```
#TIPI items, to construct OCEAN variables
personalityVariables = c('personality_extroverted', 'personality_critical', 'personality_dependable', '
#PANAS items, to construct pre, post, delta variables
preScaleItems = c('pre_Active', 'pre_Afraid', 'pre_Determined', 'pre_Nervous', 'pre_Attentive',
                   'pre_Upset', 'pre_Inspired', 'pre_Hostile', 'pre_Alert', 'pre_Ashamed')
postScaleItems = c('post_Active', 'post_Afraid', 'post_Determined', 'post_Nervous', 'post_Attentive', ')
pre_post_scale_item_column_names = c('id', 'prePositiveAffect', 'preNegativeAffect', 'postPositiveAffect')
# Co-function. Remove non alphanumerics from string, save comma and minus
parse_string <- function(x) {</pre>
 return (gsub("[^[:alnum:][:blank:],/\\-]", "", x))
create_personality_vars <- function(df) {</pre>
  ###Apply parse_string###
  df$personalityResponses <- lapply(df$responses, parse_string)</pre>
  df[personalityVariables] <- as.numeric(str_split_fixed(df$personalityResponses, ',', 10))</pre>
  df$openness <- (df$personality_open + (4 - df$personality_conventional)) / 2</pre>
  df$conscientiousness <- (df$personality_dependable + (4 - df$personality_disorganized)) / 2
  df$extroversion <- (df$personality_extroverted + (4 - df$personality_reserved)) / 2</pre>
  df$agreeableness <- (df$personality_sympathetic + (4 - df$personality_critical)) / 2
  df$emot_stability <- (df$personality_calm + (4 - df$personality_anxious)) / 2</pre>
  return (df)
create_pre_post_scale_items <- function(df) {</pre>
  #apply parse_string
  df$preSurveyResponses <- lapply(df$preSurveyResponses, parse_string)</pre>
  df$postSurveyResponses <- lapply(df$postSurveyResponses, parse_string)</pre>
  # Split SurveyResponses as numerics across new columns
  df[preScaleItems] <- as.numeric(str_split_fixed(df$preSurveyResponses, ',', 10))</pre>
  df[postScaleItems] <- as.numeric(str_split_fixed(df$postSurveyResponses, ',', 10))</pre>
  df$prePositiveAffect <- (((df$pre_Active) + (df$pre_Determined) + (df$pre_Attentive) + (df$pre_Inspir
  df$preNegativeAffect <- ((df$pre_Afraid + df$pre_Nervous + df$pre_Upset + df$pre_Hostile + df$pre_Ash
  df$postPositiveAffect <- ((df$post_Active + df$post_Determined + df$post_Attentive + df$post_Inspired
  df$postNegativeAffect <- ((df$post_Afraid + df$post_Nervous + df$post_Upset + df$post_Hostile + df$po
  df$post_pre_PositiveAffect <- df$postPositiveAffect - df$prePositiveAffect</pre>
  df$post_pre_NegativeAffect <- df$postNegativeAffect - df$preNegativeAffect</pre>
 return (df)
```

```
create_delta_scale_items <- function(df) {</pre>
  pre_items <- grep("^pre", names(df), value = TRUE)</pre>
  pre_items <- pre_items[! pre_items %in% 'preSurveyResponses']</pre>
  post_items <- grep("^post", names(df), value = TRUE)</pre>
  post_items <- post_items[! post_items %in% c('postSurveyResponses', 'post_pre_PositiveAffect', 'post_</pre>
  # Iterating over each item pair and creating a new column for the difference
  for (i in seq_along(pre_items)) {
    item <- sub("^pre", "", pre_items[i]) # Extracting the item name</pre>
    # tmp[pasteO(item, "_diff")] <- df_hostile_agent[post_items[i]] - df_hostile_agent[pre_items[i]]
    if (is.numeric(df[[pre_items[i]]]) && is.numeric(df[[post_items[i]]])) {
      df[paste0("post_pre", item)] <- df[[post_items[i]]] - df[[pre_items[i]]]</pre>
      warning(paste("Columns", pre_items[i], "and", post_items[i], "contain non-numeric data. Skipping
 }
 return (df)
}
# co-function
generate_histogram <- function(data, col, binwidth, y_limit) {</pre>
  ggplot(data, aes_string(x = col)) +
    geom_histogram(fill = "skyblue", color = "black", binwidth = binwidth) +
    xlab(col) +
    ylim(y_limit)
}
# co-function
apply_limits <- function(flag) {</pre>
  limits <- list(</pre>
    pre_post = list(y_limit = c(0, 25)),
    overall_pre_post = list(y_limit = c(0, 70)),
    overall_personality = list(y_limit = c(0, 65)),
    post_pre_differences = list(x_limit = c(-5, 5), y_limit = c(0, 30)),
    docile_post_pre_differences = list(x_limit = c(-5, 5), y_limit = c(0, 50)),
    overall_post_pre_differences = list(x_limit = c(-5, 5), y_limit = c(0, 85)),
    personality = list(y_limit = c(0, 25))
 return(limits[[flag]])
gridOfHistograms <- function(data, plot_name, flag = "None", title_flag = FALSE) {</pre>
  list <- lapply(1:ncol(data), function(col) {</pre>
    if (flag != "None") {
      limits <- apply_limits(flag)</pre>
      generate_histogram(data, colnames(data)[col], 1, limits$y_limit)
      generate_histogram(data, colnames(data)[col], 1, c(0, 10))
  })
 if (title_flag) {
```

```
title <- ggdraw() + draw_label(plot_name, fontface = 'bold')</pre>
    grid_plot <- cowplot::plot_grid(plotlist = list)</pre>
    grid_plot <- ggdraw(grid_plot) +</pre>
      ggtitle(plot_name) +
      theme(plot.title = element_text(hjust = 0.5))
    print(grid_plot)
    ggsave(paste0(plot_name, ".png"), grid_plot)
  } else {
    grid_plot <- cowplot::plot_grid(plotlist = list)</pre>
    print(grid_plot)
    ggsave(pasteO(plot_name, ".png"), grid_plot)
 return(grid_plot)
generate_boxplot <- function(data, col, x_var, num_rows, angle) {</pre>
  ggplot(data = data, aes_string(x = x_var, y = col)) +
    geom_boxplot(color = "black", fill = "blue", alpha = 0.2, outlier.shape = NA) +
    ylab(col) + xlab(NULL) +
    stat_summary(fun = mean, colour = "black", geom = "point", shape = 18, size = 3, show.legend = FALS
    theme(axis.text.x = element_text(angle = angle, hjust = 1, size = 12), axis.title.y = element_text(
}
gridOfBoxplots <- function(data, plot_name, plot_name_flag = FALSE, behaviors_flag = FALSE, by_gender =
  if (!behaviors_flag) {
    if (!by_gender) {
      if (!by_familiarity) {
        num_columns <- 4</pre>
        num_rows <- 4</pre>
        x_var <- "combined_group"</pre>
        angle <- 45
      } else {
        x_var <- "GenderXFamiliarity"</pre>
        angle <- 25
    } else {
      x_var <- "gender"</pre>
      angle <- 25
  } else {
    if (!by_gender) {
      if (!by_familiarity) {
        num_columns <- 4</pre>
```

num_rows <- 2</pre>

angle <- 45

angle <- 25

} else {

x_var <- "combined_group"</pre>

x_var <- "GenderXFamiliarity"</pre>

```
} else {
    x_var <- "gender"</pre>
    angle <- 25
}
if (!behaviors_flag) {
  list <- lapply(59:70, function(col) {</pre>
    generate_boxplot(data, colnames(data)[col], x_var, num_rows, angle)
  })
} else {
  list <- lapply(9:15, function(col) {</pre>
    generate_boxplot(data, colnames(data)[col], x_var, num_rows, angle)
  })
}
if (plot_name_flag) {
  title <- ggdraw() + draw_label(plot_name, fontface = 'bold')</pre>
  grid_plot <- cowplot::plot_grid(plotlist = list)</pre>
  grid_plot <- ggdraw(grid_plot) +</pre>
    ggtitle(plot_name) +
    theme(plot.title = element_text(hjust = 0.5))
  print(grid_plot)
} else {
  print("!plot_name_flag")
  grid_plot <- cowplot::plot_grid(plotlist = list)</pre>
  print(grid_plot)
}
return(grid_plot)
```

```
geom_boxplot(aes(ymin =min, lower = mean-sd, middle = mean, upper = mean+sd, ymax =max, fill = Subs
    geom_text(aes(label = round(mean, 3), y = mean + 0.2), size = 3, position = position_dodge(width = 0.2)
   labs(title = plot_name) +
   labs(v = "item score") +
    theme(axis.text.x = element_text(angle=75, hjust=1))
  ggsave(paste0(plot_name,".png"), meanBoxPlots)
  plot(meanBoxPlots)
 return (meanBoxPlots)
}
run_anova <- function(outcome_var, factor_1, factor_2=FALSE, interaction=FALSE, remove_outliers=FALSE){
  ##assumption 1 - normality of residuals
  # - check sample size per group, if all >= 30, continue
                                   else, run Shapiro-Wilk Test on ANOVA residuals
  # run levene test for equality of variance
  if (factor_2) {
  model_df <- mobOutcomes[c(outcome_var, factor_1, factor_2, "id")]</pre>
  df_outliers <- model_df %>%
   group_by(factor_1, factor_2) %>%
    identify_outliers(outcome_var)
  print(sprintf("Running %s model with %d outliers", outcome_var, count_extreme_outliers))
  count_extreme_outliers <- sum(df_outliers.is.extreme)</pre>
  #Run model both with and without outlier removal, if outliers present
  aov_model <- aov(outcome_var ~ factor_1 + factor_2 + factor1:factor2,</pre>
                   data = model df)
  #At least one value of the 'is.extreme' column is TRUE
  if (count_extreme_outliers > 0) {
   model_df <- model_df %>%
      anti_join(df_outliers[which(df_outliers$is.extreme %in% TRUE),], by = "id")
   aov_model <- aov(outcome_var ~ factor_1 + factor_2 + factor1:factor2,</pre>
                     data = model_df)
   aov_model_no_extreme_outliers <- aov(outcome_var ~ factor_1 + factor_2 + factor1:factor2,</pre>
                     data = model_df)
  }
  model_df <- model_df %>%
   anti_join(df_outliers[which(df_outliers$is.extreme %in% TRUE),], by = "id")
  aov_model <- aov(outcome_var ~ factor_1 + factor_2 + factor1:factor2,</pre>
                       data = model df)
  # human_agent
                                 1 1.26 1.2622 1.047 0.309
  # docile hostile
                                 1 0.76 0.7569 0.628 0.430
  # human_agent:docile_hostile 1 0.36 0.3567 0.296 0.588
  summary(aov_model)
 }
```

```
df_docile_human <-read.csv(file="docileHuman.csv", stringsAsFactors=FALSE, header=T)
df_docile_human <-as.data.frame(df_docile_human)
#30x16
dim(df_docile_human)</pre>
```

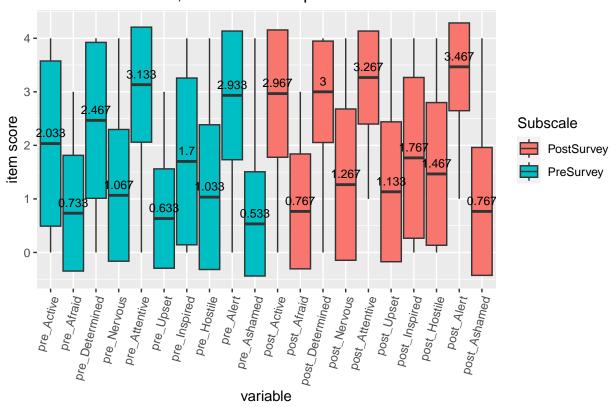
[1] 30 16

```
df_docile_human <- create_personality_vars(df_docile_human)
df_docile_human <- create_pre_post_scale_items(df_docile_human)
df_docile_human <- create_delta_scale_items(df_docile_human)
#30x70

pre_post_scale_items <- df_docile_human[c('id', preScaleItems, postScaleItems)]
pre_post_box_plots <- boxPlots_func(pre_post_scale_items, 0, "Docile Human Pre, Post Affect Boxplots")</pre>
```

Saving 6.5×4.5 in image

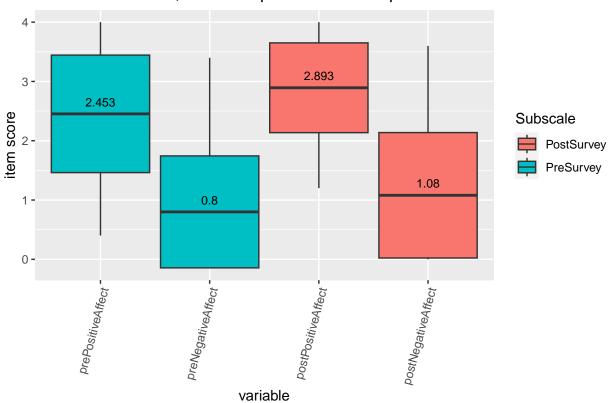
Docile Human Pre, Post Affect Boxplots



```
names.use <- names(df_docile_human) %in% pre_post_scale_item_column_names
docile_human_pre_post <- df_docile_human[, names.use]
pre_post_box_plots <- boxPlots_func(docile_human_pre_post, 1, "Docile Human Pre, Post Composite Affect in the column pre_post in the column pr
```

Saving 6.5 x 4.5 in image

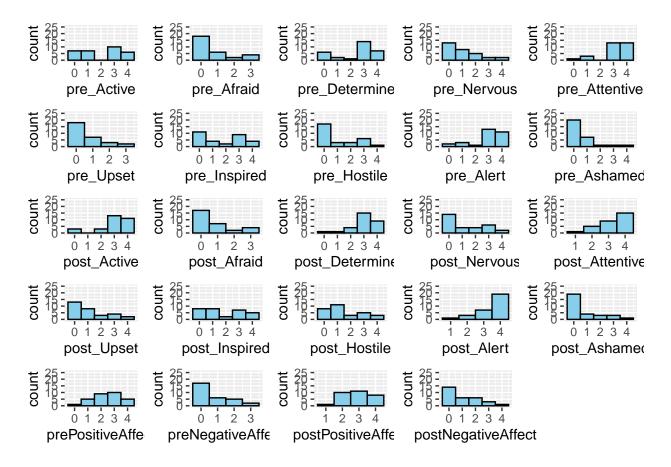




pre_post_scale_items <- df_docile_human[c(preScaleItems, postScaleItems, 'prePositiveAffect', 'preNegat
plot_docile_human_pre_post <- gridOfHistograms(pre_post_scale_items, "Docile Human Pre, Post Affect His</pre>

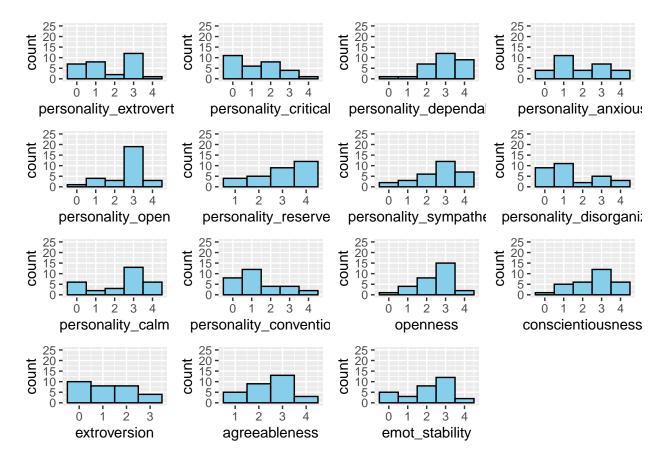
```
## Warning: `aes_string()` was deprecated in ggplot2 3.0.0.
## i Please use tidy evaluation ideoms with `aes()`
```

Saving 6.5×4.5 in image



df_docile_human_personality <- df_docile_human[, 18:32]
plot_docile_human_personality <- gridOfHistograms(df_docile_human_personality, "Docile Human Personality")</pre>

Saving 6.5×4.5 in image



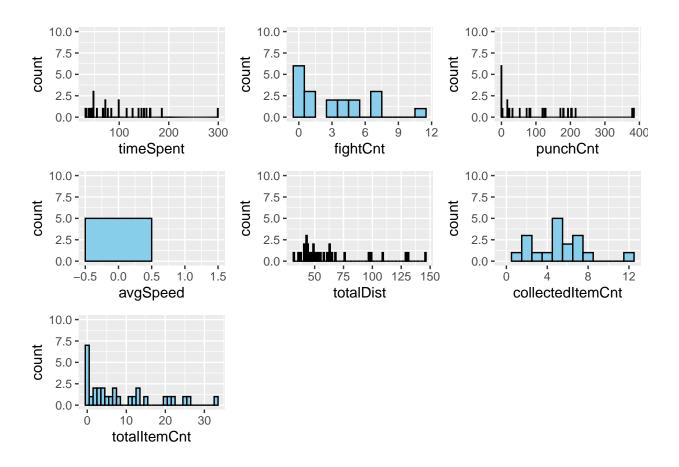
df_docile_human_behaviors <- df_docile_human[, 9:15]
plot_docile_human_behaviors <- gridOfHistograms(df_docile_human_behaviors, "Docile Human Behaviors Hist</pre>

```
## Warning: Removed 1 rows containing missing values (`geom_bar()`).
```

^{##} Removed 1 rows containing missing values (`geom_bar()`).

