Trauma Center Trauma Sensitive Yoga Study:
The relationship between Compassion Fatigue & Coping

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STAT4893W:Condulation and Communication for Statisticians

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October 12, 2023

Abstract
This research surveyed 77 trauma-sensitive yoga instructors, aiming to evaluate the relationship between their coping strategies and compassion fatigue they face. Notably, the primary demographic served by these instructors is adults, and a significant gender disparity was observed, with females comprising over 90% of respondents. A central finding highlighted the recurrent utilization of Mental Disengagement as a coping strategy for both secondary trauma and job burnout. The adaptive and maladaptive coping strategies would be worthy for further investigation.

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1. Introduction
This study surveyed 77 trauma-sensitive yoga instructors to understand their management of energy and prioritization of wellbeing. The main focus was on their self-reported compassion fatigue and their coping strategies. Initial data cleaning omitted responses with missing values. Using multiple linear regression, we explored the influence of various coping strategies on secondary trauma and job burnout. We also employed K-means clustering to categorize 15 coping strategies into three groups. Key findings revealed that most significant coping strategies for secondary trauma were Religious and Mental Disengagement, while Substance and Mental Disengagement were pivotal for job burnout. Despite various strategies, Mental Disengagement emerged as crucial for trauma-sensitive yoga instructors. Lastly, coping strategies displayed patterns of over-reliance, with certain strategies being used thoughtfully based on their categorization.

2. Method and materials
In this study, we conducted a survey with 77 trauma-sensitive yoga instructors to understand how they manage their energy and prioritize their wellbeing as trauma care providers. Specifically, we aimed to explore the instructors' self-reported compassion fatigue, alongside theri coping mechanisms and self-care strategies.

Upon initial review, we identified several rows with missing values. To ensure the integrity of our results, these rows were omitted. For our first objective, we utilized a multiple linear regression model to examine both secondary trauma and job burnout. In the model addressing secondary trauma, the mean value of secondary trauma served as the response variable, with all coping strategies acting as predictor variables. For the job burnout model, the structure was analogous, but the mean value of job burnout replaced secondary trauma as the response variable.

For our second objective, we employed a K-means clustering approach to categorize 15 coping strategies into three groups.

3. Results

In this section, I will discuss our findings in three segments. First, I will address the demographics based on our collected data. Next, under Objective 1, I will rank coping strategies concerning levels of compassion fatigue and provide a rationale for this ranking. Finally, in Objective 2, I will categorize these coping strategies into three groups.

3.1 Demographic

group_name	counts
Youth	8
Young adult	16
Adults	48
Older adults	14

The primary demographic that instructors work with is adults. (The total number will be above 66 since this question is allow to choose more than one answer.)

race_name	counts
Black or African descent	2
White or European descent	59
Chinese	1
Other South Asian	1
Other race	1
Hispanic, Latina, Spanish origin	5
White, Hispanic origin	1

Concerning the ethnicity of respondents to the questionnaire, the top two categories were “ Not Latin” and “Latin American.” The three most common races among participants were “White or European descent”, “Hispanic, Latin/o/x/e, or Spanish origin,” and “Black or African descent.”

names	value
n	66.00000
mean	44.80303
sd	11.00800

The average of the age is 44.8 years and the standard errors of the age is 11.

latin_name	counts
Not of Hispanic, Latino/a, or Spanish origin	58
Latin American	5
Audalusian	1
Catalonian	1
Central American	1
Colombian	1
Cuban	1
Dominican	1
Spaniard	1
Nicaraguan	1
Puerto Rican	1
Unknown	1
Decline to answer	1

58 of them are not Latin, 5 of them are Latin America.

Characteristic	N = 66[1]
Gender	
Female	60 (91%)
Male	3 (4.5%)
Nonbinary	2 (3.0%)
Other	1 (1.5%)
Immigrant	14 (21%)
Refugee	
Decline to answer	3 (4.5%)
No	63 (95%)
Community	
Large	20 (30%)
Rural Area	11 (17%)
Small	23 (35%)
Suburb	12 (18%)

In terms of gender, over 90% identified as female, with one respondent selecting “other” and indicating “none of the above.” Regarding immigrant status, 21% identified as immigrants, while 95% reported not being refugee. The remaining participants chose not to answer the question on refugee status.
Geographically, 35% of the participants live in small cities or towns, and 30% reside in

large cities.

