

# GLMM Analysis for Circle Time

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## Contents

<b>1</b>	<b>About the Study</b>	<b>2</b>
1.1	Introduction to Circle-Time . . . . .	2
1.2	Study Design . . . . .	2
1.2.1	Independent Variables . . . . .	3
1.2.2	Dependent Variables . . . . .	3
1.3	Data Collection . . . . .	3
1.3.1	Affect . . . . .	3
1.3.2	Communication . . . . .	3
1.3.3	Engagement . . . . .	4
1.3.4	Performance . . . . .	4
1.3.5	Inter-observer Agreement (IoA) . . . . .	4
<b>2</b>	<b>Data Analysis</b>	<b>4</b>
2.1	Additive and Interaction Models and Plots . . . . .	4
2.2	Results: Additive Model Comparison Between Human and Robot Instructors . . . . .	28
2.2.1	Affect . . . . .	39
2.2.2	Communication . . . . .	39
2.2.3	Engagement . . . . .	40
2.2.4	Performance . . . . .	40
2.2.5	Summary . . . . .	40
2.3	Interaction Effects: Moderator Influence of Time and VB-MAPP on Robot-Led Instruction . . . . .	40
2.3.1	Affect . . . . .	41
2.3.2	Communication . . . . .	41
2.3.3	Engagement . . . . .	41
2.3.4	Performance . . . . .	42
2.3.5	Summary of Interaction Effects . . . . .	42
2.4	Predictive Role of Learning Behaviors on Performance in Human vs. Robot-Led Circle Time . . . . .	42

2.4.1	Overview . . . . .	42
2.4.2	Modeling Approach . . . . .	43
2.4.3	How does each learning behavior predict performance under the human condition only? . . . . .	45
2.4.4	Summary of Results . . . . .	48
2.4.4.1	Table 1. Predictive Effects of Learning Behaviors on Performance (Robot Condition) . . . . .	48
2.4.4.2	Interpretation – Robot Condition . . . . .	48
2.4.4.3	Table 2. Predictive Effects of Learning Behaviors on Performance (Human Condition) . . . . .	48
2.4.4.4	Interpretation – Human Condition . . . . .	49
2.4.5	Comparative Insights . . . . .	49
<b>3</b>	<b>Conclusion</b>	<b>49</b>

# 1 About the Study

## 1.1 Introduction to Circle-Time

Circle-time is a group activity based on Applied Behavior Analysis (ABA) for children with Autism Spectrum Disorder (ASD) to prepare them for attending in traditional classroom activities alongside neurotypically developing children. In circle-time, children sit together semicircular, and an instructor gives them group instruction activities such as dance, yoga, labeling animals, finding objects, etc. The goal of circle-time is to improve children’s learning behaviors, which are:

- Affect
- Communication
- Engagement
- Performance

In this study, we evaluate the efficacy of a social robot in delivering group instruction activities to children with ASD. Throughout the six months of experiment, six children participants received 10 sessions of group instructions from a human instructor and 10 sessions from a Pepper humanoid social robot as a within-subject study design. To compare children’s learning behaviors between the human and the robot instructor conditions, their activities were video recorded and coded for sessions 1, 4, 7, and 10.

## 1.2 Study Design

For this longitudinal within-subject study with 6 participants we defined the following variables:

### 1.2.1 Independent Variables

- Instructor Conditions:
  - Human ~ 1
  - Robot ~ 2
- Time:
  - Session 1 ~ 1
  - Session 4 ~ 2
  - Session 7 ~ 3
  - Session 10 ~ 4

### 1.2.2 Dependent Variables

- Affect
- Communication
- Engagement
- Performance

## 1.3 Data Collection

The evaluation of the learning behavior is based on the following continuous metrics:

### 1.3.1 Affect

Children's happiness level was defined as:

- Positive
- Negative
- Neutral

A video was divided into 10-second intervals. A human coder, focusing on one child in the group, labeled that interval as Positive if the child was showing positive affective behaviors (e.g., smiling, clapping, laughing). An interval was labeled as Negative if the child was showing negative affective behaviors (e.g., crying, whining, frowning). Neutral was used when neither applied. The percentage of each type was used for analysis.