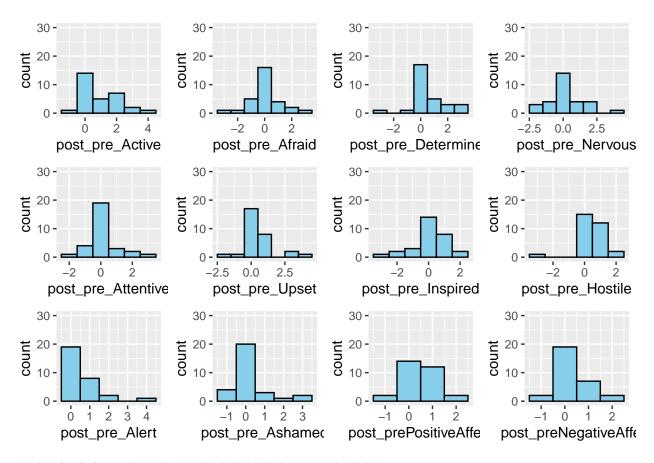
^{##} Removed 1 rows containing missing values (`geom_bar()`).

^{##} Saving 6.5 x 4.5 in image



df_docile_human_deltas <- df_docile_human[, 59:70]
plot_docile_human_deltas <- gridOfHistograms(df_docile_human_deltas, "Docile Human Post to Pre Differen</pre>

Saving 6.5×4.5 in image



```
df_docile_agent <-as.data.frame(df_docile_agent)

df_docile_agent <- create_personality_vars(df_docile_agent)

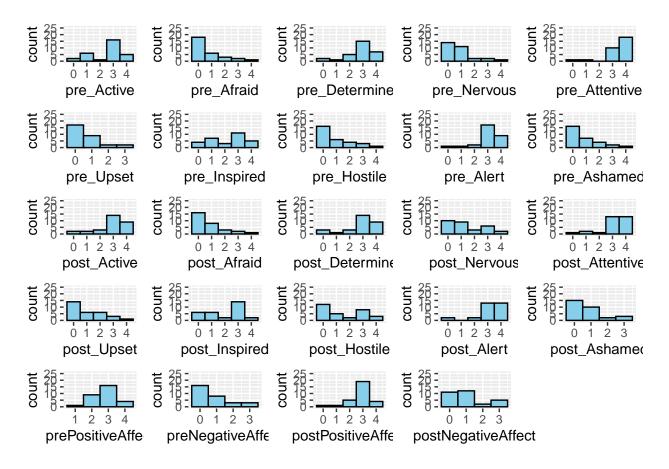
df_docile_agent <- create_pre_post_scale_items(df_docile_agent)

df_docile_agent <- create_delta_scale_items(df_docile_agent)

pre_post_scale_items <- df_docile_agent[c(preScaleItems, postScaleItems, 'prePositiveAffect', 'preNegat plot_docile_agent_pre_post <- gridOfHistograms(pre_post_scale_items, "Docile Agent Pre, Post Affect His</pre>
```

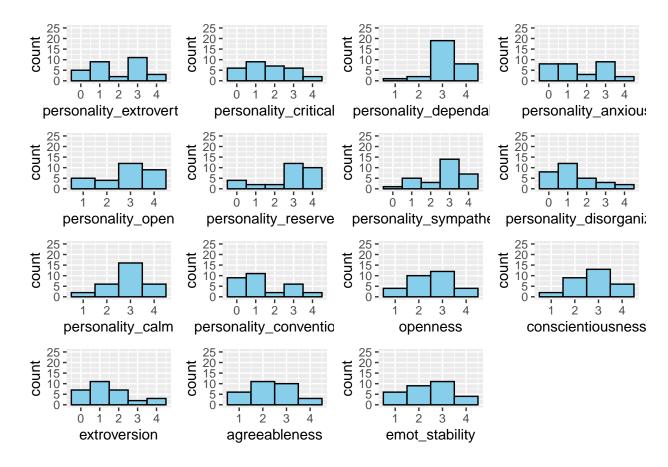
df_docile_agent <- read.csv(file="docileAgent.csv", stringsAsFactors=FALSE, header=T)</pre>

Saving 6.5×4.5 in image



df_docile_agent_personality <- df_docile_agent[, 18:32]
plot_docile_human_personality <- gridOfHistograms(df_docile_agent_personality, "Docile Agent Personality")</pre>

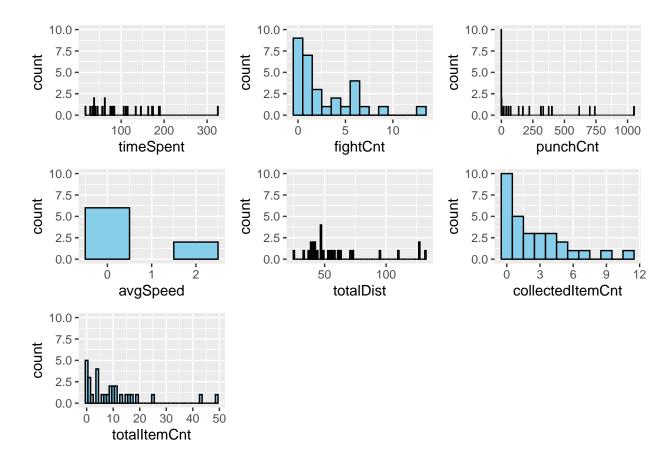
Saving 6.5×4.5 in image



df_docile_agent_behaviors <- df_docile_agent[, 9:15]
plot_docile_agent_behaviors <- gridOfHistograms(df_docile_agent_behaviors, "Docile Agent Behaviors Hist</pre>

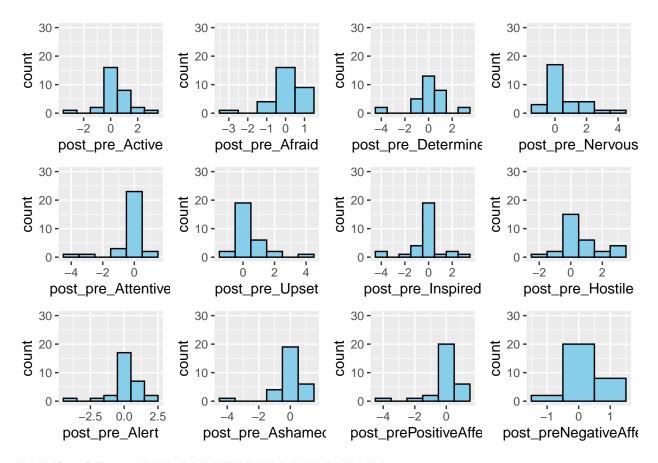
Warning: Removed 1 rows containing missing values (`geom_bar()`).

Saving 6.5×4.5 in image



df_docile_agent_deltas <- df_docile_agent[, 59:70]
plot_docile_agent_deltas <- gridOfHistograms(df_docile_agent_deltas, "Docile Agent Post to Pre Differen</pre>

Saving 6.5×4.5 in image



df_hostile_human <-read.csv(file="hostileHuman.csv", stringsAsFactors=FALSE, header=T)

####hostileHuman### ########################

Removed 1 rows containing missing values (`geom_bar()`).

df_hostile_human <-as.data.frame(df_hostile_human)</pre>

```
df_hostile_human <- select(df_hostile_human, -c(stolenItemCnt))

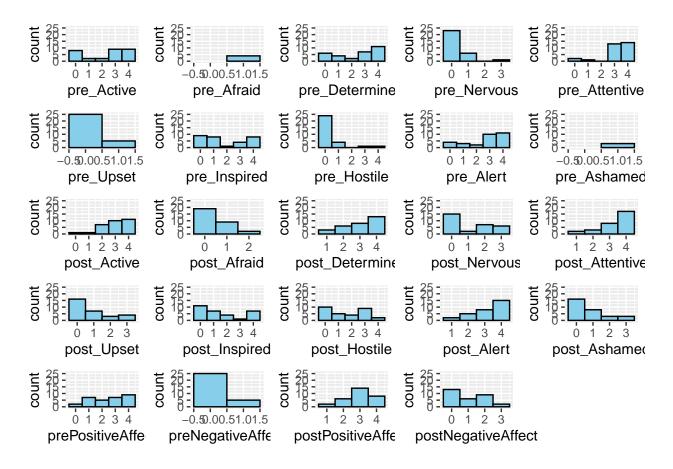
df_hostile_human <- create_personality_vars(df_hostile_human)

df_hostile_human <- create_pre_post_scale_items(df_hostile_human)

df_hostile_human <- create_delta_scale_items(df_hostile_human)

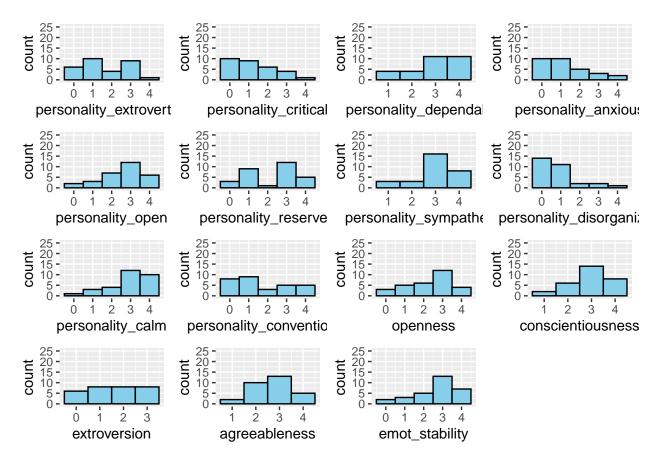
pre_post_scale_items <- df_hostile_human[c(preScaleItems, postScaleItems, 'prePositiveAffect', 'preNegate plot_hostile_human_pre_post <- gridOfHistograms(pre_post_scale_items, "Hostile Human Pre, Post Affect Human Pre,
```

Saving 6.5 x 4.5 in image



df_hostile_human_personality <- df_hostile_human[, 18:32]
plot_hostile_human_personality <- gridOfHistograms(df_hostile_human_personality, "Hostile Human Persona")</pre>

Saving 6.5×4.5 in image



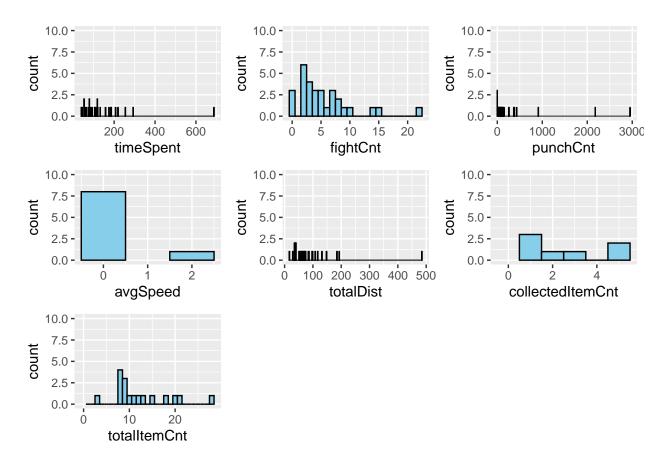
```
df_hostile_human_behaviors <- df_hostile_human[, 9:15]
plot_hostile_human_behaviors <- gridOfHistograms(df_hostile_human_behaviors, "Hostile Human Behaviors H</pre>
```

```
## Warning: Removed 1 rows containing missing values (`geom_bar()`).
```

^{##} Removed 1 rows containing missing values (`geom_bar()`).

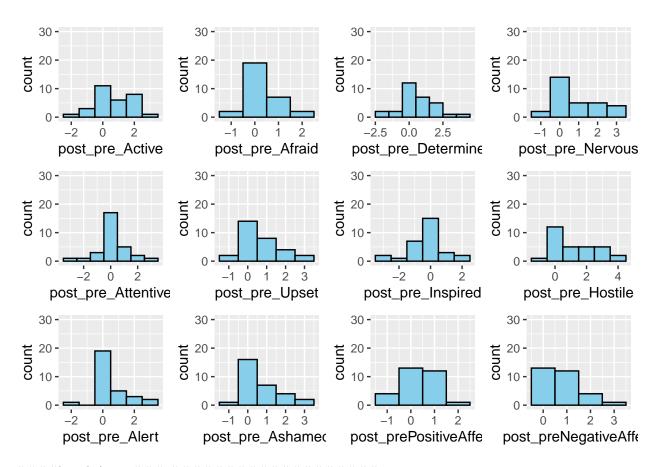
^{##} Removed 1 rows containing missing values (`geom_bar()`).