Arizona	1 (1.5%)
California	4 (6.1%)
Florida	2 (3.0%)
Georgia	1 (1.5%)
Illinois	2 (3.0%)
Indiana	1 (1.5%)
Iowa	1 (1.5%)
Maine	2 (3.0%)
Maryland	1 (1.5%)
Massachusetts	4 (6.1%)
Michigan	2 (3.0%)
Minnesota	2 (3.0%)
Missouri	1 (1.5%)
Montana	1 (1.5%)
New Jersey	2 (3.0%)
New York	4 (6.1%)
No answer	21 (32%)
North Carolina	4 (6.1%)
Ohio	2 (3.0%)
Pennsylvania	2 (3.0%)
Puerto Rico	1 (1.5%)
Washington	3 (4.5%)
Wisconsin	2 (3.0%)

Country	
Australia	3 (4.5%)
Canada	3 (4.5%)
Germany	3 (4.5%)
Ireland	1 (1.5%)
Israel	1 (1.5%)
Italy	2 (3.0%)
Mexico	1 (1.5%)
Netherlands	3 (4.5%)
New Zealand	1 (1.5%)
Singapore	1 (1.5%)
Spain	1 (1.5%)
United Kingdom of Great Britain and Northern Ireland	1 (1.5%)
United States of America	45 (68%)

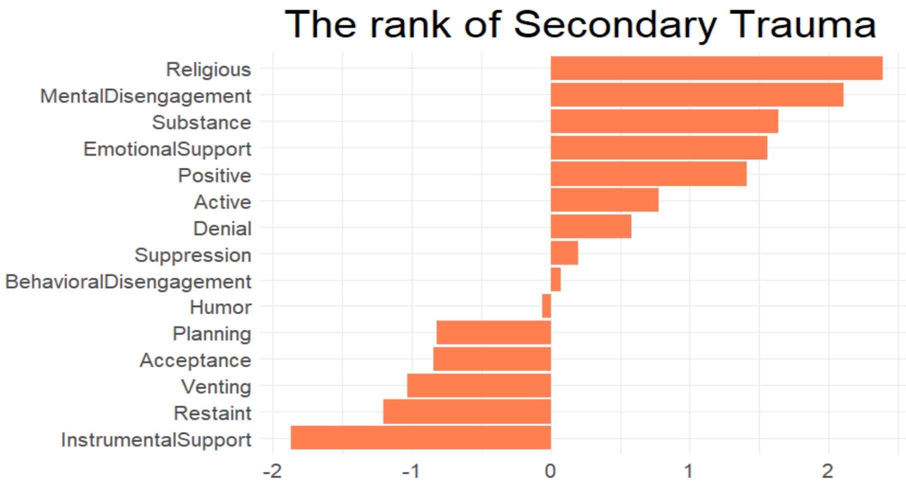
A significant portion of respondents, 68%, are from America. However, 32% opted not to specified their state or residence, making it the most common response to that particular question.

School	
Associate Degree	1 (1.5%)
Bachelor Degree	8 (12%)
Doctorate	4 (6.1%)
Master Degree	46 (70%)
Professional Qualification	2 (3.0%)
Some College	5 (7.6%)
Income	
$100000 to $150000	14 (21%)
$13000 to $26000	3 (4.5%)
$26000 to $59000	15 (23%)
$59000 to $75000	9 (14%)
$75000 to $100000	9 (14%)
< $13000	2 (3.0%)
> $150000	10 (15%)
Decline to answer	4 (6.1%)

When considering education, 70% hold master's degree. The most common annual income ranges reported were between $100,000 to $150,000 and $26,000 to $59,000.

3.2 Objective 1: The rank of the coping strategies in regard to levels of compassion fatigue(secondary trauma, job burnout).

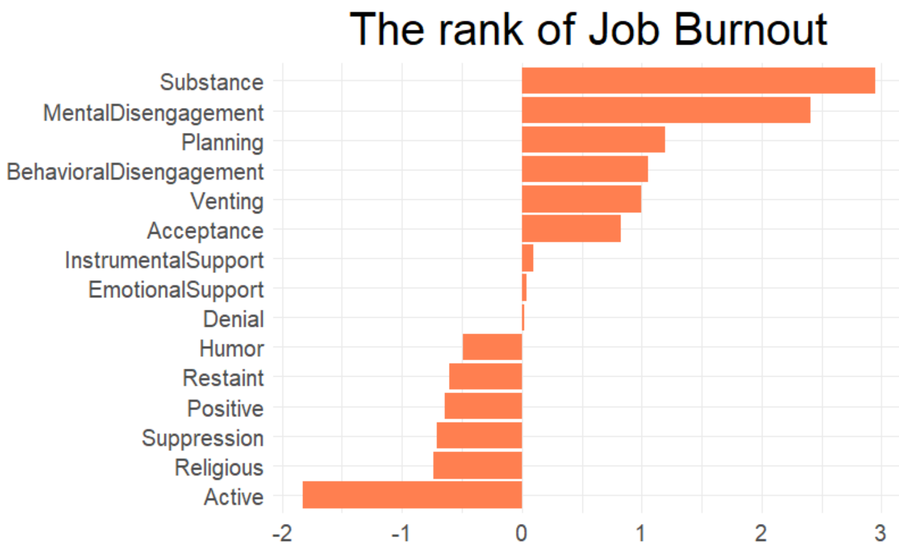
We chose to rank based on the t-vlaue, which is the coefficient divided by the standard error. Using the t-value ensure that all coefficients are on the same scale, yielding results consistent with beta coefficients. A high t-statistic suggest a small standard error relative to the coefficient. This implies that trauma-sensitive yoga instructors are likely to use that specific coping strategy when addressing compassion fatigue, encompassing both job burnout and secondary trauma.