### 1.3.2 Communication

Communication was coded into 4 categories:

- With Instructor

- Instructor-Prompted
- With Behavior Therapist (BT) or peers
- Indeterminate

### 1.3.3 Engagement

Engagement was coded into 3 categories:

- On Target (Instructor or screen)
- With BT or peers
- Off Target

### 1.3.4 Performance

Children’s performance was coded as:

- Positive
- Negative

### 1.3.5 Inter-observer Agreement (IoA)

Coders were required to exceed 80% Cohen’s Kappa IoA to code independently. All session ones and tens were double-coded, along with 30% of session fours and sevens. Disagreements were resolved through joint review to ensure 100% final agreement.

## 2 Data Analysis

### 2.1 Additive and Interaction Models and Plots

In this section, we first fit an additive model to evaluate the overall effects of instructor condition (Human vs. Robot), session time, and children’s VB-MAPP scores on each learning behavior. By including VB-MAPP as a covariate, we control for differences in individual skill levels, ensuring a fair comparison of the children’s responses across instructional conditions over time.

Next, we extend the analysis using an interaction model that tests whether the effect of instructor condition varies depending on the session time or the VB-MAPP score. This helps uncover whether certain children or timepoints show stronger effects from robot-led instruction.

To visualize the results, we generate two types of plots for each learning behavior. The first plot overlays violin plots of bootstrapped behavioral estimates across session timepoints. These violins illustrate the distribution and spread of responses for each instructor condition. We also superimpose the mean value of each group with connecting lines, providing a clear view of trends across sessions. The second plot shows the predicted behavioral outcome as a function of VB-MAPP score for both Human and Robot conditions. Shaded confidence bands represent the uncertainty around these estimates, allowing us to visualize how instructor efficacy changes as a function of the child’s developmental profile.