^{##} Saving 6.5 x 4.5 in image



df_hostile_human_deltas <- df_hostile_human[, 59:70]
plot_hostile_human_deltas <- gridOfHistograms(df_hostile_human_deltas, "Hostile Human Post to Pre Diffe</pre>

Saving 6.5×4.5 in image

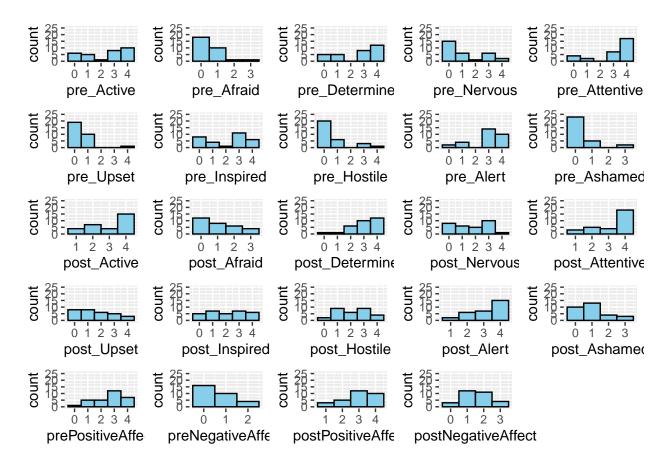


```
df_hostile_agent <-read.csv(file="hostileAgent.csv", stringsAsFactors=FALSE, header=T)
df_hostile_agent <-as.data.frame(df_hostile_agent)

df_hostile_agent <- create_personality_vars(df_hostile_agent)
df_hostile_agent <- create_pre_post_scale_items(df_hostile_agent)
df_hostile_agent <- create_delta_scale_items(df_hostile_agent)</pre>
```

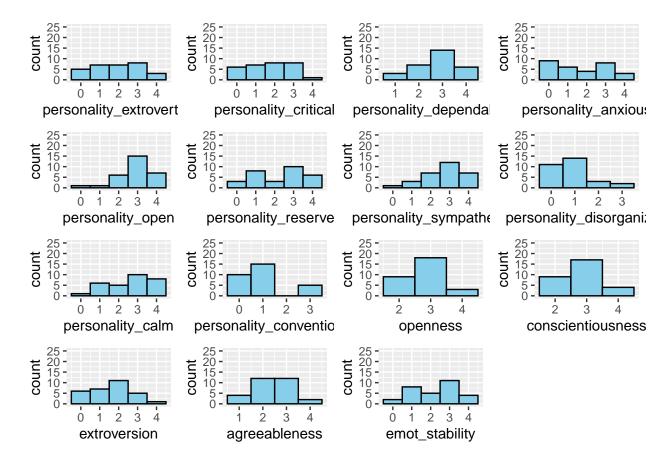
pre_post_scale_items <- df_hostile_agent[c(preScaleItems, postScaleItems, 'prePositiveAffect', 'preNega'
plot_hostile_agent_pre_post <- gridOfHistograms(pre_post_scale_items, "Hostile Agent Pre, Post Affect H</pre>

Saving 6.5×4.5 in image



df_hostile_agent_personality <- df_hostile_agent[, 18:32]
plot_hostile_human_personality <- gridOfHistograms(df_hostile_agent_personality, "Hostile Agent Persona")</pre>

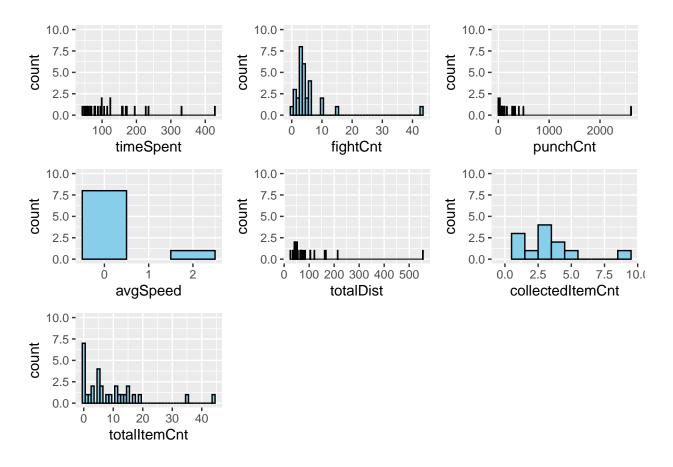
Saving 6.5×4.5 in image



```
df_hostile_agent_behaviors <- df_hostile_agent[, 9:15]
plot_hostile_agent_behaviors <- gridOfHistograms(df_hostile_agent_behaviors, "Hostile Agent Behaviors H</pre>
```

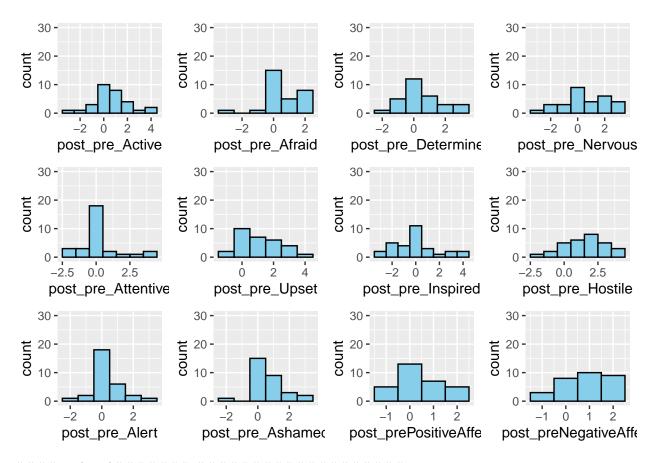
```
## Warning: Removed 1 rows containing missing values (`geom_bar()`).
## Removed 1 rows containing missing values (`geom_bar()`).
```

^{##} Saving 6.5 x 4.5 in image



df_hostile_agent_deltas <- df_hostile_agent[, 59:70]
plot_hostile_agent_deltas <- gridOfHistograms(df_hostile_agent_deltas, "Hostile Agent Post to Pre Diffe</pre>

Saving 6.5×4.5 in image



####combined##################################

```
df_docile_human$docile_hostile <- "Docile"</pre>
df_docile_human$human_agent <- "Human"</pre>
df_docile_human$combined_group <- "DocileHuman"</pre>
df_docile_agent$docile_hostile <- "Docile"</pre>
df_docile_agent$human_agent <- "Agent"</pre>
df_docile_agent$combined_group <- "DocileAgent"</pre>
df_hostile_human$docile_hostile <- "Hostile"</pre>
df_hostile_human$human_agent <- "Human"</pre>
df_hostile_human$combined_group <- "HostileHuman"</pre>
df_hostile_agent$docile_hostile <- "Hostile"</pre>
df_hostile_agent$human_agent <- "Agent"</pre>
df_hostile_agent$combined_group <- "HostileAgent"</pre>
mobOutcomes <- bind_rows(df_docile_human, df_docile_agent, df_hostile_human, df_hostile_agent)</pre>
mobOutcomes$docile_hostile<-as.factor(mobOutcomes$docile_hostile)</pre>
mobOutcomes$human_agent<-as.factor(mobOutcomes$human_agent)</pre>
mobOutcomes$combined_group<-as.factor(mobOutcomes$combined_group)</pre>
mobOutcomes$gender<-as.factor(mobOutcomes$gender)</pre>
mobOutcomes$nationality<-as.factor(mobOutcomes$nationality)</pre>
#create a punch_rate variable
mobOutcomes$punchRate <- mobOutcomes$punchCnt / mobOutcomes$timeSpent</pre>
#create a fight_rate variable
mobOutcomes$fightRate <- mobOutcomes$fightCnt / mobOutcomes$timeSpent</pre>
```

```
pre_post_scale_items <- mobOutcomes[c(preScaleItems, postScaleItems, 'prePositiveAffect', 'preNegativeA</pre>
plot_overall_pre_post <- gridOfHistograms(pre_post_scale_items, "Overall Pre, Post Affect Histograms",</pre>
## Warning: Removed 1 rows containing missing values (`geom_bar()`).
## Saving 6.5 \times 4.5 in image
      pre Active
                         pre Afraid
                                         pre Determine
                                                                                pre Attentive
                                                             pre Nervous
                                                               pre Alert
       pre_Upset
                        pre Inspired
                                           pre Hostile
                                                                               pre Ashamed
      post Active
                         post Afraid
                                         post_Determine
                                                                               post_Attentive
                                                             post Nervous
      post_Upset
                        post_Inspired
                                           post_Hostile
                                                               post_Alert
                                                                               post_Ashamed
```

```
df_overall_personality <- mobOutcomes[, 18:32]
plot_overall_personality <- gridOfHistograms(df_overall_personality, "Overall Personality Histograms",</pre>
```

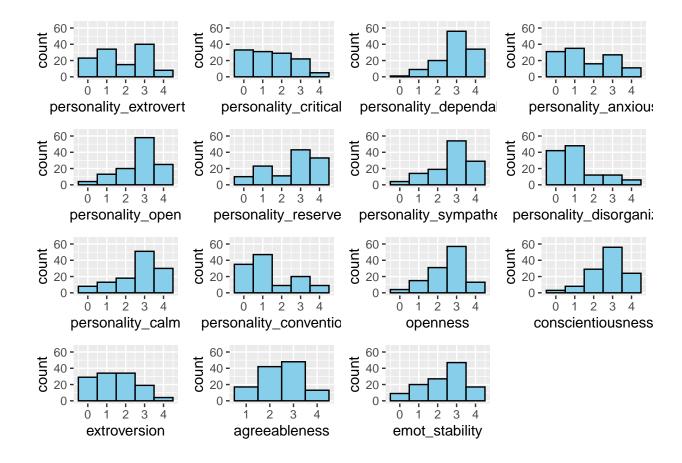
postNegativeAffect

postPositiveAffe

Saving 6.5×4.5 in image

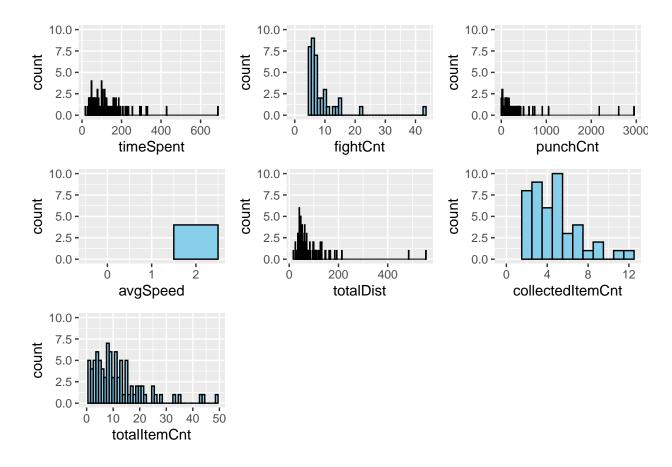
preNegativeAffe

prePositiveAffe



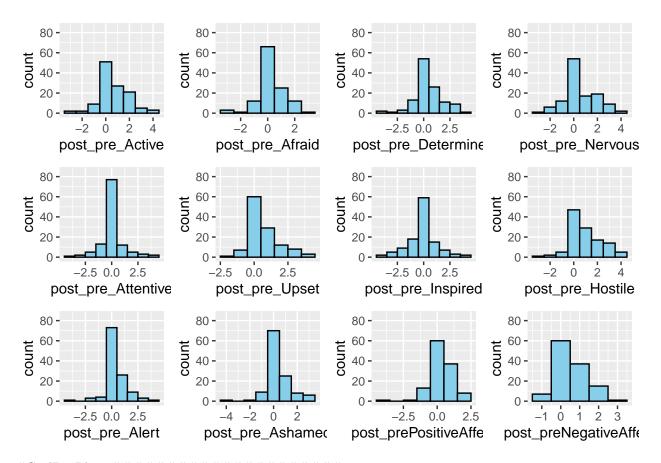
df_overall_behaviors <- mobOutcomes[, 9:15]
plot_overall_behaviors <- gridOfHistograms(df_overall_behaviors, "Behavior Frequency Distributions")</pre>

- ## Warning: Removed 5 rows containing missing values (`geom_bar()`).
- ## Warning: Removed 1 rows containing missing values (`geom_bar()`).
- ## Warning: Removed 2 rows containing missing values (`geom_bar()`).
- ## Removed 2 rows containing missing values (`geom_bar()`).
- ## Warning: Removed 1 rows containing missing values (`geom_bar()`).
- ## Saving 6.5 x 4.5 in image

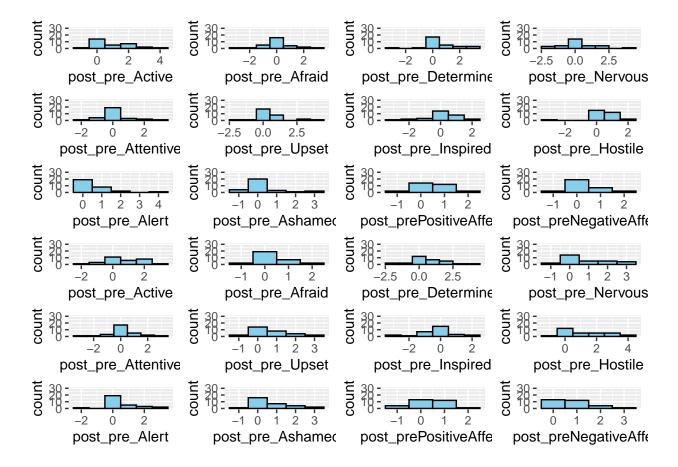


df_overall_deltas <- mobOutcomes[, 59:70]
plot_overall_deltas <- gridOfHistograms(df_overall_deltas, "Overall Post to Pre Differences Histograms"</pre>

Saving 6.5×4.5 in image



#GridBoxPlots ########################



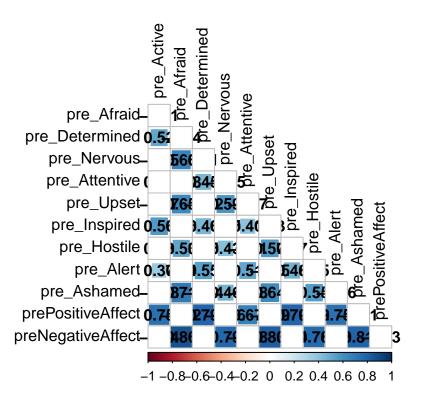
```
post_pre_Afraid
                                                                                                                                                  post_pre_Nervous
             post_pre_Active
                                                                                                  post_pre_Determine
                                                                                            count
                                                          post_pre_Upset
          post_pre_Attentive
                                                                                                      post_pre_Inspired
                                                                                                                                                     post_pre_Hostile
                                                                                   tunos 
              post_pre Alert
                                                                                                  post_prePositiveAffe
                                                       post_pre_Ashamed
                                                                                                                                              post_preNegativeAffe
                                                                                           post pre Active
                                                          post_pre_Afraid
                                                                                                  post_pre_Determine
                                                                                                                                                   post_pre_Nervous
                                                                                            unos 18 - - 2 0 2 4
          post_pre_Attentive
                                                          post_pre_Upset
                                                                                                      post_pre_Inspired
                                                                                                                                                     post_pre_Hostile
              post_pre_Alert
                                                                                                  post_prePositiveAffe
                                                       post_pre_Ashamed
                                                                                                                                              post_preNegativeAffe
df_group_deltas <- subset(mobOutcomes, select = c(59:70))</pre>
docile_human <- bind_rows(docile, human)</pre>
docile_agent <- bind_rows(docile, agent)</pre>
hostile_human <- bind_rows(hostile, human)</pre>
hostile_agent <- bind_rows(hostile, agent)</pre>
subset_vars_pre <- mobOutcomes[, c(preScaleItems, 'prePositiveAffect', 'preNegativeAffect')]</pre>
# Calculate correlation and p-value matrices
p_mat_vars_pre <- cor_pmat(subset_vars_pre, method="pearson")</pre>
str(p_mat_vars_pre)
## pvalue [12 x 13] (S3: pvalue/tbl_df/tbl/data.frame)
##
       $ rowname
                                               : chr [1:12] "pre_Active" "pre_Afraid" "pre_Determined" "pre_Nervous" ...
                                               : num [1:12] 0.00 9.23e-01 1.70e-09 1.12e-01 2.11e-03 ...
       $ pre_Active
                                               : num [1:12] 9.23e-01 0.00 6.33e-01 2.22e-16 1.82e-03 ...
##
       $ pre_Afraid
##
       $ pre_Determined
                                               : num [1:12] 1.70e-09 6.33e-01 0.00 8.97e-01 1.94e-07 8.54e-01 1.52e-07 5.80e-01
                                               : num [1:12] 1.12e-01 2.22e-16 8.97e-01 0.00 6.55e-03 ...
##
       $ pre_Nervous
       $ pre_Attentive
                                               : num [1:12] 2.11e-03 1.82e-03 1.94e-07 6.55e-03 0.00 2.96e-03 3.79e-06 2.33e-01
                                               : num [1:12] 4.63e-01 1.77e-15 8.54e-01 1.71e-12 2.96e-03 ...
##
       $ pre_Upset
##
       $ pre_Inspired
                                               : num [1:12] 2.59e-11 8.05e-02 1.52e-07 6.05e-01 3.79e-06 ...
##
       $ pre_Hostile
                                               : num [1:12] 1.44e-01 7.18e-10 5.80e-01 1.20e-06 2.33e-01 ...
                                               : num [1:12] 3.37e-05 6.82e-01 1.19e-10 2.65e-01 2.27e-09 5.78e-01 3.85e-08 6.24
       $ pre_Alert
                                               : num [1:12] 4.09e-01 1.62e-19 6.57e-01 1.22e-07 1.95e-03 ...
       $ pre_Ashamed
```

```
## $ prePositiveAffect: num [1:12] 6.66e-23 8.16e-01 3.45e-27 5.41e-01 4.12e-17 ...
## $ preNegativeAffect: num [1:12] 7.01e-01 1.76e-36 9.65e-01 1.63e-26 1.63e-03 ...

cor_matrix_vars_pre <- cor(subset_vars_pre, method = "pearson")
#convert p_mat to a matrix of doubles
#exclude first element
p_mat_vars_pre_test <- unlist(p_mat_vars_pre[-1])
#p_mat_vars_pre_4 <- matrix(unlist(p_mat_vars_pre), ncol = 10, byrow = FALSE)

# p adjust
p_adj_mat_vars_pre <- p.adjust(p_mat_vars_pre_test, method = "holm", n = length(p_mat_vars_pre_test))
matrix_p_adj_holm <- matrix(p_adj_mat_vars_pre, nrow = 12, ncol = 12)
rownames(matrix_p_adj_holm) <- c(preScaleItems, 'prePositiveAffect', 'preNegativeAffect')
colnames(matrix_p_adj_holm) <- c(preScaleItems, 'prePositiveAffect', 'preNegativeAffect')
pre_affect_corrs <- corrplot(cor_matrix_vars_pre, p.mat = matrix_p_adj_holm, method="square", type = 'l</pre>
```