trauma.

```
Coefficients:
                            Estimate Std. Error t value Pr(>|t|)
(Intercept)                  0.43865    9.76577   0.045   0.9644
COPE_Positive                0.73391    0.51877   1.415   0.1633
COPE_MentalDisengagement     0.99629    0.47277   2.107   0.0401 *
COPE_Venting                -0.52687    0.51194  -1.029   0.3084
COPE_InstrumentalSupport    -1.05623    0.56490  -1.870   0.0674 .
COPE_Active                  0.46220    0.59218   0.780   0.4388
COPE_Denial                  0.44587    0.76618   0.582   0.5632
COPE_Religious               0.61508    0.25746   2.389   0.0207 *
COPE_Humor                  -0.01803    0.31158  -0.058   0.9541
COPE_BehavioralDisengagement 0.03730    0.55378   0.067   0.9466
COPE_Restaint               -0.44903    0.37487  -1.198   0.2366
COPE_EmotionalSupport        0.86552    0.55436   1.561   0.1248
COPE_Substance               0.76828    0.46838   1.640   0.1072
COPE_Acceptance             -0.34934    0.41448  -0.843   0.4033
COPE_Suppression             0.12759    0.65161   0.196   0.8456
COPE_Planning               -0.53888    0.65500  -0.823   0.4146
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

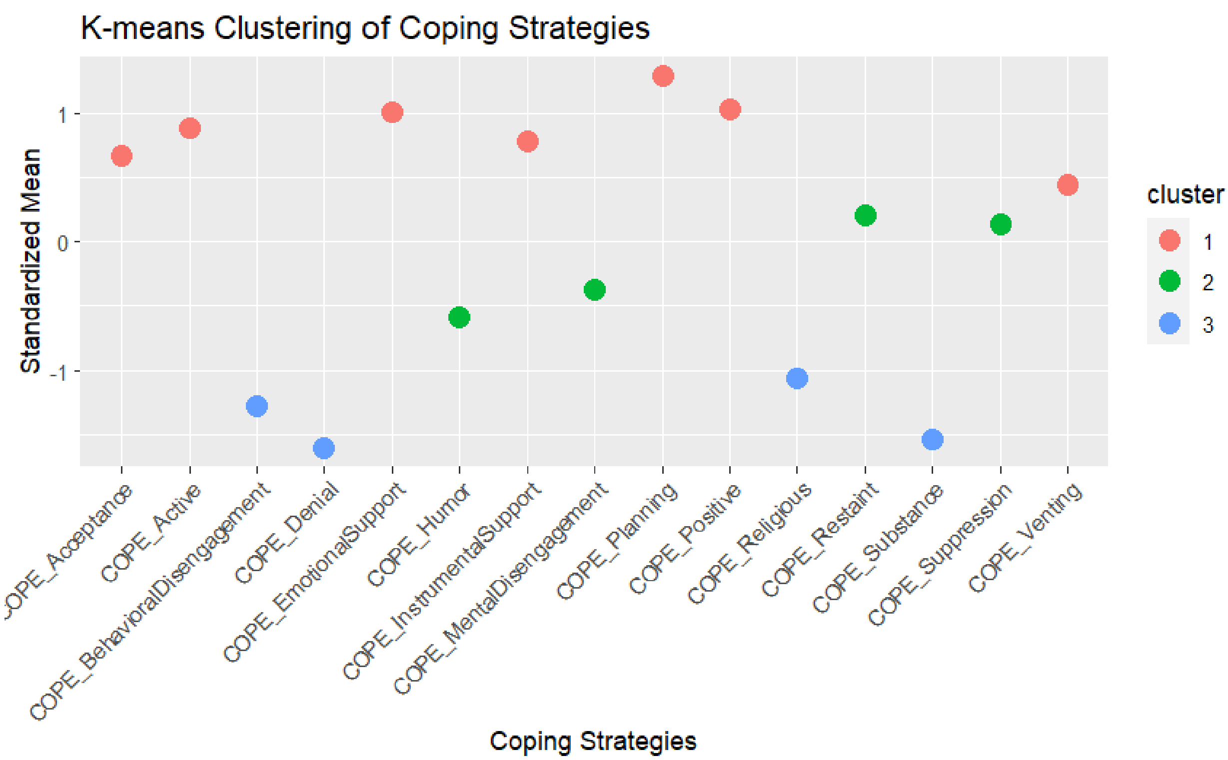
For secondary trauma, the top three coping strategies are Religious, Mental Disengagement, and Substance.However, examining the graph reveals that only the p-values for Religious and Mental Disengagement are below 0.05. Thus, I think I have the evidence to say that only Religious and Mental Disengagement are significantly relevant to secondary trauma.