Together, these analyses and visualizations offer a comprehensive understanding of how social robot instruction compares to human-led instruction across time and learner profiles.

```
library(glmTMB)
library(performance)
library(DHARMa)
```

```
## This is DHARMa 0.4.7. For overview type '?DHARMa'. For recent changes, type news(package = 'DHARMa')
```

```
library(ggplot2)
library(broom.mixed)
library(dplyr)
```

```
##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##   filter, lag

## The following objects are masked from 'package:base':
##
##   intersect, setdiff, setequal, union
```

```
library(boot)
library(tidyr)

# Load and preprocess data
df <- read.csv("~/GitHub/Circle-Time-Data-Analyses/CircleTimeData-VBMAPP.csv")
df$Condition <- factor(df$Condition, levels = c(1, 2), labels = c("Human", "Robot"))
df$time_c <- scale(df$time, center = TRUE, scale = FALSE)

vars <- c(
  "Affect_Positive", "Affect_Negative",
  "Communication_with_Instructor", "Communication_with_Instructor_Prompted",
  "Communication_with_Therapist", "Communication_with_Indeterminent",
  "Engagement_OnTarget", "Engagement_Therapist", "Engagement_OffTarget",
  "Performance_Positive"
)

# Apply beta transformation
epsilon <- 0.0001
for (v in vars) {
  df[[v]] <- (df[[v]] * (nrow(df) - 1) + epsilon) / nrow(df)
}

# Significance stars function
sig_stars <- function(p) {
  if (is.na(p)) return("")
  if (p < 0.001) return("***")
  else if (p < 0.01) return("**")
  else if (p < 0.05) return("*")
}
```

```

else if (p < 0.1) return(".")
else return("")
}

## Additive and Interaction Models and Plots ##
## This section evaluates the behavioral metrics of interest (e.g., Affect, Engagement) through two models
## 1. An additive model controlling for VB-MAPP scores.
## 2. An interaction model examining moderation effects of Condition with time and VB-MAPP.
##
## We then visualize the bootstrapped confidence distributions using violin plots, mean trends, and the

for (var in vars) {
  cat("\n===== \n")
  cat("Behavior:", var, "\n")

  # --- Additive Model ---
  form_add <- as.formula(paste0(var, " ~ Condition + time_c + VBMAPP + (1 | Subject)"))
  model_add <- glmmTMB(form_add, data = df, family = beta_family())

  table_add <- broom.mixed::tidy(model_add, effects = "fixed")
  table_add$stars <- sapply(table_add$p.value, sig_stars)

  cat("\nAdditive Model Summary:\n")
  print(table_add[, c("term", "estimate", "std.error", "statistic", "p.value", "stars")])

  # --- Interaction Model ---
  form_int <- as.formula(paste0(var, " ~ Condition * time_c + Condition * VBMAPP + (1 | Subject)"))
  model_int <- glmmTMB(form_int, data = df, family = beta_family())

  table_int <- broom.mixed::tidy(model_int, effects = "fixed")
  table_int$stars <- sapply(table_int$p.value, sig_stars)

  cat("\nInteraction Model Summary:\n")
  print(table_int[, c("term", "estimate", "std.error", "statistic", "p.value", "stars")])

  # --- Bootstrap Violin Plots with Mean Line ---
  mean_df <- df %>%
    group_by(Condition, time) %>%
    summarise(mean_value = mean(.data[[var]]), .groups = "drop")

  bootstrap_samples <- df %>%
    group_by(Condition, time) %>%
    group_modify(~ {
      boot_result <- boot(.x[[var]], statistic = function(d, i) mean(d[i]), R = 1000)
      tibble(bootstrap = boot_result$t[, 1])
    }) %>%
    ungroup()

  p_violin_line <- ggplot() +
    geom_violin(
      data = bootstrap_samples,
      aes(x = factor(time), y = bootstrap, fill = Condition),
      position = position_identity(),

```

```

    alpha = 0.4,
    trim = FALSE,
    width = 1
  ) +
  geom_line(
    data = mean_df,
    aes(x = as.numeric(factor(time)), y = mean_value, color = Condition, group = Condition),
    linewidth = 1.2
  ) +
  geom_point(
    data = mean_df,
    aes(x = as.numeric(factor(time)), y = mean_value, fill = Condition),
    color = "black",
    shape = 21,
    size = 3
  ) +
  scale_x_discrete(
    name = "Session",
    labels = c("1st", "4th", "7th", "10th")
  ) +
  labs(
    title = paste(var, "-- Confidence Distributions with Mean Trends"),
    y = "Bootstrapped Mean",
    fill = "Condition",
    color = "Condition"
  ) +
  theme_minimal(base_size = 10) +
  theme(
    plot.title = element_text(size = 10),
    axis.title = element_text(size = 9),
    axis.text = element_text(size = 8),
    legend.title = element_text(size = 9),
    legend.text = element_text(size = 8)
  )

print(p_violin_line)

# --- VB-MAPP Interaction Plot ---
new_data <- expand.grid(
  Condition = factor(c("Human", "Robot"), levels = c("Human", "Robot")),
  time_c = 0,
  VBMAP = seq(min(df$VBMAP), max(df$VBMAP), length.out = 100),
  Subject = NA
)

pred <- predict(model_int, newdata = new_data, type = "response", se.fit = TRUE)
new_data$predicted <- pred$fit
new_data$conf.low <- pred$fit - 1.96 * pred$se.fit
new_data$conf.high <- pred$fit + 1.96 * pred$se.fit
new_data$group <- new_data$Condition

p2 <- ggplot(new_data, aes(x = VBMAP, y = predicted, color = group)) +
  geom_line(size = 1.3) +
  geom_ribbon(aes(ymin = conf.low, ymax = conf.high, fill = group), alpha = 0.2, color = NA) +