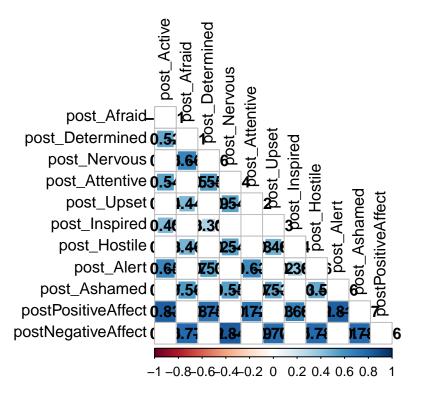
Pre Affect Items Correlation Matrix



```
subset_vars_pre <- mobOutcomes[, c(postScaleItems, 'postPositiveAffect', 'postNegativeAffect')]
# Calculate correlation and p-value matrices
p_mat_vars_pre <- cor_pmat(subset_vars_pre, method="pearson")
str(p_mat_vars_pre)</pre>
```

```
$ post Determined
                        : num [1:12] 1.53e-09 1.92e-02 0.00 7.47e-02 4.79e-11 ...
                        : num [1:12] 4.90e-01 2.23e-16 7.47e-02 0.00 1.18e-01 ...
##
  $ post_Nervous
  $ post Attentive
                        : num [1:12] 2.76e-10 1.07e-01 4.79e-11 1.18e-01 0.00 ...
                        : num [1:12] 7.01e-01 3.73e-07 1.16e-03 2.83e-10 1.64e-02 0.00 7.14e-01 2.11e-0
##
  $ post_Upset
##
   $ post_Inspired
                        : num [1:12] 2.62e-07 3.64e-01 5.70e-04 1.31e-01 4.48e-02 7.14e-01 0.00 6.55e-0
                        : num [1:12] 4.02e-01 9.66e-08 8.01e-01 2.47e-10 3.61e-01 2.11e-08 6.55e-01 0.0
##
   $ post Hostile
                        : num [1:12] 7.57e-16 4.46e-01 3.11e-10 8.71e-01 2.19e-14 ...
##
  $ post_Alert
##
   $ post_Ashamed
                        : num [1:12] 4.75e-01 1.84e-11 2.88e-01 8.58e-11 6.69e-02 ...
##
   $ postPositiveAffect: num [1:12] 2.19e-31 4.00e-01 8.04e-23 9.54e-01 1.48e-20 ...
   $ postNegativeAffect: num [1:12] 5.02e-01 3.35e-25 3.11e-02 4.60e-33 3.68e-02 ...
cor_matrix_vars_post <- cor(subset_vars_pre, method = "pearson")</pre>
#convert p_mat to a matrix of doubles
#exclude first element
p_mat_vars_pre_test <- unlist(p_mat_vars_pre[-1])</pre>
# p adjust
p_adj_mat_vars_pre <- p.adjust(p_mat_vars_pre_test, method = "holm", n = length(p_mat_vars_pre_test))</pre>
matrix_p_adj_holm_2 <- matrix(p_adj_mat_vars_pre, nrow = 12, ncol = 12)</pre>
rownames(matrix_p_adj_holm_2) <- c(postScaleItems, 'postPositiveAffect', 'postNegativeAffect')
colnames(matrix_p_adj_holm_2) <- c(postScaleItems, 'postPositiveAffect', 'postNegativeAffect')</pre>
post_affect_cors <- corrplot(cor_matrix_vars_post, p.mat = matrix_p_adj_holm_2, method="square", type =
```

Post Affect Items Correlation Matrix

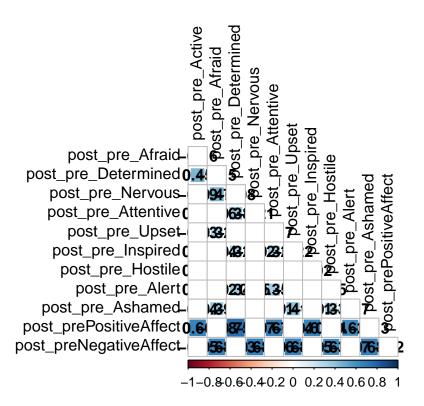


```
subset_vars_pre <- mobOutcomes[, 59:70]
# Calculate correlation and p-value matrices</pre>
```

```
str(p_mat_vars_pre)
## pvalue [12 x 13] (S3: pvalue/tbl_df/tbl/data.frame)
                            : chr [1:12] "post_pre_Active" "post_pre_Afraid" "post_pre_Determined" "post
                            : num [1:12] 0.00 8.51e-02 2.41e-07 3.87e-02 5.98e-03 1.56e-01 8.22e-03 9.3
## $ post_pre_Active
## $ post_pre_Afraid
                            : num [1:12] 8.51e-02 0.00 1.01e-01 7.97e-08 7.25e-02 4.41e-04 6.53e-01 3.6
## $ post_pre_Determined : num [1:12] 2.41e-07 1.01e-01 0.00 3.72e-01 1.42e-05 4.92e-02 4.27e-04 9.6
                            : num [1:12] 3.87e-02 7.97e-08 3.72e-01 0.00 2.06e-02 8.87e-04 1.88e-01 4.1
## $ post_pre_Nervous
                            : num [1:12] 5.98e-03 7.25e-02 1.42e-05 2.06e-02 0.00 5.90e-02 3.26e-04 2.3
## $ post_pre_Attentive
## $ post_pre_Upset
                           : num [1:12] 1.56e-01 4.41e-04 4.92e-02 8.87e-04 5.90e-02 0.00 1.41e-02 2.3
                           : num [1:12] 0.00822 0.653 0.000427 0.188 0.000326 0.0141 0 0.856 0.00211 0
## $ post_pre_Inspired
## $ post_pre_Hostile
                           : num [1:12] 0.937 0.0365 0.966 0.0415 0.233 0.00232 0.856 0 0.571 0.000216
## $ post_pre_Alert
                            : num [1:12] 0.0042 0.191 0.000117 0.621 0.000111 0.356 0.00211 0.571 0 0.0
                           : num [1:12] 6.59e-01 9.63e-06 6.90e-01 4.94e-03 2.37e-01 3.43e-06 2.17e-01
## $ post_pre_Ashamed
## $ post prePositiveAffect: num [1:12] 2.39e-16 4.35e-02 3.02e-23 6.11e-02 8.48e-17 ...
## $ post_preNegativeAffect: num [1:12] 9.84e-02 2.45e-17 1.66e-01 8.93e-18 8.96e-02 ...
cor_matrix_vars_post_pre <- cor(subset_vars_pre, method = "pearson")</pre>
#convert p_mat to a matrix of doubles
#exclude first element
p_mat_vars_pre_test <- unlist(p_mat_vars_pre[-1])</pre>
# p adjust
p_adj_mat_vars_pre <- p.adjust(p_mat_vars_pre_test, method = "holm", n = length(p_mat_vars_pre_test))</pre>
matrix p adj holm 3 <- matrix(p adj mat vars pre, nrow = 12, ncol = 12)
rownames(matrix_p_adj_holm_3) <- colnames(subset_vars_pre)</pre>
colnames(matrix_p_adj_holm_3) <- colnames(subset_vars_pre)</pre>
post_pre_affect_cors <- corrplot(cor_matrix_vars_post_pre, p.mat = matrix_p_adj_holm_3, method="square"
```

p_mat_vars_pre <- cor_pmat(subset_vars_pre, method="pearson")</pre>

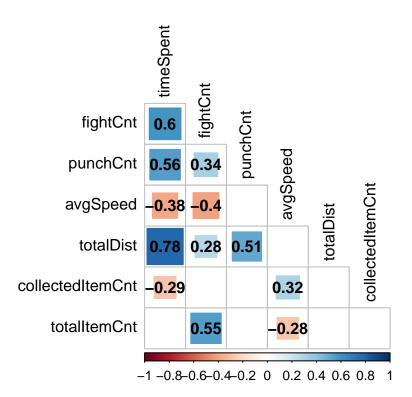
Post-Pre Affect Items Correlation Matrix



```
subset_vars_pre \leftarrow mobOutcomes[, c(9,10,11,12,13,14,15)]
# Calculate correlation and p-value matrices
p_mat_vars_pre <- cor_pmat(subset_vars_pre, method="pearson")</pre>
str(p_mat_vars_pre)
## pvalue [7 x 8] (S3: pvalue/tbl_df/tbl/data.frame)
                      : chr [1:7] "timeSpent" "fightCnt" "punchCnt" "avgSpeed" ...
## $ rowname
                      : num [1:7] 0.00 4.53e-13 3.08e-11 1.62e-05 4.63e-26 ...
## $ timeSpent
                      : num [1:7] 4.53e-13 0.00 1.84e-04 5.09e-06 1.62e-03 ...
## $ fightCnt
## $ punchCnt
                      : num [1:7] 3.08e-11 1.84e-04 0.00 3.05e-01 2.14e-09 ...
## $ avgSpeed
                      : num [1:7] 1.62e-05 5.09e-06 3.05e-01 0.00 1.26e-01 3.71e-04 2.05e-03
## $ totalDist
                      : num [1:7] 4.63e-26 1.62e-03 2.14e-09 1.26e-01 0.00 ...
## $ collectedItemCnt: num [1:7] 0.00138 0.00394 0.158 0.000371 0.11 0 0.462
                      : num [1:7] 7.45e-03 6.30e-11 1.05e-01 2.05e-03 8.49e-01 ...
## $ totalItemCnt
cor_matrix_vars_pre <- cor(subset_vars_pre, method = "pearson")</pre>
#convert p_mat to a matrix of doubles
#exclude first element
p_mat_vars_pre_test <- unlist(p_mat_vars_pre[-1])</pre>
\#p\_mat\_vars\_pre\_4 \leftarrow matrix(unlist(p\_mat\_vars\_pre), ncol = 10, byrow = FALSE)
# p adjust
p_adj_mat_vars_pre <- p.adjust(p_mat_vars_pre_test, method = "holm", n = length(p_mat_vars_pre_test))</pre>
matrix_p_adj_holm <- matrix(p_adj_mat_vars_pre, nrow = 7, ncol = 7)</pre>
rownames(matrix_p_adj_holm) <- colnames(subset_vars_pre)</pre>
```

```
colnames(matrix_p_adj_holm) <- colnames(subset_vars_pre)
corrplot(cor_matrix_vars_pre, p.mat = matrix_p_adj_holm, method="square", type = 'lower', diag = FALSE,</pre>
```

Behaviors Correlation Matrix



```
# Select variables for correlation calculation
vars_X <- c("timeSpent", "fightCnt", "punchCnt", "avgSpeed", "totalDist", "collectedItemCnt", "totalIter
vars_Y <- c("openness", "conscientiousness", "extroversion", "agreeableness", "emot_stability")
selected_vars <- c(vars_X, vars_Y)

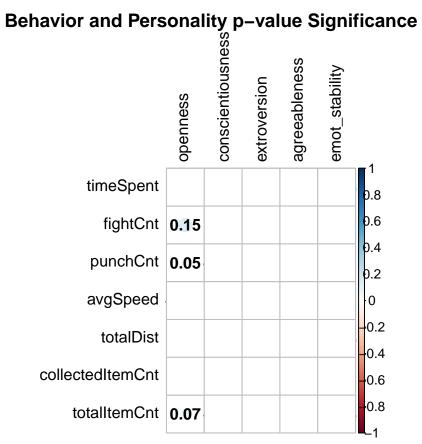
# Subset the data based on selected variables
subset_df <- mobOutcomes[, selected_vars]

# Calculate correlation matrix
p.mat <- cor_pmat(subset_df, method="spearman")
cor_matrix <- cor(subset_df, method = "spearman")

# Specify the quadrant you want to display (e.g., upper right)
quadrant_rows <- 1:length(vars_X)
quadrant_cols <- (length(vars_X) + 1):ncol(cor_matrix)
quadrant_matrix <- cor_matrix[quadrant_rows, quadrant_cols]
quadrant_p.mat <- p.mat[quadrant_rows, quadrant_cols]
dim(quadrant_p.mat)</pre>
```

[1] 7 5

```
matrix_quadrant_p <- matrix(unlist(quadrant_p.mat), ncol = 5, byrow = FALSE)</pre>
#quadrant_p_adj.mat = num[1:35]
quadrant_p_adj.mat <- p.adjust(matrix_quadrant_p, method = "holm", n = length(matrix_quadrant_p))</pre>
View(quadrant_p_adj.mat)
matrix_quadrant_p_adj_holm <- matrix(quadrant_p_adj.mat, nrow = 7, ncol = 5)</pre>
rownames(matrix_quadrant_p_adj_holm) <- vars_X</pre>
colnames(matrix_quadrant_p_adj_holm) <- vars_Y</pre>
plot1 <- corrplot(quadrant_matrix, p.mat = matrix_quadrant_p_adj_holm, method="circle", tl.col="black",</pre>
```



```
vars_X2 <- c("pre_Active", "pre_Afraid", "pre_Determined", "pre_Nervous", "pre_Attentive", "pre_Upset",</pre>
vars_X3 <- c("post_pre_Active", "post_pre_Afraid", "post_pre_Determined", "post_pre_Nervous", "post_pre</pre>
selected_vars_2 <- c(vars_X2, vars_X)</pre>
subset_df_2 <- mobOutcomes[, selected_vars_2]</pre>
p.mat_2 <- cor_pmat(subset_df_2, method="spearman")</pre>
cor_matrix_2 <- cor(subset_df_2, method="spearman")</pre>
quadrant_rows_2 <- 1:length(vars_X2)</pre>
quadrant_cols_2 <- (length(vars_X2) + 1):ncol(cor_matrix_2)</pre>
quadrant_matrix_2 <- cor_matrix_2[quadrant_rows_2, quadrant_cols_2]</pre>
quadrant_p.mat_2 <- p.mat_2[quadrant_rows_2, quadrant_cols_2]</pre>
dim(quadrant p.mat 2)
```

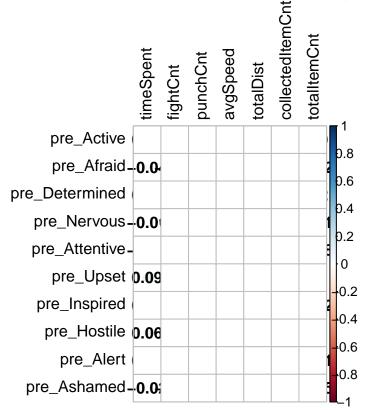
```
## [1] 10 7
```

```
matrix_quadrant_p_2 <- matrix(unlist(quadrant_p.mat_2), ncol = 7, byrow = FALSE)
typeof(matrix_quadrant_p_2)</pre>
```