```
Coefficients:
                             Estimate Std. Error t value Pr(>|t|)
(Intercept)                   2.41366   17.34758   0.139  0.88990
COPE_Positive                -0.58708    0.92152  -0.637  0.52698
COPE_MentalDisengagement      2.02159    0.83981   2.407  0.01981 *
COPE_Venting                  0.91393    0.90940   1.005  0.31974
COPE_InstrumentalSupport      0.09650    1.00346   0.096  0.92377
COPE_Active                  -1.92944    1.05193  -1.834  0.07258 .
COPE_Denial                   0.03232    1.36101   0.024  0.98115
COPE_Religious               -0.33929    0.45735  -0.742  0.46164
COPE_Humor                   -0.26985    0.55348  -0.488  0.62800
COPE_BehavioralDisengagement  1.03559    0.98371   1.053  0.29752
COPE_Restaint                -0.39797    0.66591  -0.598  0.55278
COPE_EmotionalSupport         0.03459    0.98474   0.035  0.97212
COPE_Substance                2.45143    0.83202   2.946  0.00487 **
COPE_Acceptance               0.61016    0.73627   0.829  0.41121
COPE_Suppression             -0.81882    1.15750  -0.707  0.48260
COPE_Planning                 1.40140    1.16352   1.204  0.23409
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

For Job burnout, the top three coping strategies are Substance, MentalDisengagement and Planning. Yet, the graph shows that only the p-values for Substance and Mental Disengagement fall below 0.05. Hence, only Substancce and Mental Disenegagement significantly relate to job burnout. Despite examining the order or coping strategies for various compassion fatigue types, Mental Disengagement appears to be the sole strategy of significant importance to trauma-sensitive yoga instructors.

3.3 Objective 2: Categorize the coping strategies into three groups



The coping strategies in cluster 1(High Standardized Mean) such as Acceptance, Behavioral Disengagement, Emotional Support, Positive, Suppression, Venting, are more frequently employed by individuals facing job burnout and secondary trauma. In contrast, Cluster 3 strategies(with low standardized means) like Behavioral Disengagement, Denial, Religious, and Substance are used less often, possibly because individuals deploy them only when needed, indicating a more targeted approach. The frequent use of strategies in Cluster 1 suggests an over-reliance on specific methods by instructors.

4. Discussion and Summary

The result obtained from the survey of 77 trauma-sensitive yoga instructors provided insightful finding on their wellbeing management strategies, especially when facing job burnout and secondary trauma.

A notable gender disparity emerged, with over 90% of instructors bring female. This could reflect the broader yoga community's composition or suggest a gender-specific inclination towards trauma-sensitive yoga instruction, which could potentially become an interesting topic to explore.

It is significant that Religious, Mental Disengagement and Substance emerged as a top three coping strategies for Secondary Trauma, and Substance, Mental Disengagement and Planning for Job burnout. However, we found that Mental Disengagement is the most importatnt strategy, this might suggest that trauma-sensitive yoga instructors, when overwhelmed, might distance themselves mentally from their work's emotional toll. The adaptive and maladaptive nature of such strategy would be worthy of further investigation.

In summary, as trauma-sensitive yoga gains prominence as a therapeutic discipline, the importance of understanding and bolstering the instructors's wellbeing becomes increasingly crucial. The study underscores the necessity for a balanced coping strategies for not only patients but also instruators.

