest a need for some form of preventive and educational interventions that teach undergraduate students how to critically engage with political media content without internalizing distressing narratives.

4.4 Future Research Directions

The most immediate next step would be to expand the sample size and diversity of participants in order to strengthen generalizability. To build upon this research, future research should recruit from multiple universities or community populations and ensure balanced political representation. A more novel direction would be to experimentally manipulate exposure to polarizing versus non-polarizing content in a controlled setting while measuring psychophysiological indicators (e.g. heart rate variability) or real-time emotional changes. This approach would move beyond self-report data and allow researchers to observe the immediate stress response triggered by politically polarizing media. If this research were employed again, a longitudinal study tracking how repeated exposure to politically polarizing content affects students' mental health may also be beneficial.

5 Appendix A

Variable	n	mean	sd	range
PREZEROSUM*	80	2.48	0.65	1.00-5.33
POSTZEROSUM*	80	2.48	0.57	1.00-3.78
POLARALIGN*	80	2.48	0.16	2.67-3.50
LEANALIGN*	80	2.86	0.25	2.67-3.83
POLARENGAGEMENT*	80	4.25	0.70	2.62-6.00
LEANENGAGEMENT*	80	4.27	0.80	2.67-6.00
ZSPRE_IMM	79	2.20	1.33	1.00-6.00
ZSPRE_HEALTH	75	2.11	1.40	1.00-6.00
ZSPRE_WOMEN1	78	1.99	1.44	1.00-6.00
ZSPRE_WOMEN2	79	1.49	0.85	1.00-6.00
ZSPRE_ECONOMY	78	4.79	1.34	1.00-6.00
ZSPRE_DEI1	76	2.03	1.26	1.00-6.00
ZSPRE_DEI2	78	1.37	0.85	1.00-6.00
ZSPRE_ENVIRO1	76	2.05	1.16	1.00-6.00
ZSPRE_ENVIRO2	77	4.26	1.58	1.00-6.00
ZSPOST_IMMI	76	1.96	1.26	1.00-6.00

Variable	n	mean	sd	range
ZSPOST_HEALTH	74	1.77	1.14	1.00-6.00
ZSPOST_WOMEN1	77	1.95	1.36	1.00-6.00
ZSPOST_WOMEN2	77	1.45	0.75	1.00-5.00
ZSPOST_ECONOMY	76	4.37	1.62	1.00-6.00
ZSPOST_DEI1	76	1.82	1.08	1.00-6.00
ZSPOST_DEI2	77	1.45	0.75	1.00-5.00
ZSPOST_ENVIRO1	77	1.96	0.97	1.00-5.00
ZSPOST_ENVIRO2	71	4.06	1.58	1.00-6.00
PRE_HOPE	80	2.56	1.14	1.00-5.00
PRE_ANXIETY	80	3.74	1.11	1.00-5.00
POST_HOPE	76	2.49	1.09	1.00-5.00
POST_ANXIETY	76	3.59	1.12	1.00-5.00
POL_IMM_ALIGN	38	1.50	0.98	1.00-5.00
POL_HEALTHC_ALIGN	37	3.86	0.92	1.00-5.00
POL_WOMEN_ALIGN	37	1.65	1.06	1.00-5.00
POL_ECONOMY_ALIGN	33	3.85	0.94	1.00-5.00
POL_DEI_ALIGN	26	3.85	0.96	1.00-5.00
POL_ENVI_ALIGN	34	3.97	1.03	1.00-5.00
LEAN_IMM_ALIGN	40	1.43	0.84	1.00-5.00
LEAN_HEALTHC_ALIGN	39	4.36	0.67	2.00-5.00
LEAN_WOMEN_ALIGN	41	1.54	0.90	1.00-5.00
POL_ECONOMY_ALIGN	33	3.85	0.94	1.00-5.00
LEAN_DEI_ALIGN	37	2.49	1.10	1.00-5.00
LEAN_ENVIRO_ALIGN	38	4.37	0.59	3.00-5.00
POL_IMM_ENGAGE	30	5.83	0.59	3.00-6.00
POL_HEALTHC_ENGAGE	35	3.23	2.46	1.00-6.00
POL_WOMEN_ENGAGE	30	5.7	0.95	1.00-6.00
POL_ECONOMY_ENGAGE	35	3.14	2.51	1.00-6.00
POL_DEI_ENGAGE	28	4.75	2.20	1.00-6.00
POL_ENVI_ENGAGE	33	2.85	2.43	1.00-6.00
LEAN_IMM_ENGAGE	41	5.51	1.10	1.00-6.00
LEAN_HEALTHC_ENGAGE	41	2.80	2.38	1.00-6.00
LEAN_WOMEN_ENGAGE	41	5.71	0.64	3.00-6.00
LEAN_ECONOMY_ENGAGE	41	3.32	2.41	1.00-6.00
LEAN_DEI_ENGAGE	38	5.5	1.43	1.00-6.00
LEAN_ENVIRO_ENGAGE	40	2.8	2.34	1.00-6.00

*asterisk = composite of other listed variables

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