[1] "double"

```
#quadrant_p_adj.mat_2 = num[1:70]
quadrant_p_adj.mat_2 <- p.adjust(matrix_quadrant_p_2, method = "holm", n = length(matrix_quadrant_p_2))
matrix_quadrant_p_adj_holm_2 <- matrix(quadrant_p_adj.mat_2, nrow = 10, ncol = 7)
rownames(matrix_quadrant_p_adj_holm_2) <- vars_X2
colnames(matrix_quadrant_p_adj_holm_2) <- vars_X</pre>
corrplot(quadrant_matrix_2, p.mat = matrix_quadrant_p_adj_holm_2, method="circle", tl.col="black", titl
```

Pre Emotional State and Behaviors p-value Significance



```
selected_vars_3 <- c(vars_X3, vars_X)
subset_df_3 <- mobOutcomes[, selected_vars_3]
p.mat_3 <- cor_pmat(subset_df_3, method = "spearman")
cor_matrix_3 <- cor(subset_df_3, method = "spearman")

quadrant_rows_3 <- 1:length(vars_X3)
quadrant_cols_3 <- (length(vars_X3) + 1):ncol(cor_matrix_3)
quadrant_matrix_3 <- cor_matrix_3[quadrant_rows_3, quadrant_cols_3]</pre>
```

```
dim(quadrant_p.mat_3)

## [1] 10 7

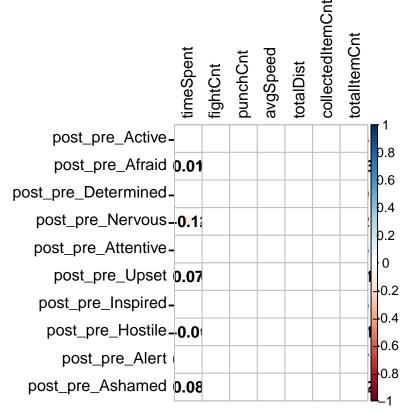
matrix_quadrant_p_3 <- matrix(unlist(quadrant_p.mat_3), ncol = 7, byrow = FALSE)

#quadrant_p_adj.mat_3 = num[1:70]
quadrant_p_adj.mat_3 <- p.adjust(matrix_quadrant_p_3, method = "BH", n = length(matrix_quadrant_p_3))
matrix_quadrant_p_adj_holm_3 <- matrix(quadrant_p_adj.mat_3, nrow = 10, ncol = 7)
rownames(matrix_quadrant_p_adj_holm_3) <- vars_X3
colnames(matrix_quadrant_p_adj_holm_3) <- vars_X

plot_corr_3 <- corrplot(quadrant_matrix_3, p.mat = matrix_quadrant_p_adj_holm_3, method="circle", tl.co")</pre>
```

Behavior and Personality p-value Significance

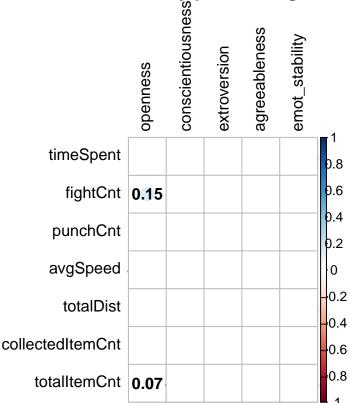
quadrant_p.mat_3 <- p.mat_3[quadrant_rows_3, quadrant_cols_3]</pre>



```
#combine all 3 matrices by flattening
#7x5, 10x7, 10x7
#list of 5 (column wise elements)
vector_quadrant_p.mat=c(quadrant_p.mat)
#list of 7
vector_quadrant_p.mat_2=c(quadrant_p.mat_2)
#list of 7
vector_quadrant_p.mat_3=c(quadrant_p.mat_3)
#list of 19 (also column wise elements)
```

```
vector_concatenated_quadrant_p.mat <- c(vector_quadrant_p.mat, vector_quadrant_p.mat_2, vector_quadrant_</pre>
double_concatenated_quadrant_p.mat <- as.numeric(unlist(vector_concatenated_quadrant_p.mat))</pre>
#num[1:175]
list_concatenated_adjusted_p_values <- p.adjust(double_concatenated_quadrant_p.mat, method = "holm", n
#get first matrix set of adjusted p_values
list_1_adj_p_values_columns <- list(list_concatenated_adjusted_p_values[1:7], list_concatenated_adjuste
matrix_1_adj_p_values <- matrix(unlist(list_1_adj_p_values_columns), ncol = 5, byrow = FALSE)</pre>
rownames(matrix_1_adj_p_values) <- vars_X</pre>
colnames(matrix_1_adj_p_values) <- vars_Y</pre>
#get second matrix set of adjusted p_values
list_2_adj_p_values_columns <- list(list_concatenated_adjusted_p_values[36:45], list_concatenated_adjus
matrix_2_adj_p_values <- matrix(unlist(list_2_adj_p_values_columns), ncol = 7, byrow = FALSE)
rownames(matrix_2_adj_p_values) <- vars_X2</pre>
colnames(matrix_2_adj_p_values) <- vars_X</pre>
#get third matrix set of adjusted p_values
list_3_adj_p_values_columns <- list(list_concatenated_adjusted_p_values[106:115], list_concatenated_adj
matrix_3_adj_p_values <- matrix(unlist(list_3_adj_p_values_columns), ncol = 7, byrow = FALSE)
rownames(matrix_3_adj_p_values) <- vars_X3</pre>
colnames(matrix_3_adj_p_values) <- vars_X</pre>
corrplot(quadrant_matrix, p.mat = matrix_1_adj_p_values, method="circle", tl.col="black", title = "Beha"
```





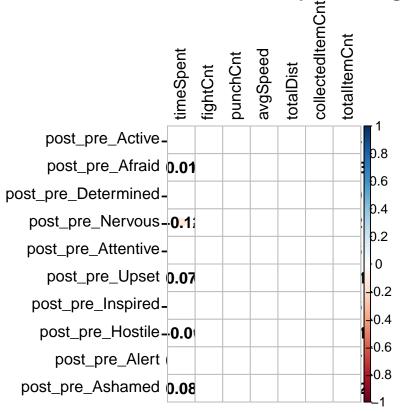
```
plot.new();
```

```
dev.off();

## null device
## 1

par(mfrow=c(1,2), mai = c(1, 0.1, 0.1, 0.1))
corrplot(quadrant_matrix_2, p.mat = matrix_2_adj_p_values, method="circle", tl.col="black", title= "Pre
corrplot(quadrant_matrix_3, p.mat = matrix_3_adj_p_values, method="circle", tl.col="black", title= "Emo-
corrplot(quadrant_matrix_3, p.mat = matrix_3_adj_p_values, method="circle", tl.col="black", title= "Emo-
```

Emotional State Differences and Behaviors p-value Significance



#ANOVA for Affective Variables with respect to Agency and Hostility #Independence of the observations is assumed as measurements within and between the 4 groups are not related. # Normality. With a sample size 0f 30 per group, and given that ANOVA is robust to the assumption of narmality, we do not need to check normality. # Nevertheless, from observing frequency histograms we find that the affective variables appear approximately normal across groups. # Equality of variances. We Perform Bartlett's test of the null that the variances in each of the groups (samples) are the same #Bartlett's test with multiple independent variables: the interaction() function must be used to collapse multiple factors into a single variable containing all combinations of the factors

Note: researchers should select only

variables for which there is a theoretical basis for inclusion. Then they should explore the data

with univariate and bivariate analyses, and only include variables that have potentially

informative results, or which are needed to serve as controls.

#Check for Outlier #two-way ANOVA tests #post_pre_Active #p = 0.21, we fail to reject the null of equal variances across factor levels bartlett.test(post_pre_Active \sim interaction(human_agent,

 $\label{eq:continuous} $$\operatorname{docile_hostile}$), \ data = mobOutcomes) \ \#Identify \ Outliers \ and \ run \ model \ mobOutcomesActive <-mobOutcomes[c("human_agent", "docile_hostile", "combined_group", "post_pre_Active", "id")] \ df_outliers <- mobOutcomesActive %>% group_by(human_agent, docile_hostile) %>% identify_outliers(post_pre_Active)$

#Remove 0 Extreme Outliers (n = 120) mobOutcomesActive <- mobOutcomesActive %>% anti_join(df_outliers[which(df_own TRUE),], by = "id")

 $aov_active <- aov(post_pre_Active \sim human_agent + docile_hostile + human_agent:docile_hostile, data = mobOutcomesActive)$

Df Sum Sq Mean Sq F value Pr(>F)

human_agent 1 3.01 3.0083 1.895 0.171

docile hostile 1 0.01 0.0083 0.005 0.942

human agent:docile hostile 1 2.41 2.4083 1.517 0.221

Residuals 116 184.17 1.5876

summary(aov_active) #run model without removal of outliers #NA

#post_pre_Nervous #p = 0.2084, we fail to reject the null of equal variances across factor levels bartlett.test(post_pre_Nervous ~ interaction(human_agent, docide_hostile), data = mobOutcomes)

mobOutcomesNervous<-mobOutcomes[c("human_agent", "docile_hostile", "combined_group", "post_pre_Nervous", "id")] df_outliers <- mobOutcomesNervous %>% group_by(human_agent, docile_hostile) %>% identify_outliers(post_pre_Nervous)

#Remove 0 Extreme Outliers (n = 120) mobOutcomesNervous <- mobOutcomesNervous %>% anti_join(df_outliers[which(df_outliers\$is.extreme %in% TRUE),], by = "id")

aov_nervous <- aov(post_pre_Nervous ~ human_agent + docile_hostile + human_agent:docile_hostile, data = mobOutcomesNervous)

Df Sum Sq Mean Sq F value Pr(>F)

 $human_agent\ 1\ 0.01\ 0.0083\ 0.005\ 0.946$

 $docile_hostile 1 3.01 3.0083 1.647 0.202$

human_agent:docile_hostile 1 3.01 3.0083 1.647 0.202

Residuals 116 211.90 1.8267

summary(aov_nervous)

#post_preNegativeAffect #p = 0.05365, we fail to reject the null of equal variances across factor levels bartlett.test(post_pre_NegativeAffect ~ interaction(human_agent, docide_hostile), data = mobOutcomes)

 $mobOutcomes Negative <- mobOutcomes [c("human_agent", "docile_hostile", "combined_group", "post_pre_Negative Affect "id")] \ df_outliers <- mobOutcomes Negative %>% group_by(human_agent, docile_hostile) %>% identify_outliers (post_pre_Negative Affect)$

#Remove 0 Extreme Outliers (n = 120) mobOutcomesNegative <- mobOutcomesNegative %>% anti_join(df_outliers[which(df_outliers\$is.extreme %in% TRUE),], by = "id") aov_negative <- aov(post_pre_NegativeAffect ~ human_agent + docile_hostile + human_agent:docile_hostile, data = mobOutcomesNegative)

Df Sum Sq Mean Sq F value Pr(>F)

human_agent 1 0.18 0.176 0.315 0.575505

docile_hostile 1 7.80 7.803 13.954 0.000292 ***

human agent:docile hostile 1 0.08 0.075 0.134 0.714861

Residuals 116 64.87 0.559

summary(aov_negative) TukeyHSD(aov_negative)

#post_pre_ashamed #p = 0.962, we fail to reject the null of equal variances across factor levels bartlett.test(post_pre_Ashamed ~ interaction(human_agent, docile_hostile), data = mobOutcomes) mobOutcomesAshamed<- mobOutcomes[c("human_agent", "docile_hostile", "combined_group", "post_pre_Ashamed", "id")] df_outliers <- mobOutcomesAshamed %>% group_by(human_agent, docile_hostile) %>% identify_outliers(post_pre_Ashamed)

#Remove 21 Extreme Outliers (n = 99) and run model mobOutcomes Ashamed <- mobOutcomes Ashamed %>% anti_join(df_outliers [which(df_outliers\$is.extreme %in% TRUE),], by = "id")

 $aov_ashamed <- aov(post_pre_Ashamed \sim human_agent + docile_hostile + human_agent:docile_hostile, \\ data = mobOutcomesAshamed)$

Df Sum Sq Mean Sq F value Pr(>F)

human_agent 1 0.00 0.004 0.006 0.93888

docile_hostile 1 9.99 9.993 15.919 0.00013 ***

human_agent:docile_hostile 1 0.01 0.007 0.010 0.91877

Residuals 95 59.63 0.628

summary(aov_ashamed) TukeyHSD(aov_ashamed)

#post_pre_Hostile #!!!p = 0.0343, we reject the null of equal variances across factor levels and run a Welch ANOVA on a single extended factor instead!! bartlett.test(post_pre_Hostile ~ interaction(human_agent, docile_hostile), data = mobOutcomes)

mobOutcomesHostile<- mobOutcomes[c("combined_group","post_pre_Hostile", "id")] df_outliers <- mobOutcomesHostile %>% group_by(combined_group) %>% identify_outliers(post_pre_Hostile)

 $\#Remove\ 0\ Extreme\ Outliers\ (n=120)\ mobOutcomes Hostile <-\ mobOutcomes\ \%>\%\ anti_join(df_outliers[which(df_outliers, which(df_outliers, wh$

#perform Welch's ANOVA # data: post_pre_Hostile and combined_group # F = 4.7989, num df = 3.000, denom df = 62.972, p-value = 0.004496 oneway.test(post_pre_Hostile ~ combined_group, data = mobOutcomesHostile, var.equal = FALSE)

> games_howell_test(mobOutcomesHostile, post_pre_Hostile ~ combined group, conf.level = 0.95, detailed = FALSE)

A tibble: 6×8

*

.y. group1 group2 estimate conf.low conf.high p.adj p.adj.signif

1 post_pre_Hostile DocileAgent DocileHuman -0.167 -0.911 0.578 0.934 ns

2 post_pre_Hostile DocileAgent HostileAgent 0.9 -0.0617 1.86 $0.074~\mathrm{ns}$

3 post_pre_Hostile Docile Agent Hostile Human
 0.633 -0.275 1.54 $0.264~\mathrm{ns}$

4 post_pre_Hostile Docile Human Hostile Agent 1.07 0.196 1.94 0.011 *

5 post_pre_Hostile Docile Human Hostile Human
 0.8 -0.00998 1.61 $0.054~\mathrm{ns}$

6 post_pre_Hostile Hostile Agent Hostile Human -0.267 -1.28 0.744 0.897 ns

 $means_by_factor <- aggregate(post_pre_Hostile \sim combined_group, \ data = mobOutcomesHostile, \ FUN = mean) \ means \ by \ factor$

combined group post pre Hostile

- 1 DocileAgent 0.6000000
- 2 DocileHuman 0.4333333
- 3 HostileAgent 1.5000000
- 4 HostileHuman 1.2333333

games_howell_test(mobOutcomesHostile, post_pre_Hostile \sim combined_group, conf.level = 0.95, detailed = FALSE)

 $aov_hostile <- aov(post_pre_Hostile \sim human_agent + docile_hostile + human_agent:docile_hostile,\\ data = mobOutcomesHostile) TukeyHSD(aov_hostile) ##### #post_pre_Afraid mobOutcomesAfraid <- mobOutcomes[c("human_agent", "docile_hostile", "combined_group","post_pre_Afraid", "id")] df_outliers <- mobOutcomesAfraid %>% group_by(human_agent, docile_hostile) %>% identify_outliers(post_pre_Afraid)$

#Remove 14 Extreme Outliers (n = 106) mobOutcomes Afraid <- mobOutcomes %>% anti_join(df_outliers[which(df_outliers which(df_outliers)], by = "id")

 $aov_afraid <- aov(post_pre_Afraid \sim human_agent + docile_hostile + human_agent:docile_hostile, data = mobOutcomesAfraid)$

Df Sum Sq Mean Sq F value Pr(>F)

human_agent 1 0.38 0.381 0.529 0.4687

docile_hostile 1 4.44 4.443 6.163 0.0147 *

human_agent:docile_hostile 1 0.25 0.246 0.341 0.5603

Residuals 102 73.53 0.721

Signif. codes: 0 '' 0.001 '' 0.01 " 0.05 '' 0.1 ' ' 1

summary(aov_afraid)