Appendix

````
```{r}
# libraries
library(readr)
library(ggplot2)
library(cowplot)
library(randomForest)
library(dplyr)
library(corrplot)
library(fastDummies)
library(glmnet)
library(lm.beta)
library(tidyverse)
library(cluster)
library(knitr)
library(factoextra)
library(car)
library(gt)
library(gtsummary)
library(huxtable)
```


```{r}
# Data cleaned
original_data <- Data_STAT4893W

# Remove several rows
rows_to_delete <- c(1, 14, 15, 34, 35, 36, 38, 39, 47, 75, 77, 78)

cleaned_data <- original_data[-rows_to_delete, ]

cleaned_data[cleaned_data == ' '] <- 0

# convert data into numeric
cleaned_data[] <- lapply(cleaned_data, as.numeric)

cleaned_data <- cleaned_data %>% rename(
                          "COPE_Positive" ="V161",
                          "COPE_MentalDisengagement" = "V162",
                          "COPE_Venting" = "V163",
                          "COPE_InstrumentalSupport" = "V164",
                          "COPE_Active" = "V165",
                          "COPE_Denial" = "V166",
                          "COPE_Religious" = "V167",
                          "COPE_Humor" = "V168",
                          "COPE_BehavioralDisengagement" = "V169",
                          "COPE_Restaint" = "V170",
````
````

```
                              "COPE_EmotionalSupport" = "V171",
                              "COPE_Substance" = "V172",
                              "COPE_Acceptance" = "V173",
                              "COPE_Suppression" = "V174",
                              "COPE_Planning" = "V175",
                              "CFS" = "V176",
                              "CFS_SecondaryTrauma" = "V177",
                              "CFS_JobBurnout" = "V178",
                              "CFS_ln" = "V179",
                              "CFS_SecondaryTrauma_ln" = "V180",
                              "CFS_JobBurnout_ln" = "V181",
                              )


# Remove V8 and V80 columns(text, )
cleaned_data <- cleaned_data[,-8]
cleaned_data <- cleaned_data[,-80]
cleaned_data <- cleaned_data[,-129]
cleaned_data <- cleaned_data[,-155]
```

```{r}
# demographic
demographic_data <- cleaned_data

demographic_data[demographic_data == ' '] <- 0
demographic_data[] <- lapply(demographic_data, as.numeric)


# Gender
demographic_data[demographic_data$V7 == 1,]$V7 <- "Female"
demographic_data[demographic_data$V7 == 2,]$V7 <- "Male"
demographic_data[demographic_data$V7 == 3,]$V7 <- "Nonbinary"
demographic_data[demographic_data$V7 == 4,]$V7 <- "Other"


# Immigrant
demographic_data[demographic_data$V78 == 0,]$V78 <- "No"
demographic_data[demographic_data$V78 == 1,]$V78 <- "Yes"


# Refugee
demographic_data[demographic_data$V79 == 0,]$V79 <- "No"
demographic_data[demographic_data$V79 == 999,]$V79 <- "Decline to answer"


# Community
demographic_data[demographic_data$V80 == 1,]$V80 <- "Rural Area"
demographic_data[demographic_data$V80 == 2,]$V80 <- "Small"
```

```
demographic_data[demographic_data$V80 == 3,]$V80 <- "Large"
demographic_data[demographic_data$V80 == 4,]$V80 <- "Suburb"


# School
demographic_data[demographic_data$V82 == 4,]$V82 <- "Professional Qualification"
demographic_data[demographic_data$V82 == 5,]$V82 <- "Associate Degree"
demographic_data[demographic_data$V82 == 6,]$V82 <- "Some College"
demographic_data[demographic_data$V82 == 7,]$V82 <- "Bachelor Degree"
demographic_data[demographic_data$V82 == 8,]$V82 <- "Master Degree"
demographic_data[demographic_data$V82 == 9,]$V82 <- "Doctorate"


# Income
demographic_data[demographic_data$V83 == 1,]$V83 <- "< $13000"
demographic_data[demographic_data$V83 == 2,]$V83 <- "$13000 to $26000"
demographic_data[demographic_data$V83 == 3,]$V83 <- "$26000 to $59000"
demographic_data[demographic_data$V83 == 4,]$V83 <- "$59000 to $75000"
demographic_data[demographic_data$V83 == 5,]$V83 <- "$75000 to $100000"
demographic_data[demographic_data$V83 == 6,]$V83 <- "$100000 to $150000"
demographic_data[demographic_data$V83 == 7,]$V83 <- "> $150000"
demographic_data[demographic_data$V83 == 999,]$V83 <- "Decline to answer"


# Country
demographic_data[demographic_data$V84 == 9,]$V84 <- "Australia"
demographic_data[demographic_data$V84 == 31,]$V84 <- "Canada"
demographic_data[demographic_data$V84 == 65,]$V84 <- "Germany"
demographic_data[demographic_data$V84 == 82,]$V84 <- "Ireland"
demographic_data[demographic_data$V84 == 83,]$V84 <- "Israel"
demographic_data[demographic_data$V84 == 84,]$V84 <- "Italy"
demographic_data[demographic_data$V84 == 111,]$V84 <- "Mexico"
demographic_data[demographic_data$V84 == 122,]$V84 <- "Netherlands"
demographic_data[demographic_data$V84 == 123,]$V84 <- "New Zealand"
demographic_data[demographic_data$V84 == 156,]$V84 <- "Singapore"
demographic_data[demographic_data$V84 == 163,]$V84 <- "Spain"
demographic_data[demographic_data$V84 == 185,]$V84 <- "United Kingdom of Great Britain and Northern Ireland"
demographic_data[demographic_data$V84 == 187,]$V84 <- "United States of America"


# State
demographic_data[demographic_data$V85 == 0,]$V85 <- "No answer"
demographic_data[demographic_data$V85 == 3,]$V85 <- "Arizona"
demographic_data[demographic_data$V85 == 5,]$V85 <- "California"
demographic_data[demographic_data$V85 == 10,]$V85 <- "Florida"