```

```

labs(
  x = "VB-MAPP Score",
  y = paste("Predicted", gsub("_", " ", var)),
  color = "Instructor",
  fill = "Instructor",
  title = paste("Interaction of VB-MAPP and Instructor on", gsub("_", " ", var))
) +
theme_minimal(base_size = 10) +
theme(
  plot.title = element_text(size = 10),
  axis.title = element_text(size = 9),
  axis.text = element_text(size = 8),
  legend.title = element_text(size = 9),
  legend.text = element_text(size = 8)
)

print(p2)
}

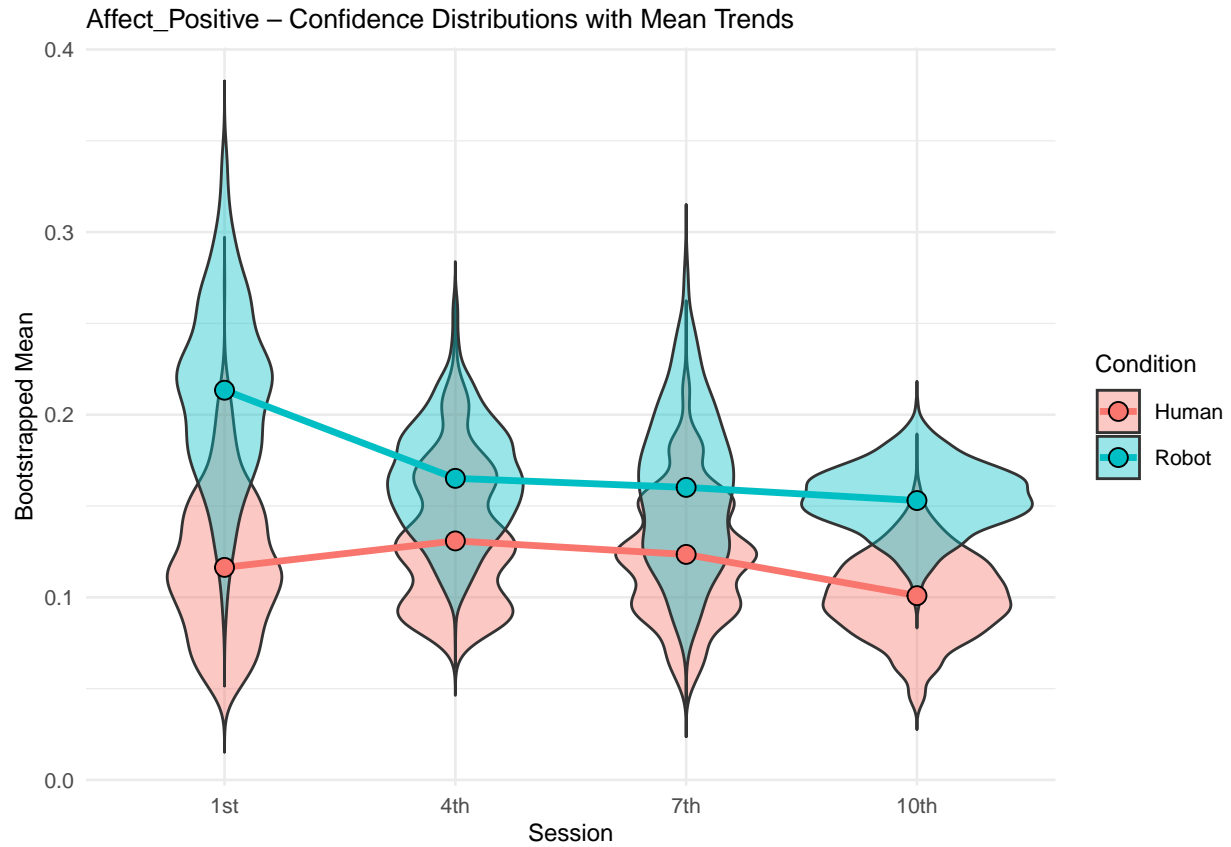
```

```

##
## =====
## Behavior: Affect_Positive
##
## Additive Model Summary:
## # A tibble: 4 x 6
##   term          estimate std.error statistic p.value stars
##   <chr>          <dbl>    <dbl>    <dbl>   <dbl> <chr>
## 1 (Intercept)      2.23      2.89      0.770 