Repeat by Subset candidate variables to test group differences for (based on boxplot visualizations):

Active, Nervous, Negative, Ashamed, Hostile, Afraid

 $\begin{array}{l} \textbf{p_vector_subset} <-c(0.171, 0.942, 0.221, 0.946, 0.202, 0.202, 0.575505, 0.000292, 0.714861, 0.93888, 0.00013, \\ 0.91877, 0.362463, 0.000491, 0.833266, 0.4687, 0.0147, 0.5603) \#bonferroni \# [1] 1.000000 1.000000 1.000000 \\ 1.000000 1.000000 1.000000 1.000000 0.005256 1.000000 1.000000 0.002340 1.000000 1.000000 0.008838 \\ 1.000000 1.000000 0.264600 1.000000 \#holm \# [1] 1.000000 1.000000 1.000000 1.000000 1.000000 \\ 1.000000 0.004964 1.000000 1.000000 0.002340 1.000000 1.000000 0.007856 1.000000 1.000000 \\ 1.000000 p.adjust(p_vector_subset, method = "bonferroni", n = length(p_vector_subset)) \end{array}$

Repeat by Subset candidate variables to test group differences for (based on boxplot visualizations):

Active, Nervous, Negative, Ashamed, Hostile, Afraid, Determined, Attentive, Upset, Inspired, Alert, Positive

```
#post_pre_Determined mobOutcomesDetermined <- mobOutcomes[c("human_agent", "docile_hostile", "human_agent", "combined_group", "post_pre_Determined", "id")] df_outliers <- mobOutcomesDetermined %>% group_by(human_agent, docile_hostile) %>% identify_outliers(post_pre_Determined)
```

#Remove 2 Extreme Outliers (n = 118) mobOutcomesDetermined <- mobOutcomes %>% anti_join(df_outliers[which(df_outliers[w

 $aov_determined <- aov(post_pre_Determined \sim human_agent + docile_hostile + human_agent:docile_hostile,\\ data = mobOutcomesDetermined)$

human_agent 1 0.11 0.1062 0.175 0.6764

docile_hostile 1 2.05 2.0495 3.381 0.0691 .

human_agent:docile_hostile 1 1.31 1.3058 2.154 0.1456

summary(aov determined)

```
#post_pre_Attentive
```

 $mobOutcomes Attentive <- mobOutcomes [c("human_agent", "docile_hostile", "human_agent", "combined_group", "post_pre_Attentive", "id")] df_outliers <- mobOutcomes Attentive %>% group_by(human_agent, docile_hostile) %>% identify_outliers(post_pre_Attentive)$

#Remove 30 Extreme Outliers (n = 90) mobOutcomesAttentive <- mobOutcomes %>% anti_join(df_outliers[which(df_outliers which(df_outliers)], by = "id")

 $aov_attentive <- aov(post_pre_Attentive \sim human_agent + docile_hostile + human_agent: docile_hostile,\\ data = mobOutcomesAttentive)$

human agent 1 1.26 1.2622 1.047 0.309

docile_hostile 1 0.76 0.7569 0.628 0.430

human_agent:docile_hostile 1 0.36 0.3567 0.296 0.588

summary(aov attentive)

#post_pre_Upset

 $mobOutcomes Upset <- mobOutcomes [c("human_agent", "docile_hostile", "human_agent", "combined_group", "post_pre_Upset", "id")] df_outliers <- mobOutcomes Upset %>% group_by(human_agent, docile_hostile) %>% identify_outliers(post_pre_Upset)$

 $\#Remove\ 12\ Extreme\ Outliers\ (n=108)\ mobOutcomes Upset <-\ mobOutcomes\ \%>\%\ anti_join(df_outliers[which(df_outliers, which(df_outliers, whi$

 $aov_upset <- aov(post_pre_Upset \sim human_agent + docile_hostile + human_agent:docile_hostile, data = mobOutcomesUpset)$

human agent 1 6.78 6.778 6.081 0.0153 *

docile_hostile 1 1.31 1.315 1.180 0.2800

human agent:docile hostile 1 0.71 0.714 0.641 0.4253

summary(aov_upset)

#post_pre_Inspired

 $mobOutcomes Inspired <- mobOutcomes [c("human_agent", "docile_hostile", "human_agent", "combined_group", "post_pre_Inspired", "id")] df_outliers <- mobOutcomes Inspired %>% group_by(human_agent, docile_hostile) %>% identify_outliers (post_pre_Inspired)$

#Remove 49 Extreme Outliers (n = 71) mobOutcomesInspired <- mobOutcomes %>% anti_join(df_outliers[which(df_outliers[whic

aov_inspired <- aov(post_pre_Inspired ~ human_agent + docile_hostile + human_agent:docile_hostile, data = mobOutcomesInspired)

human_agent 1 0 0 NaN NaN

docile_hostile 1 0 0 NaN NaN

human_agent:docile_hostile 1 0 0 NaN NaN

summary(aov inspired)

```
#post pre Alert
mobOutcomesAlert<- mobOutcomes[c("human_agent",
                                                   "docile hostile", "human agent",
bined_group", "post_pre_Alert", "id")] df_outliers <- mobOutcomesAlert %>% group_by(human_agent,
docile_hostile) %>% identify_outliers(post_pre_Alert)
#Remove 15 Extreme Outliers (n = 105) mobOutcomesAlert <- mobOutcomes %>% anti join(df outliers[which(df outliers
\%in\% TRUE),], by = "id")
aov alert <- aov(post pre Alert ~ human agent + docile hostile + human agent:docile hostile, data =
mobOutcomesAlert)
human agent 1 0.31 0.3095 0.408 0.525
docile hostile 1 0.24 0.2413 0.318 0.574
human agent:docile hostile 1 0.84 0.8397 1.106 0.295
summary(aov alert)
  \#post\_prePositiveAffect
mobOutcomesPositive<- mobOutcomes[c("human_agent", "docile_hostile", "combined_group", "post_pre_PositiveAffect",
"id")] df_outliers <- mobOutcomesPositive %>% group_by(human_agent, docile_hostile) %>% iden-
tify outliers(post pre PositiveAffect)
```

#Remove 3 Extreme Outliers (n = 117) mobOutcomesPositive <- mobOutcomesPositive %>% anti_join(df_outliers[which(df_outliers\$is.extreme %in% TRUE),], by = "id")

 $aov_positive <- aov(post_pre_Positive Affect \sim human_agent + docile_hostile + human_agent: docile_hostile, \\ data = mobOutcomesPositive)$

#Compute Shapiro-Wilk test of normality #Significant p value shapiro_test(residuals(aov_positive))

human_agent 1 0.53 0.5308 1.592 0.20963

docile_hostile 1 2.59 2.5921 7.774 0.00622 **

 $human_agent: docile_hostile \ 1\ 0.01\ 0.0064\ 0.019\ 0.88980$

summary(aov positive)

Active, Nervous, Negative, Ashamed, Hostile, Afraid, Determined, Attentive, Upset, Inspired, Alert, Positive

#Bonferroni

[1] 1.000 0.048 1.000

#holm

[1] 1.0000 0.0480 1.0000 1.0

 $p.adjust(p_vector, method = "holm", n = length(p_vector))$

- $\begin{bmatrix} 29 \end{bmatrix} \ 0.7912421 \ 0.8632575 \ 0.7080000 \ 0.9730286 \ 0.9730286 \ 0.7912421 \\ 0.9910000 \ 0.7912421$

```
p.adjust(p_vector_subset, "holm", n = length(p_vector_subset))
```

- 1.000000 1.000000 1.000000 1.000000 1.000000 1.000000 1.000000 0.010220 1.000000 1.000000 0.004680 1.000000 1.000000 0.016694 1.000000 1.000000 0.485100 1.000000
- $1.000000\ 1.000000\ 1.000000\ 1.000000\ 1.000000\ 1.000000\ 1.000000\ 1.000000\ 1.000000\ 1.000000\ 1.000000\ 1.000000\ 1.000000\ 1.000000$

Perform ANOVA for Behavior Vars boxplots_behaviors_by_gender <- gridOfBoxplots(mobOutcomes, "Behavior by Gender Boxplots", behaviors_flag = TRUE, by_gender = TRUE)

 $\# Identify Outliers mobOutcomes AvgSpeed <- mobOutcomes [c("human_agent", "docile_hostile", "avgSpeed", "id")] df_outliers <- mobOutcomes AvgSpeed %>% group_by(human_agent, docile_hostile) %>% identify_outliers (avgSpeed)$

#Remove 0 Extreme Outlier (n = 120) mobOutcomesAvgSpeed <- mobOutcomes %>% anti_join(df_outliers[which(df_outliers[wh

aovAvgSpeed <- aov(avgSpeed ~ human_agent + docile_hostile + human_agent:docile_hostile, data = mobOutcomesAvgSpeed) # Df Sum Sq Mean Sq F value Pr(>F) # human_agent 1 0.032 0.03216 0.308 0.580 # docile_hostile 1 0.232 0.23163 2.215 0.139 # human_agent:docile_hostile 1 0.014 0.01435 0.137 0.712 # Residuals 116 12.131 0.10458 summary(aovAvgSpeed)

```
ggplot(data=mobOutcomes, aes(x=human_agent, y= mobOut-
comes[, "avgSpeed"])) + geom_boxplot(color="black", fill="blue",
alpha=0.2, outlier.shape = NA) +
stat summary(fun=mean, colour="black", geom="text", aes(label
= round(..y.., 2))
  #Identify Outliers mobOutcomesTimeSpent <- mobOutcomes[c("human agent", "docile hostile",
"timeSpent", "id")] df_outliers <- mobOutcomesTimeSpent %>% group_by(human_agent, docile_hostile)
%>% identify outliers(timeSpent)
#Remove 1 Extreme Outlier (n = 119) mobOutcomesTimeSpent <- mobOutcomes %>% anti_join(df_outliers[which(df_outliers])
\%in% TRUE),], by = "id")
aovTimeSpent <- aov(timeSpent ~ human agent + docile hostile + human agent:docile hostile, data =
mobOutcomesTimeSpent) # Df Sum Sq Mean Sq F value Pr(>F)
# human agent 1 299 299 0.058 0.8108
\# \ docile\_hostile \ 1 \ 22974 \ 22974 \ 4.425 \ 0.0376 \ ^* \ \# \ human\_agent: docile\_hostile \ 1 \ 565 \ 565 \ 0.109 \ 0.7421
\# Residuals 115 597028 5192
summary(aovTimeSpent) TukeyHSD(aovTimeSpent)
  #Identify Outliers mobOutcomesFightCnt <- mobOutcomes[c("human_agent", "docile_hostile", "fight-
Cnt", "id")] df outliers <- mobOutcomesFightCnt %>% group by(human agent, docile hostile) %>%
identify outliers(fightCnt)
\#Remove 2 Extreme Outlier (n = 118) mobOutcomesFightCnt <- mobOutcomes \% > \% anti_join(df_outliers[which(df_outliers]) and outliers[which(df_outliers]) and outliers[which(df_outliers]).
\%in% TRUE),], by = "id")
aovFightCnt<- aov(fightCnt ~ human agent + docile hostile + human agent:docile hostile, data =
mobOutcomesFightCnt) # Df Sum Sq Mean Sq F value Pr(>F)
# human agent 1 18.4 18.42 1.576 0.21193
\# docile_hostile 1 115.3 115.26 9.862 0.00215 ** \# human_agent:docile_hostile 1 19.0 19.03 1.628 0.20451
# Residuals 114 1332.3 11.69
summary(aovFightCnt) TukeyHSD(aovFightCnt)
#Identify Outliers mobOutcomesPunchCnt <- mobOutcomes[c("human agent", "docile hostile",
"punchCnt", "id")] df outliers <- mobOutcomesPunchCnt %>% group by(human agent, docile hostile)
%>% identify_outliers(punchCnt)
#Remove 4 Extreme Outlier (n = 116) mobOutcomesPunchCnt <- mobOutcomes %>% anti_join(df_outliers[which(df_outli
\%in% TRUE),], by = "id")
aovPunchCnt<- aov(punchCnt ~ human_agent + docile_hostile + human_agent:docile_hostile, data =
mobOutcomesPunchCnt) # Df Sum Sq Mean Sq F value Pr(>F) # human_agent 1 33314 33314 1.083
0.300 \# docile\_hostile 1 \ 26142 \ 26142 \ 26142 \ 0.850 \ 0.359 \# human\_agent: docile\_hostile 1 \ 29493 \ 29493 \ 0.959 \ 0.330 
# Residuals 112 3445188 30761
```

#Remove 7 Extreme Outlier (n = 113) mobOutcomesTotalDist <- mobOutcomes %>% anti_join(df_outliers[which(df_outliers[whi

 $\# Identify Outliers mobOutcomes Total Dist <- mobOutcomes [c("human_agent", "docile_hostile", "total Dist", "id")] df_outliers <- mobOutcomes Total Dist %>% group_by(human_agent, docile_hostile) %>%$

summary(aovPunchCnt)

identify outliers(totalDist)

```
aovTotalDist <- aov(totalDist ~ human agent + docile hostile + human agent:docile hostile, data =
mobOutcomesTotalDist) # Df Sum Sq Mean Sq F value Pr(>F)
# human agent 1 1956 1956 1.810 0.1813
\# docile_hostile 1 6362 6362 5.888 0.0169 * \# human_agent:docile_hostile 1 0 0 0.000 0.9857
# Residuals 109 117762 1080
summary(aovTotalDist)
#Identify Outliers mobOutcomesCollectedItem <- mobOutcomes[c("human_agent", "docile_hostile",
"collectedItemCnt", "id")] df_outliers <- mobOutcomesCollectedItem %>% group_by(human_agent,
docile_hostile) %>% identify_outliers(collectedItemCnt)
#Remove 7 Extreme Outlier (n = 113) mobOutcomesCollectedItem <- mobOutcomes %>% anti_join(df_outliers[which(df_outliers])
\%in% TRUE),], by = "id")
aovCollectedItem <- aov(collectedItemCnt ~ human agent + docile hostile + human agent:docile hostile,
data = mobOutcomesCollectedItem) # Df Sum Sq Mean Sq F value Pr(>F)
# human agent 1 0.8 0.76 0.122 0.728
\# docile_hostile 1 119.7 119.75 19.205 2.71e-05 *** \# human_agent:docile_hostile 1 24.3 24.29 3.895 0.051
# Residuals 109 679.7 6.24
summary(aovCollectedItem) TukeyHSD(aovCollectedItem)
#Identify Outliers mobOutcomesTotalItem <- mobOutcomes[c("human_agent", "docile_hostile", "total-
ItemCnt", "id")] df outliers <- mobOutcomesTotalItem %>% group by(human agent, docile hostile)
%>% identify_outliers(totalItemCnt)
#Remove 1 Extreme Outlier (n = 119) mobOutcomesTotalItem <- mobOutcomes %>% anti join(df outliers[which(df outli
```

 $aovTotalItem <- \ aov(totalItemCnt \sim human_agent + docile_hostile + human_agent:docile_hostile, \ data = mobOutcomesTotalItem) \# Df Sum Sq Mean Sq F value Pr(>F) \# human_agent 1 20 20.42 0.241 0.624 \# docile_hostile 1 19 19.13 0.226 0.635 \# human_agent:docile_hostile 1 28 28.16 0.333 0.565 summary(aovTotalItem) TukeyHSD(aovTotalItem)$