demographic_data[demographic_data$V85 == 11,]$V85 <- "Georgia"
demographic_data[demographic_data$V85 == 14,]$V85 <- "Illinois"
demographic_data[demographic_data$V85 == 15,]$V85 <- "Indiana"
```

```
demographic_data[demographic_data$V85 == 16,]$V85 <- "Iowa"
demographic_data[demographic_data$V85 == 20,]$V85 <- "Maine"
demographic_data[demographic_data$V85 == 21,]$V85 <- "Maryland"
demographic_data[demographic_data$V85 == 22,]$V85 <- "Massachusetts"
demographic_data[demographic_data$V85 == 23,]$V85 <- "Michigan"
demographic_data[demographic_data$V85 == 24,]$V85 <- "Minnesota"
demographic_data[demographic_data$V85 == 26,]$V85 <- "Missouri"
demographic_data[demographic_data$V85 == 27,]$V85 <- "Montana"
demographic_data[demographic_data$V85 == 31,]$V85 <- "New Jersey"
demographic_data[demographic_data$V85 == 33,]$V85 <- "New York"
demographic_data[demographic_data$V85 == 34,]$V85 <- "North Carolina"
demographic_data[demographic_data$V85 == 36,]$V85 <- "Ohio"
demographic_data[demographic_data$V85 == 39,]$V85 <- "Pennsylvania"
demographic_data[demographic_data$V85 == 40,]$V85 <- "Puerto Rico"
demographic_data[demographic_data$V85 == 49,]$V85 <- "Washington"
demographic_data[demographic_data$V85 == 51,]$V85 <- "Wisconsin"



demographic_data <- demographic_data %>% rename("StudyID" ="V1",
                          "AgeGroup_1" = "V2",
                          "AgeGroup_2" = "V3",
                          "AgeGroup_3" = "V4",
                          "AgeGroup_4" = "V5",
                          "Age" = "V6",
                          "Gender" = "V7",
                          "Immigrant" = "V78",
                          "Refugee" = "V79",
                          "Community" = "V80",
                          "School" = "V82",
                          "Income" = "V83",
                          "Country" = "V84",
                          "State" = "V85",
                          "Not of Hispanic, Latino/a, or Spanish origin" = "V9",
                          "Unknown" = "V10",
                          "Latin American" = "V11",
                          "Audalusian" = "V12",
                          "Catalonian" = "V20",
                          "Central American" = "V21",
                          "Colombian" = "V25",
                          "Cuban" = "V28",
                          "Dominican" = "V29",
                          "Spaniard" = "V36",
                          "Nicaraguan" = "V38",
                          "Puerto Rican" = "V42",
                          "Decline to answer" = "V52"
                          )

# Age_Groups
```

```
group1 <- sum(demographic_data$AgeGroup_1)
group2 <- sum(demographic_data$AgeGroup_2)
group3 <- sum(demographic_data$AgeGroup_3)
group4 <- sum(demographic_data$AgeGroup_4)


age_group <- data.frame(
  group_name = c("Youth", "Young adult", "Adults", "Older adults"),
  counts = c(group1, group2, group3, group4)
)
kable(age_group)


# Latin_groups
latin0 <- sum(cleaned_data$V9)
latin888 <- sum(cleaned_data$V10)
latin1 <- sum(cleaned_data$V11)
latin2 <- sum(cleaned_data$V12)
latin10 <- sum(cleaned_data$V20)
latin11 <- sum(cleaned_data$V21)
latin15 <- sum(cleaned_data$V25)
latin18 <- sum(cleaned_data$V28)
latin19 <- sum(cleaned_data$V29)
latin26 <- sum(cleaned_data$V36)
latin28 <- sum(cleaned_data$V38)
latin32 <- sum(cleaned_data$V42)
latin999 <- sum(cleaned_data$V52)

latin_group <- data.frame(
      latin_name = c("Not of Hispanic, Latino/a, or Spanish origin",
                                    "Latin American",
                                    "Audalusian",
                                    "Catalonian",
                                    "Central American",
                                    "Colombian",
                                    "Cuban",
                                    "Dominican",
                                    "Spaniard",
                                    "Nicaraguan",
                                    "Puerto Rican",
                                    "Unknown",
                                    "Decline to answer"),
        counts = c(latin0, latin1, latin2, latin10, latin11, latin15, latin18, latin19, latin26, latin28, latin32,
latin888, latin999)
)
kable(latin_group)


# Race_groups
```

```
race2 <- sum(cleaned_data$V54)
race3 <- sum(cleaned_data$V55)
race6 <- sum(cleaned_data$V58)
race13 <- sum(cleaned_data$V65)
race22 <- sum(cleaned_data$V74)
race23 <- sum(cleaned_data$V75)
race24 <- sum(cleaned_data$V76)

race_group <- data.frame(
  race_name = c("Black or African descent", "White or European descent", "Chinese", "Other South
Asian", "Other race", "Hispanic, Latina, Spanish origin", "White, Hispanic origin"),
  counts = c(race2, race3, race6, race13, race22, race23, race24)
)
kable(race_group)


age <- data.frame(
  names = c("n", "mean", "sd"),
  value = c(length(cleaned_data$V6), mean(cleaned_data$V6), sd(cleaned_data$V6))
)
kable(age)


barplot(table(demographic_data$Age), main = "Age distribution", xlab = "Age", ylab = "Count")

trial2 <- demographic_data %>% select( Gender, Immigrant, Refugee, Community, School, Income,
Country, State )
trial2 %>% tbl_summary()