0.441   ""
## 2 ConditionRobot   0.435     0.151      2.89 0.00390 ***
## 3 time_c          -0.0776    0.0658     -1.18 0.238   ""
## 4 VBMAP           -2.66      1.79      -1.49 0.138   ""
##
## Interaction Model Summary:
## # A tibble: 6 x 6
##   term          estimate std.error statistic p.value stars
##   <chr>          <dbl>    <dbl>    <dbl>   <dbl> <chr>
## 1 (Intercept)      6.01      3.19      1.88 0.0597   "."
## 2 ConditionRobot   -6.28      2.35      -2.67 0.00755 ***
## 3 time_c          -0.0472    0.0901     -0.523 0.601   ""
## 4 VBMAP           -5.05      1.99      -2.54 0.0112   "*"
## 5 ConditionRobot:time_c -0.0696    0.121     -0.574 0.566   ""
## 6 ConditionRobot:VBMAP  4.22      1.48      2.86 0.00426 ***

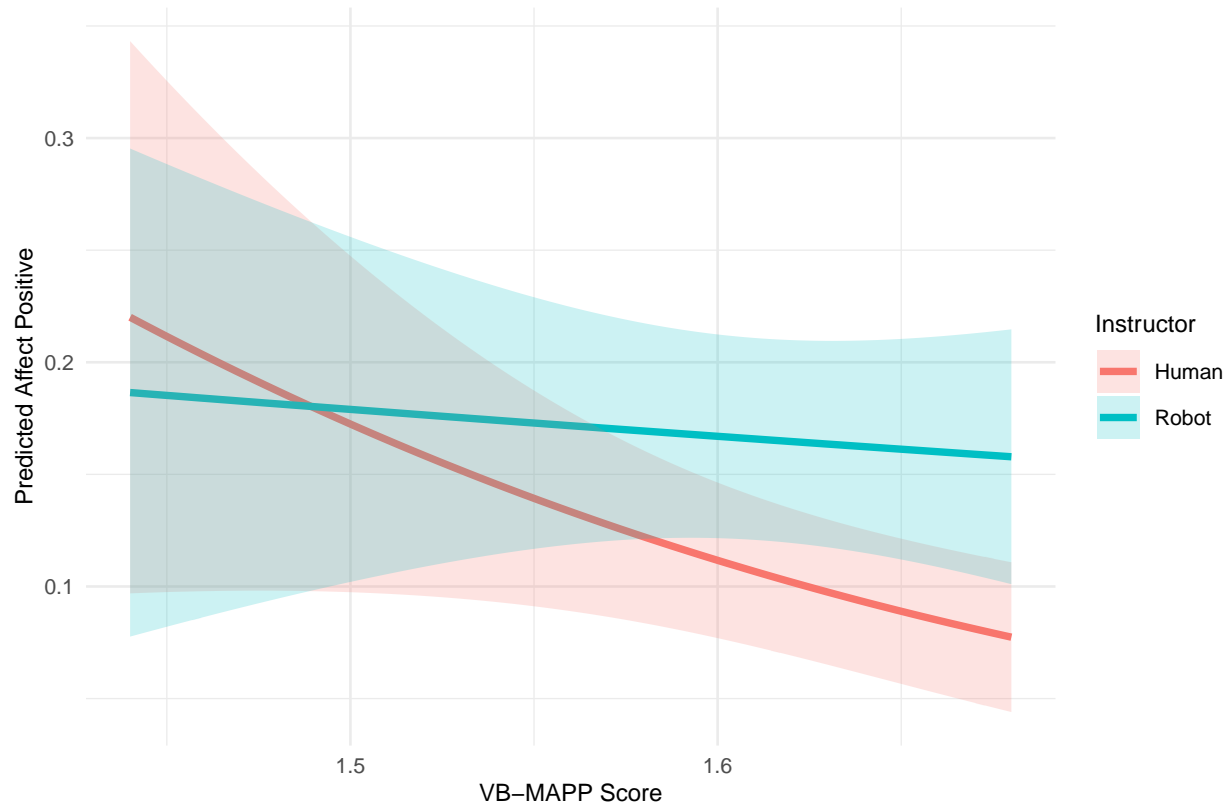
```