 $\#avgSpeed, timeSpent, -fightCnt, punchCnt, totalDist, -collectedItemCnt, totalItemCnt p_vector <-c(.580, .139, .712, .8108, .0376, .7421, .21193, .00215, .20451, .300, .359, .330, .1813, .0169, .9857, .728, .0000271, .051, .624, .635, .565) p.adjust(p_vector, method = "holm", n = length(p_vector)) # [1] 1.0000000 1.0000000 1.0000000 1.0000000 1.0000000 1.0000000 1.0000000 1.0000000 1.0000000 1.0000000 1.0000000 1.0000000 1.0000000 1.0000000 1.0000000 1.0000000 1.0000000 # [16] 1.0000000 0.0005691 0.8670000 1.0000000 1.0000000 1.0000000 # [16] 1.0000000 0.8202158 0.4945033 0.0225750 0.4945033 0.6282500 0.6282500 0.6282500 0.4945033 0.1183000 # 0.9857000 0.8202158 0.0005691 0.2142000 0.8202158 0.8202158 0.8202158$

#avgSpeed, timeSpent, fightCnt, punchCnt, totalDist, collectedItemCnt, totalItemCnt

%in% TRUE),], by = "id")

Perform ANOVA for Affective changes wrt gender X familiarity boxplots_behaviors_by_gender_familiarity <- gridOfBoxplots(mobOutcomes, "Behaviors by Familiarity Boxplots", behaviors_flag=TRUE, by_familiarity = TRUE)

$$\label{eq:comes} \begin{split} &\text{mobOutcomes} familiarity < -as. factor(mobOutcomes \text{familiarity}) \operatorname{str}(\text{mobOutcomes} familiarity) levels_to_b in_lower_end < \\ &-c("-3","-2","-1") mobOutcomes \text{familiarity_binned} < \\ &-\text{factor}(\text{mobOutcomes} \text{familiarity_binned}, \text{ levels} = c("\text{low_familiarity}", "\text{high_familiarity}")) \end{split}$$

make an interaction between two factors

on x axis

```
mobOutcomes Gender X Familiarity < -interaction (mobOutcomes {\tt gender}, mobOutcomes {\tt familiarity\_binned})
```

#Identify Outliers Active mobOutcomesActive <- mobOutcomes[c("gender", "familiarity_binned", "GenderXFamiliarity", "post_pre_Active", "id")] df_outliers <- mobOutcomesActive %>% group_by(gender, familiarity_binned) %>% identify_outliers(post_pre_Active)

#Remove 0 Extreme Outliers (n = 120) mobOutcomesActive <- mobOutcomes %>% anti_join(df_outliers[which(df_outliers win% TRUE),], by = "id")

 $aov_active <- aov(post_pre_Active \sim gender + familiarity_binned + gender:familiarity_binned, \ data = mobOutcomesActive)$

Df Sum Sq Mean Sq F value Pr(>F)

gender 1 0.00 0.0026 0.002 0.968

familiarity_binned 1 0.01 0.0066 0.004 0.950

gender:familiarity binned 1 0.27 0.2682 0.164 0.686

Residuals 116 189.31 1.6320

summary(aov active)

#Identify Outliers post pre Nervous

 $mobOutcomes Nervous <- mobOutcomes [c ("gender", "familiarity_binned", "Gender X Familiarity", "post_pre_Nervous", "id")] df_outliers <- mobOutcomes Nervous %>% group_by (gender, familiarity_binned) %>% identify_outliers (post_pre_Nervous)$

#Remove 0 Extreme Outliers (n = 120) mobOutcomesNervous <- mobOutcomes %>% anti_join(df_outliers[which(df_outliers[wh

aov_nervous <- aov(post_pre_Nervous ~ gender + familiarity_binned + gender:familiarity_binned, data = mobOutcomesNervous)

gender 1 0.23 0.2298 0.122 0.727

familiarity_binned 1 0.00 0.0009 0.000 0.983

gender:familiarity_binned 1 0.04 0.0419 0.022 0.881

summary(aov nervous)

#Identify Outliers post_preNegativeAffect

 $mobOutcomes Negative <- mobOutcomes [c("gender", "familiarity_binned", "GenderXFamiliarity", "post_pre_NegativeAffect" id")] df_outliers <- mobOutcomes Negative %>% group_by(gender, familiarity_binned) %>% identify_outliers (post_pre_NegativeAffect)$

#Remove 0 Extreme Outliers (n = 120) mobOutcomesNegative <- mobOutcomesNegative %>% anti_join(df_outliers[which(df_outliers\$is.extreme %in% TRUE),], by = "id") aov_negative <- aov(post_pre_NegativeAffect ~ gender + familiarity_binned + gender:familiarity_binned, data = mobOutcomesNegative)

gender 1 0.59 0.5908 0.981 0.324

familiarity binned 1 1.37 1.3650 2.267 0.135

gender:familiarity_binned 1 1.12 1.1207 1.861 0.175

Residuals 116 64.87 0.559

summary(aov negative) ##### #post pre ashamed

 $mobOutcomes A shamed <- mobOutcomes [c("gender", "familiarity_binned", "Gender X Familiarity", "post_pre_A shamed", "id")] \ df_outliers <- mobOutcomes A shamed %>% group_by(gender, familiarity_binned) %>% identify_outliers(post_pre_A shamed)$

#Remove 11 Extreme Outliers (n = 109) mobOutcomes Ashamed <- mobOutcomes %>% anti_join(df_outliers[which(df_out

%in% TRUE),], by = "id")

 $aov_ashamed <- aov(post_pre_Ashamed \sim gender + familiarity_binned + gender:familiarity_binned, data = mobOutcomesAshamed)$

gender 1 3.91 3.907 5.127 0.02560 *

familiarity_binned 1 6.44 6.437 8.448 0.00446 **

gender: familiarity_binned 1 2.97 2.971 3.900 0.05092.

Residuals 105 80.01 0.762

summary (aov_ashamed) # \$gender # diff lwr upr p adj # Male-Female 0.4385727 0.05453599 0.8226094 0.0256048 # # \$familiarity_binned # diff lwr upr p adj # high_familiarity-low_familiarity -0.6907865 -1.172016 -0.2095573 0.0053209 Tukey HSD(aov_ashamed)

```
#post pre Hostile
```

 $mobOutcomes Hostile <- mobOutcomes [c ("gender", "familiarity_binned", "Gender X Familiarity", "post_pre_Hostile", "id")] df_outliers <- mobOutcomes Hostile %>% group_by (gender, familiarity_binned) %>% identify_outliers (post_pre_Hostile)$

#Remove 0 Extreme Outliers (n = 120) mobOutcomesHostile <- mobOutcomes %>% anti_join(df_outliers[which(df_outliers which(df_outliers which(df_outliers))], by = "id")

 $aov_hostile <- aov(post_pre_Hostile \sim gender + familiarity_binned + gender:familiarity_binned, data = mobOutcomesHostile)$

Df Sum Sq Mean Sq F value Pr(>F)

gender 1 0.32 0.3155 0.169 0.682

familiarity_binned 1 0.01 0.0056 0.003 0.957

gender:familiarity_binned 1 1.25 1.2468 0.666 0.416

summary(aov_hostile)

#post_pre_Afraid mobOutcomesAfraid <- mobOutcomes[c("gender", "familiarity_binned", "GenderX-Familiarity", "post_pre_Afraid", "id")] df_outliers <- mobOutcomesAfraid %>% group_by(gender, familiarity_binned) %>% identify_outliers(post_pre_Afraid)

%in% TRUE),], by = "id")

#Remove 9 Extreme Outliers (n = 111) mobOutcomesAfraid <- mobOutcomesAfraid %>% anti_join(df_outliers[which(df_outliers])

 $aov_afraid <- aov(post_pre_Afraid \sim gender + familiarity_binned + gender:familiarity_binned, data = mobOutcomesAfraid)$

gender 1 0.60 0.6048 0.644 0.4241

familiarity_binned 1 2.71 2.7132 2.888 0.0921 .

gender:familiarity_binned 1 0.07 0.0702 0.075 0.7851

Residuals 107 100.52 0.9395

summary(aov afraid)

Repeat by Subset candidate variables to test group differences for (based on boxplot visualizations):

Active, Nervous, Negative, Ashamed, Hostile, Afraid, Determined, Attentive, Upset, Inspired, Alert, Positive

 $\#post_pre_Determined\ mobOutcomesDetermined<-\ mobOutcomes[c("gender", "familiarity_binned", "GenderXFamiliarity", "post_pre_Determined", "id")]\ df_outliers<-\ mobOutcomesDetermined\ \%>\%\ group_by(gender, familiarity_binned)\ \%>\%\ identify_outliers(post_pre_Determined)$

```
#Remove 2 Extreme Outliers (n = 118) mobOutcomesDetermined <- mobOutcomesDetermined %>% anti_join(df_outliers[which(df_outliers$is.extreme %in% TRUE),], by = "id")
```

 $aov_determined <- aov(post_pre_Determined \sim gender + familiarity_binned + gender:familiarity_binned,\\ data = mobOutcomesDetermined)$

gender 1 0.01 0.0149 0.010 0.921

familiarity_binned 1 0.05 0.0482 0.032 0.859

gender:familiarity_binned 1 0.79 0.7925 0.523 0.471

Residuals 114 172.61 1.5141

summary(aov_determined)

```
#post_pre_Attentive
```

 $mobOutcomes Attentive <- mobOutcomes [c("gender", "familiarity_binned", "GenderXFamiliarity", "post_pre_Attentive", "id")] df_outliers <- mobOutcomes Attentive %>% group_by(gender, familiarity_binned) %>% identify_outliers(post_pre_Attentive)$

 $\#Remove~40~Extreme~Outliers~(n=80)~mobOutcomes\\Attentive<-~mobOutcomes~\%>\%~anti_join(df_outliers[which(df_outliers[whi$

 $aov_attentive <- aov(post_pre_Attentive \sim human_agent + docile_hostile + human_agent: docile_hostile, \\ data = mobOutcomesAttentive)$

human_agent 1 1.26 1.2622 1.047 0.309

docile hostile 1 0.76 0.7569 0.628 0.430

human_agent:docile_hostile 1 0.36 0.3567 0.296 0.588

summary(aov attentive)

```
#post_pre_Upset
```

 $mobOutcomes Upset <- mobOutcomes [c("human_agent", "docile_hostile", "human_agent", "combined_group", "post_pre_Upset", "id")] df_outliers <- mobOutcomes Upset %>% group_by(human_agent, docile_hostile) %>% identify_outliers (post_pre_Upset)$

#Remove 12 Extreme Outliers (n = 108) mobOutcomesUpset <- mobOutcomes %>% anti_join(df_outliers[which(df_outliers which(df_outliers which(df_outliers which(df_outliers))], by = "id")

aov_upset <- aov(post_pre_Upset ~ human_agent + docile_hostile + human_agent:docile_hostile, data = mobOutcomesUpset)

```
human_agent 1 6.78 6.778 6.081 0.0153 *
```

docile hostile 1 1.31 1.315 1.180 0.2800

human_agent:docile_hostile 1 0.71 0.714 0.641 0.4253

summary(aov_upset)

#post_pre_Inspired

 $mobOutcomes Inspired <- mobOutcomes [c("human_agent", "docile_hostile", "human_agent", "combined_group", "post_pre_Inspired", "id")] \\ df_outliers <- mobOutcomes Inspired %>% group_by(human_agent, docile_hostile) %>% identify_outliers(post_pre_Inspired)$

 $\#Remove~49~Extreme~Outliers~(n=71)~mobOutcomesInspired <-~mobOutcomes~\%>\%~anti_join(df_outliers[which(df_outliers[whic$

 $aov_inspired <- aov(post_pre_Inspired \sim human_agent + docile_hostile + human_agent:docile_hostile, \\ data = mobOutcomesInspired)$

human_agent 1 0 0 NaN NaN

docile_hostile 1 0 0 NaN NaN

human_agent:docile_hostile 1 0 0 NaN NaN

summary(aov inspired)

#post pre Alert

 $mobOutcomesAlert<-mobOutcomes[c("human_agent", "docile_hostile", "human_agent", "combined_group", "post_pre_Alert", "id")] df_outliers<-mobOutcomesAlert %>% group_by(human_agent, docile_hostile) %>% identify_outliers(post_pre_Alert)$

#Remove 15 Extreme Outliers (n = 105) mobOutcomesAlert <- mobOutcomes %>% anti_join(df_outliers[which(df_outliers %in% TRUE),], by = "id")

 $aov_alert <- aov(post_pre_Alert \sim human_agent + docile_hostile + human_agent:docile_hostile, data = mobOutcomesAlert)$

human agent 1 0.31 0.3095 0.408 0.525

docile hostile 1 0.24 0.2413 0.318 0.574

human_agent:docile_hostile 1 0.84 0.8397 1.106 0.295

summary(aov_alert)

#post_prePositiveAffect

 $mobOutcomesPositive <- mobOutcomes[c("human_agent", "docile_hostile", "combined_group", "post_pre_PositiveAffect", "id")] df_outliers <- mobOutcomesPositive %>% group_by(human_agent, docile_hostile) %>% identify_outliers(post_pre_PositiveAffect)$

#Remove 3 Extreme Outliers (n = 117) mobOutcomesPositive <- mobOutcomesPositive %>% anti_join(df_outliers[which(df_outliers\$is.extreme %in% TRUE),], by = "id")

 $aov_positive <- aov(post_pre_Positive \\ Affect \sim human_agent + docile_hostile + human_agent: docile_hostile, \\ data = mobOutcomesPositive)$

#Compute Shapiro-Wilk test of normality #Significant p value shapiro_test(residuals(aov_positive))

human_agent 1 0.53 0.5308 1.592 0.20963

docile_hostile 1 2.59 2.5921 7.774 0.00622 **

human_agent:docile_hostile 1 0.01 0.0064 0.019 0.88980

summary(aov_positive)

Active, Nervous, Negative, Ashamed, Hostile, Afraid, Determined, Attentive, Upset, Inspired, Alert, Positive

#Bonferroni

[1] 1.000 0.048 1.000

#holm

[1] 1.0000 0.0480 1.0000 1.0

 $p.adjust(p_vector, method = "holm", n = length(p_vector))$

$[29] \ 0.7912421 \ 0.8632575 \ 0.7080000 \ 0.9730286 \ 0.9730286 \ 0.7912421 \\ 0.9910000 \ 0.7912421$

Perform ANOVA for Behaviors wrt gender X familiarity boxplots_behaviors_by_gender_familiarity <- gridOfBoxplots(mobOutcomes, "Behaviors by Familiarity Boxplots", behaviors_flag=TRUE, by_familiarity = TRUE)

#Identify Outliers fightCnt mobOutcomesFightFamiliarity <- mobOutcomes[c("familiarity_binned", "fightCnt", "id")] df_outliers <- mobOutcomesFightFamiliarity %>% group_by(familiarity_binned) %>% identify_outliers(fightCnt)

#Remove 1 Extreme Outlier (n = 119) mobOutcomesFightFamiliarity <- mobOutcomes %>% anti_join(df_outliers[which(df_outliers\$is.extreme %in% TRUE),], by = "id")

aovFightFamiliarity <- aov(fightCnt \sim gender + familiarity_binned + gender:familiarity_binned, data = mobOutcomesFightFamiliarity) # gender 1 0.4 0.41 0.032 0.85864

familiarity_binned 1 136.4 136.38 10.641 0.00146 ** # gender:familiarity_binned 1 1.0 1.03 0.081 0.77707 # Residuals 115 1473.9 12.82

summary (aovFightFamiliarity) # \$familiarity_binned # diff lwr upr p adj # (1,2,3)-(-3,-2,-1) -3.171312 -5.129895 -1.212729 0.0017357 Tukey HSD(aovFightFamiliarity)

#Identify Outliers punchCnt mobOutcomesPunchFamiliarity <- mobOutcomes[c("familiarity_binned", "punchCnt", "id")] df_outliers <- mobOutcomesPunchFamiliarity %>% group_by(familiarity_binned) %>% identify outliers(punchCnt)