```

```{r}
# Multiple Regression for secondary trauma
SE5_model <- 5*cleaned_data$CFS_SecondaryTrauma

SE_model <- lm(SE5_model ~  COPE_Positive +
                              COPE_MentalDisengagement +
                              COPE_Venting +
                              COPE_InstrumentalSupport +
                              COPE_Active +
                              COPE_Denial +
                              COPE_Religious +
                              COPE_Humor +
                              COPE_BehavioralDisengagement +
                              COPE_Restaint +
                              COPE_EmotionalSupport +
                              COPE_Substance +
                              COPE_Acceptance +
```

```
                                    COPE_Suppression +
                                    COPE_Planning
                                  , data = cleaned_data)
SE_model
summary(SE_model)
# compared with SE in beta
beta_SE <- lm.beta(SE_model)$coef

# Standardize variables to get standardized coefficients
mtcars.std <- lapply(mtcars, scale)
# Gather summary statistics
stats.table <- as.data.frame(summary(SE_model)$coefficients)
# Add a row to join the variables names and CI to the stats
stats.table <- cbind(row.names(stats.table), stats.table, beta_SE)
# Rename the columns appropriately
names(stats.table) <- cbind("Term", "Estimate", "SE", "t", "p-value", "beta.coef")
nice_table(stats.table)


rank <- data.frame(
  rank_name = c("Religious", "MentalDisengagement", "Substance", "EmotionalSupport", "Positive",
"Active", "Denial", "Suppression", "BehavioralDisengagement", "Humor", "Planning", "Acceptance",
"Venting", "Restaint", "InstrumentalSupport"),
  ranked = c(2.39, 2.11, 1.64, 1.56, 1.41, 0.78, 0.58, 0.20, 0.07, -0.06, -0.82, -0.84, -1.03, -1.2, -1.87)
)
rank$rank_name <- factor(rank$rank_name, levels = rank$rank_name[order(rank$ranked)])


ggplot(rank, aes(x = rank_name, y = ranked)) +
  geom_bar(stat = "identity", fill = "coral") +
  coord_flip() +  # This makes the bars horizontal
  labs(title = "The rank of Secondary Trauma ",
       x = "",
       y = "") +
  theme_minimal() +
  theme(
    plot.title = element_text(size = 24, hjust = 0.5),
    axis.text = element_text(size = 12)
  )


par(mfrow = c(1, 3))
qqnorm(residuals(SE_model))
qqline(residuals(SE_model))

plot(SE_model)

vif(SE_model)
```

````
```

```{r}
#Multiple Regression for Job Burnout
CFS_JB <- 8*cleaned_data$CFS_JobBurnout
JB_model <- lm(CFS_JB ~  COPE_Positive +
                     COPE_MentalDisengagement +
                     COPE_Venting +
                     COPE_InstrumentalSupport +
                     COPE_Active +
                     COPE_Denial +
                     COPE_Religious +
                     COPE_Humor +
                     COPE_BehavioralDisengagement +
                     COPE_Restaint +
                     COPE_EmotionalSupport +
                     COPE_Substance +
                     COPE_Acceptance +
                     COPE_Suppression +
                     COPE_Planning
                    , data = cleaned_data)
summary(JB_model)

# compared with JB in beta
beta_JB <- lm.beta(JB_model)$coef

# Gather summary statistics
stats.table <- as.data.frame(summary(JB_model)$coefficients)
stats.table
# Add a row to join the variables names and CI to the stats
stats.table <- cbind(row.names(stats.table), stats.table, beta_JB)
stats.table
# Rename the columns appropriately
names(stats.table) <- cbind("Term", "Estimate", "SE", "t", "p-value", "beta.coef")
stats.table
nice_table(stats.table)
rank(stats.table$t)


rank <- data.frame(
  rank_name = c("Religious", "MentalDisengagement", "Substance", "EmotionalSupport", "Positive",
"Active", "Denial", "Suppression", "BehavioralDisengagement", "Humor", "Planning", "Acceptance",
"Venting", "Restaint", "InstrumentalSupport"),
  ranked = c(-0.74, 2.41, 2.95, 0.04, -0.64, -1.83, 0.02, -0.71, 1.05, -0.49, 1.20, 0.83, 1, -0.6, 0.1)
)
rank$rank_name <- factor(rank$rank_name, levels = rank$rank_name[order(rank$ranked)])


ggplot(rank, aes(x = rank_name, y = ranked)) +
````

````
  geom_bar(stat = "identity", fill = "coral") +
  coord_flip() +  # This makes the bars horizontal
  labs(title = "The rank of Job Burnout",
       x = "",
       y = "") +
  theme_minimal() +
  theme(
    plot.title = element_text(size = 24, hjust = 0.5),
    axis.text = element_text(size = 12)
  )