#Remove 6 Extreme Outlier (n = 114) mobOutcomesPunchFamiliarity <- mobOutcomes %>% anti_join(df_outliers[which(df_outliers\$is.extreme %in% TRUE),], by = "id")

aov Punch Familiarity <- aov (punch Cnt ~ gender + familiarity_binned + gender:familiarity_binned, data = mob Outcomes Punch Familiarity) # Df Sum Sq Mean Sq F value Pr (>F) # gender 1 43547 43547 2.152 0.145 # familiarity_binned 1 13049 13049 0.645 0.424 # gender:familiarity_binned 1 12808 12808 0.633 0.428 # Residuals 110 2226450 20240

summary(aovPunchFamiliarity)

 $\# Identify Outliers avgSpeed mobOutcomesSpeedFamiliarity <- mobOutcomes[c("familiarity_binned", "avgSpeed", "id")] df_outliers <- mobOutcomesSpeedFamiliarity %>% group_by(familiarity_binned) %>% identify_outliers(avgSpeed)$

#Remove 0 Extreme Outlier (n = 120) mobOutcomesSpeedFamiliarity <- mobOutcomes %>% anti_join(df_outliers[which(df_outliers]sis.extreme %in% TRUE),], by = "id")

 $aovSpeedFamiliarity <- \ aov(avgSpeed \sim gender + familiarity_binned + gender:familiarity_binned, \ data = mobOutcomesSpeedFamiliarity) \# Df Sum Sq Mean Sq F value Pr(>F)$

gender 1 0.122 0.1223 1.254 0.26517

familiarity_binned 1 0.690 0.6896 7.070 0.00895 ** # gender:familiarity_binned 1 0.282 0.2819 2.890 0.09179 . # Residuals 116 11.315 0.0975

```
summary(aovSpeedFamiliarity) # $familiarity_binned # diff lwr upr p adj # (1,2,3)-(-3,-2,-1) 0.2200336 0.05391286 0.3861544 0.0098752 TukeyHSD(aovSpeedFamiliarity)
```

#Identify Outliers timeSpent mobOutcomesTimeFamiliarity <- mobOutcomes[c("familiarity_binned", "timeSpent", "id")] df_outliers <- mobOutcomesTimeFamiliarity %>% group_by(familiarity_binned) %>% identify outliers(timeSpent)

#Remove 0 Extreme Outlier (n = 120) mobOutcomesTimeFamiliarity <- mobOutcomes %>% anti_join(df_outliers[which(df_outliers\$is.extreme %in% TRUE),], by = "id")

aov TimeFamiliarity <- aov (timeSpent ~ gender + familiarity_binned + gender:familiarity_binned, data = mobOutcomes TimeFamiliarity) # Df Sum Sq Mean Sq F value Pr(>F)

gender 1 4979 4979 0.721 0.397

familiarity_binned 1 135018 135018 19.560 2.21e-05 *** # gender:familiarity_binned 1 15464 15464 2.240 0.137

Residuals 116 800702 6903

summary(aovTimeFamiliarity) # $familiarity_binned # diff lwr upr p adj # (1,2,3)-(-3,-2,-1) -97.35925 -141.5491 -53.16935 2.79e-05 TukeyHSD(aovTimeFamiliarity)$

#Identify Outliers totalDist mobOutcomesDistFamiliarity <- mobOutcomes[c("familiarity_binned", "totalDist", "id")] df_outliers <- mobOutcomesDistFamiliarity %>% group_by(familiarity_binned) %>% identify_outliers(totalDist)

#Remove 7 Extreme Outlier (n = 113) mobOutcomesDistFamiliarity <- mobOutcomes %>% anti_join(df_outliers[which(df_outliers\$is.extreme %in% TRUE),], by = "id")

aov DistFamiliarity <- aov (total Dist ~ gender + familiarity_binned + gender:familiarity_binned, data = mob Outcomes DistFamiliarity) # Df Sum Sq Mean Sq F value Pr(>F) # gender 1 789 789.3 0.930 0.337 # familiarity_binned 1 315 315.0 0.371 0.544 # gender:familiarity_binned 1 4 3.6 0.004 0.948 # Residuals 109 92551 849.1

summary(aovDistFamiliarity)

#Identify Outliers collectedItemCnt mobOutcomesCollectedItemFamiliarity <- mobOutcomes[c("familiarity_binned", "collectedItemCnt", "id")] df_outliers <- mobOutcomesCollectedItemFamiliarity %>% group_by(familiarity_binned) %>% identify outliers(collectedItemCnt)

#Remove 3 Extreme Outlier (n = 117) mobOutcomesCollectedItemFamiliarity <- mobOutcomes %>% anti_join(df_outliers[which(df_outliers\$is.extreme %in% TRUE),], by = "id")

 $aovCollectedItemFamiliarity <- \ aov(collectedItemCnt \sim gender + familiarity_binned + gender:familiarity_binned, \\ data = mobOutcomesCollectedItemFamiliarity) \ \# \ Df \ Sum \ Sq \ Mean \ Sq \ F \ value \ Pr(>F)$

gender 1 22.7 22.73 3.338 0.0703 . # familiarity_binned 1 42.4 42.43 6.229 0.0140 * # gender:familiarity_binned 1 2.4 2.37 0.347 0.5568

Residuals 113 769.7 6.81

summary(aovCollectedItemFamiliarity) # \$familiarity_binned # diff lwr upr p adj # (1,2,3)-(-3,-2,-1) 1.901042 0.3799676 3.422116 0.0147658 TukeyHSD(aovCollectedItemFamiliarity)

 $\label{lem:comes} $$\# Identify Outliers total ItemCnt mobOutcomes Total ItemFamiliarity <- mobOutcomes [c("familiarity_binned", "total ItemCnt", "id")] df_outliers <- mobOutcomes Collected ItemFamiliarity %>% group_by(familiarity_binned) %>% identify_outliers(total ItemCnt)$

#Remove 3 Extreme Outlier (n = 117) mobOutcomesTotalItemFamiliarity <- mobOutcomes %>% anti_join(df_outliers[which(df_outliers\$is.extreme %in% TRUE),], by = "id")

aov Total ItemFamiliarity <- aov (total ItemCnt ~ gender + familiarity_binned + gender:familiarity_binned, data = mob OutcomesTotal ItemFamiliarity) # Df Sum Sq Mean Sq F value Pr (>F) # gender 1 25 25.38 0.291 0.590 # familiarity_binned 1 137 137.30 1.576 0.212 # gender:familiarity_binned 1 4 3.76 0.043 0.836 # Residuals 115 10020 87.13

 $summary (a ov Total Item Familiarity) \ Tukey HSD (a ov Total Item Familiarity) \\$

#fight, punch, avgSPeed, timeSpent, totalDist, collectedItem, totalItemCnt p_vector <- c(0.85864, 0.00146, 0.7707, 0.145, 0.424, 0.428, 0.26517, 0.00895, 0.09179, 0.397, 0.0000221, 0.137, 0.337, 0.544, 0.948, 0.0703, 0.0140, 0.5568, 0.590, 0.212, 0.836) p.adjust(p_vector, "holm", n = length(p_vector)) # 1.0000000 0.0292000 1.0000000 1.0000000 1.0000000 1.0000000 1.0000000 1.0000000 1.0000000 1.0000000 1.0000000 1.0000000 1.0000000 1.0000000 1.0000000 1.0000000 1.0000000 1.0000000 p.adjust(p_vector, "BH", n = length(p_vector)) # 0.9015720 0.0153300 0.8991500 0.3806250 0.6420000 0.6420000 0.5568570 0.0626500 0.3212650 0.6420000 0.0004641 0.3806250 0.6420000 0.7288235 # 0.9480000 0.2952600 0.0735000 0.7288235 0.7288235 0.4946667 0.9015720

#boxplots for sig. response vars, one versus multiple

Generate Grid of Boxplots

Perform the ART ANOVA

artTimeSpent <- art(timeSpent ~ human_agent * docile_hostile, data = mobOutcomes) # Print the test results # 1 human_agent 1 116 0.002763 0.9581697 # 2 docile_hostile 1 116 0.401034 0.0026985 ** # 3 human_agent:docile_hostile 1 116 0.547492 0.4608392 anova(artTimeSpent)

Perform the ART ANOVA

artPunchCnt <- art(punchCnt ~ human_agent * docile_hostile, data = mobOutcomes) # Print the test results # 1 human_agent 1 116 3.0420 0.083785 . # 2 docile_hostile 1 116 18.9281 2.9354e-05 *** # 3 human_agent:docile_hostile 1 116 1.3125 0.254292 anova(artPunchCnt)

Perform the ART ANOVA

artPunchRate <- art(punchRate ~ human agent * docile hostile, data = mobOutcomes)

Print the test results

- 1 human_agent 1 116 2.45459 0.11991
- 2 docile_hostile 1 116 0.12982 0.71928
- 3 human_agent:docile_hostile 1 116 0.13589 0.71307

anova(artPunchRate)

Perform the ART ANOVA

```
artTotalDist <- art(totalDist ~ human_agent * docile_hostile, data = mobOutcomes) # 1 human_agent 1 116 2.2367 0.137481 # 2 docile_hostile 1 116 6.5171 0.011982 * # 3 human_agent:docile_hostile 1 116 2.3118 0.131113 anova(artTotalDist)
```

Perform ANOVA #Identify Outliers mobOutcomesAvgSpeed <- mobOutcomes[c("human_agent", "docile_hostile", "avgSpeed", "id")] df_outliers <- mobOutcomesAvgSpeed %>% group_by(human_agent, docile_hostile) %>% identify_outliers(avgSpeed)

#Remove 1 Extreme Outlier (n = 120) mobOutcomesAvgSpeed <- mobOutcomes %>% anti_join(df_outliers[which(df_outliers[whic

aovAvgSpeed <- aov(avgSpeed ~ human_agent + docile_hostile + human_agent:docile_hostile, data = mobOutcomes) # human_agent 1 0.522 0.5223 4.450 0.037 * # docile_hostile 1 0.393 0.3926 3.345 0.070 . # human_agent:docile_hostile 1 0.009 0.0095 0.081 0.777 summary(aovAvgSpeed)

$$\begin{split} & ggplot(data=mobOutcomes, aes(x=human_agent, y=mobOutcomes[, "avgSpeed"])) + geom_boxplot(color="black", fill="blue", alpha=0.2, outlier.shape = NA) + stat_summary(fun=mean, colour="black", geom="text", aes(label = round(..y.., 2))) \end{split}$$

$[13]\ 0.44400000\ 0.77000000\ 1.00000000$

```
\begin{split} &p.adjust(p\_vector\_art,\,method="holm",\,n=length(p\_vector\_art))\\ &list\_multi\_plot<-\,lapply(c(8,10),\,function(col)~\{ \end{split}
```

ggplot(data=mobOutcomes, aes(x=docile_hostile, y= mobOutcomes[, col])) + geom_boxplot(color
stat summary(fun=mean, colour="black", geom="point",

```
shape=18, size=3, show.legend=FALSE) +
                        theme(axis.text.x = element text(angle = 25, hjust = 1), legend.position="none") + ggplo
                 })
multi plot <- cowplot::plot grid(plotlist = list multi plot) multi plot <- ggdraw(multi plot) + ggti-
tle("Significant Behavior Group Differences Boxplots") + theme(plot.title = element text(hjust = 0.5))
print(multi_plot)
##Visualization## #####################
#Get means and std deviations by group, post_pre_PositiveAffect means_pos_affect <- aggre-
gate(post_pre_PositiveAffect ~ human_agent, mobOutcomesCombined, mean) h_a_pos_affect <- gg-
plot(data=mobOutcomesCombined, aes(x=human agent, y=post pre PositiveAffect, fill=post pre PositiveAffect))
+ geom_boxplot() + stat_summary(fun=mean, colour="gray", geom="point", shape=18, size=3,
show.legend=FALSE) + geom text(data = means pos affect, aes(label = sprintf("%0.2f", round(post pre PositiveAffect,
digits = 3)), y = post pre PositiveAffect+ .14)) + theme(legend.position="none")
plot(h a pos affect)
means_pos_affect_2 <- aggregate(post_pre_PositiveAffect ~ docile_hostile, mobOutcomesCombined,
mean) d h pos affect <- ggplot(data=mobOutcomesCombined, aes(x=docile hostile, y=post pre PositiveAffect,
fill=post pre PositiveAffect)) + geom boxplot() + stat summary(fun=mean, colour="gray", geom="point",
shape=18, size=3, show.legend=FALSE) + geom_text(data = means_pos_affect_2, aes(label
=sprintf("%0.2f", round(post pre PositiveAffect, digits = 3)), y = post pre PositiveAffect+ .14))
+ theme(legend.position="none")
means_pos_affect_3 <- aggregate(post_pre_PositiveAffect ~ group, mobOutcomesCombined, mean)
g pos affect <- ggplot(data=mobOutcomesCombined, aes(x=group, y=post pre PositiveAffect,
fill=post pre PositiveAffect)) + geom boxplot() + stat summary(fun=mean, colour="gray", geom="point",
shape=18, size=3, show.legend=FALSE) + geom_text(data = means_pos_affect_3, aes(label
=sprintf("%0.2f", round(post pre PositiveAffect, digits = 3)), v = post pre PositiveAffect+ .14))
+ theme(legend.position="none")
ggarrange(h a pos affect, d h pos affect, g pos affect, ncol = 2, nrow = 2)
mobOutcomesCombined ~\%>\% ~~group\_by(group) ~\%>\% ~~get\_summary\_stats(totalItemCnt, ~~type ~~=~ 1000 cm^{-3} c
"mean_sd") #Plot them totalItemCnt = ggboxplot(mobOutcomesCombined, x = "group", y =
"post pre PositiveAffect") ggsave(paste0("post pre PositiveAffect", ".png"), totalItemCnt)
#Get means and std deviations by group, post pre NegativeAffect mobOutcomesCombined %>%
group by(group) %>% get summary stats(totalItemCnt, type = "mean sd") #Plot them to-
talItemCnt = ggboxplot(mobOutcomesCombined, x = "group", y = "post_pre_NegativeAffect")
ggsave(paste0("post_pre_NegativeAffect",".png"), totalItemCnt)
#Get means and std deviations by group, fightcount mobOutcomesCombined %>% group_by(group) %>%
get_summary_stats(fightCnt, type = "mean_sd") #Plot them fightCount = ggboxplot(mobOutcomes, x
= "group", y = "fightCnt") ggsave(paste0("Fight Count By Group", ".png"), fightCount)
#Get means and std deviations by group, punchcount mobOutcomesCombined %>% group_by(group)
%>% get_summary_stats(fightCnt, type = "mean_sd") #Plot them punchCount = ggboxplot(mobOutcomesCombined,
x = "group", y = "punchCnt") ggsave(paste0("Punch Count By Group", ".png"), punchCount)
#Get means and std deviations by group, avgSpeed mobOutcomesCombined %>% group_by(group) %>%
get_summary_stats(fightCnt, type = "mean_sd") #Plot them punchCount = ggboxplot(mobOutcomesCombined,
x = "group", y = "avgSpeed") ggsave(paste0("Avg Speed By Group", ".png"), punchCount)
#Get means and std deviations by group, totalDist mobOutcomesCombined %>% group by(group) %>%
get_summary_stats(fightCnt, type = "mean_sd") #Plot them punchCount = ggboxplot(mobOutcomesCombined,
x = "group", y = "totalDist") ggsave(paste0("Total Dist By Group", ".png"), punchCount)
```

#Get means and std deviations by group, collectedItemCnt mobOutcomes %>% group_by(group) %>% get_summary_stats(collectedItemCnt, type = "mean_sd") #Plot them collectedItemCnt = ggbox-plot(mobOutcomesCombined, x = "group", y = "collectedItemCnt") ggsave(paste0("Collected_Item_Count_By_Group", ".procollectedItemCnt")

#Get means and std deviations by group, totalItemCnt mobOutcomesCombined %>% group_by(group) %>% get_summary_stats(totalItemCnt, type = "mean_sd") #Plot them totalItemCnt = ggboxplot(mobOutcomesCombined, x = "group", y = "totalItemCnt") ggsave(paste0("totalItemCnt",".png"), totalItemCnt)