```

```{r}
# Objective 2
coping_data <- cleaned_data[, -(1:156)]
coping_data <- coping_data[, -(16:22)]

# PCA
pca.out <- prcomp(coping_data, scale = TRUE)
pca.out
summary(pca.out)
plot(pca.out, type = "l", main = "Variance")

pca.var <- pca.out$sdev^2
pca.var.per <- round(pca.var/sum(pca.var)*100, 1)
barplot(pca.var.per, main = "Scree Plot", xlab = "PC", ylab = "Percent Variation")


# K-mean clustering

# Entities (e.g., States)
entities <- c("COPE_Positive",
                                "COPE_MentalDisengagement",
                                "COPE_Venting" ,
                                "COPE_InstrumentalSupport" ,
                                "COPE_Active",
                                "COPE_Denial",
                                "COPE_Religious",
                                "COPE_Humor",
                                "COPE_BehavioralDisengagement",
                                "COPE_Restaint",
                                "COPE_EmotionalSupport",
                                "COPE_Substance",
                                "COPE_Acceptance" ,
                                "COPE_Suppression",
                                "COPE_Planning")
````

```
positive <- mean(cleaned_data$COPE_Positive)
mentaldis <- mean(cleaned_data$COPE_MentalDisengagement)
venting <- mean(cleaned_data$COPE_Venting)
instumentalsupport <- mean(cleaned_data$COPE_InstrumentalSupport)
active <- mean(cleaned_data$COPE_Active)
denial <- mean(cleaned_data$COPE_Denial)
religious <- mean(cleaned_data$COPE_Religious)
humor <- mean(cleaned_data$COPE_Humor)
behavioraldis <- mean(cleaned_data$COPE_BehavioralDisengagement)
restaint <- mean(cleaned_data$COPE_Restaint)
emotionalsup <- mean(cleaned_data$COPE_EmotionalSupport)
substance <- mean(cleaned_data$COPE_Substance)
acceptance <- mean(cleaned_data$COPE_Acceptance)
suppression <- mean(cleaned_data$COPE_Suppression)
planning <- mean(cleaned_data$COPE_Planning)

# Features
Feature1 <- c(positive, mentaldis, venting, instumentalsupport, active, denial, religious, humor,
behavioraldis, restaint, emotionalsup, substance, acceptance, suppression, planning )

Feature1 <- scale(Feature1)
Feature1
# Combine the data
my_dataset <- data.frame(Entity = entities,
                         mean = Feature1)

# Standardize the Data
my_dataset$mean_scaled <- scale(my_dataset$mean)

# Apply k-means clustering
set.seed(123)  # Setting seed for reproducibility
k3 <- kmeans(my_dataset$mean_scaled, centers=3)

# Add cluster assignment to your data
my_dataset$cluster <- as.factor(k3$cluster)

# Visualize the results
ggplot(my_dataset, aes(x=Entity, y=mean_scaled, color=cluster)) +
  geom_point(size=4) +
  theme(axis.text.x = element_text(angle=45, hjust=1)) +
  labs(title="K-means Clustering of Coping Strategies", y="Standardized Mean", x="Coping Strategies")

```