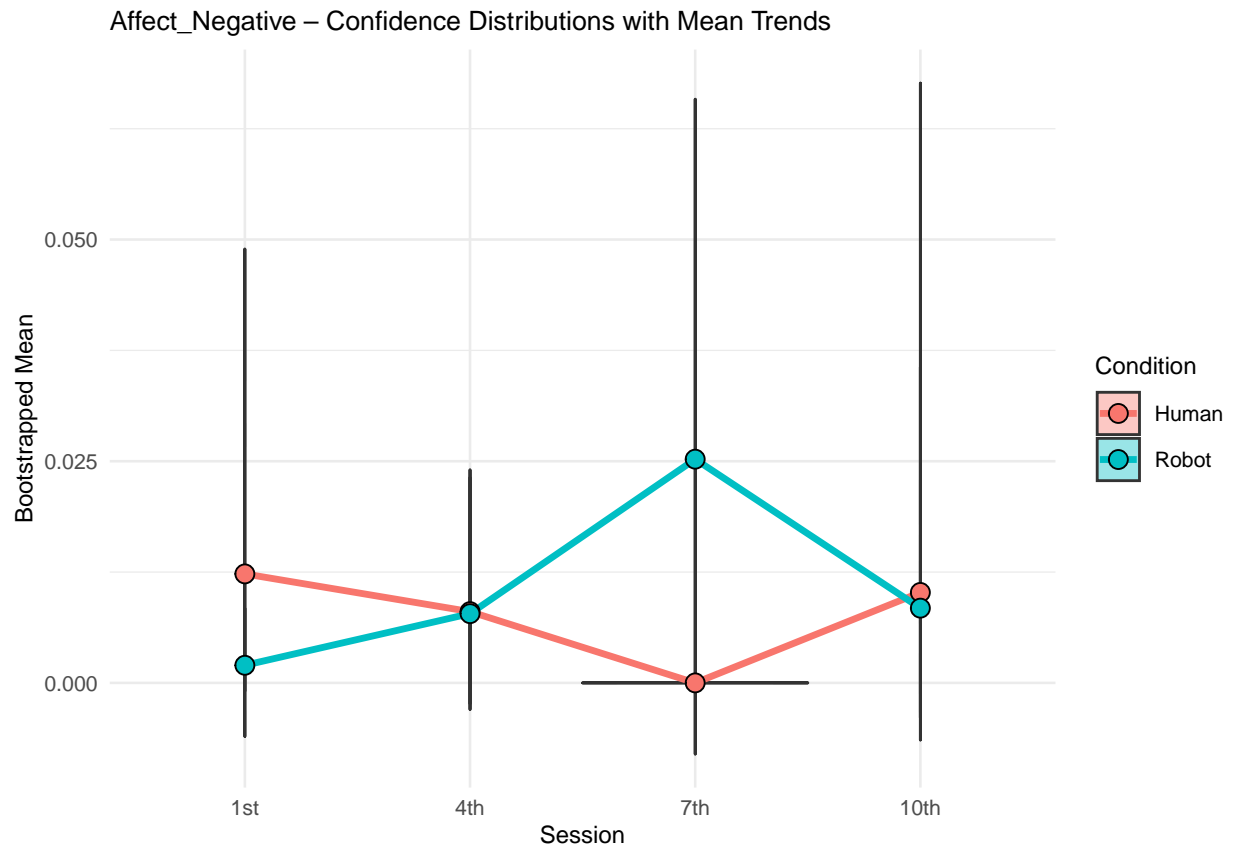


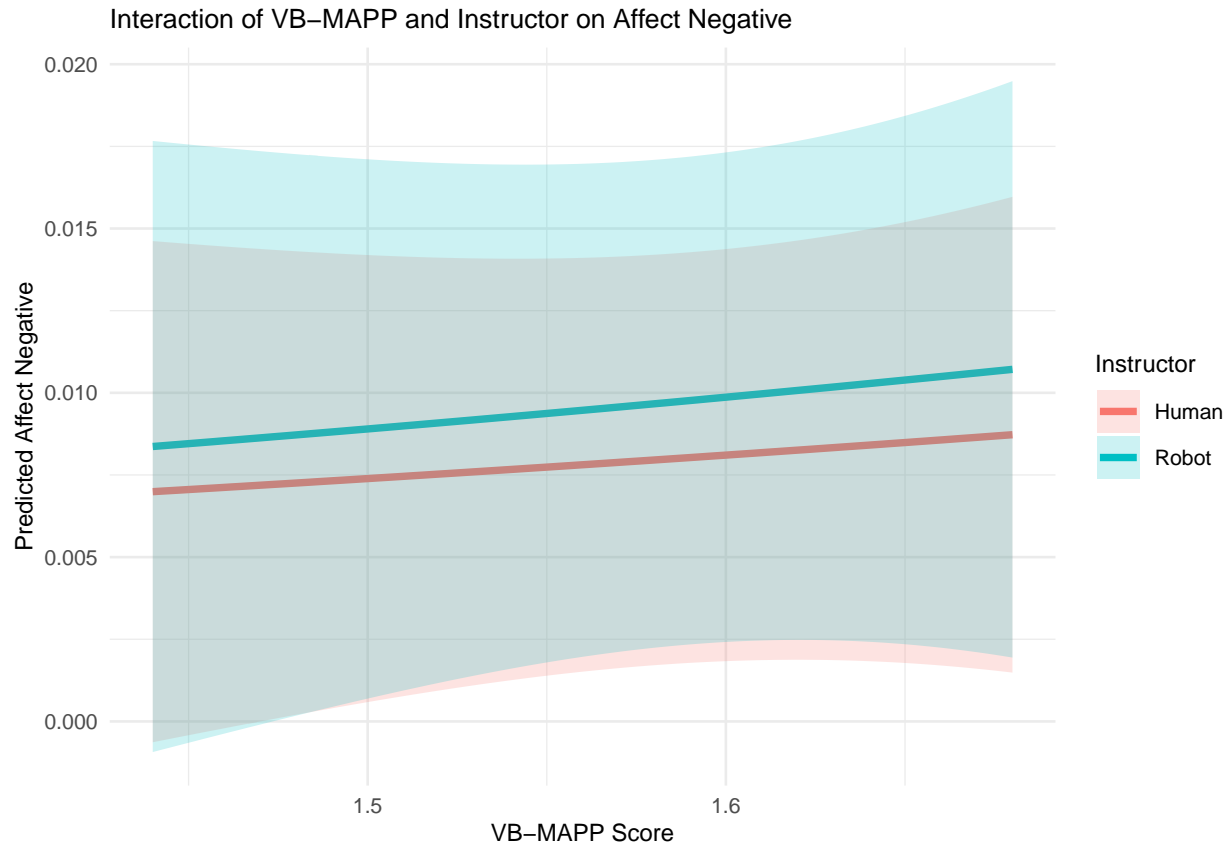
```
## Warning: Using `size` aesthetic for lines was deprecated in ggplot2 3.4.0.  
## i Please use `linewidth` instead.  
## This warning is displayed once every 8 hours.  
## Call `lifecycle::last_lifecycle_warnings()` to see where this warning was  
## generated.
```

Interaction of VB-MAPP and Instructor on Affect Positive

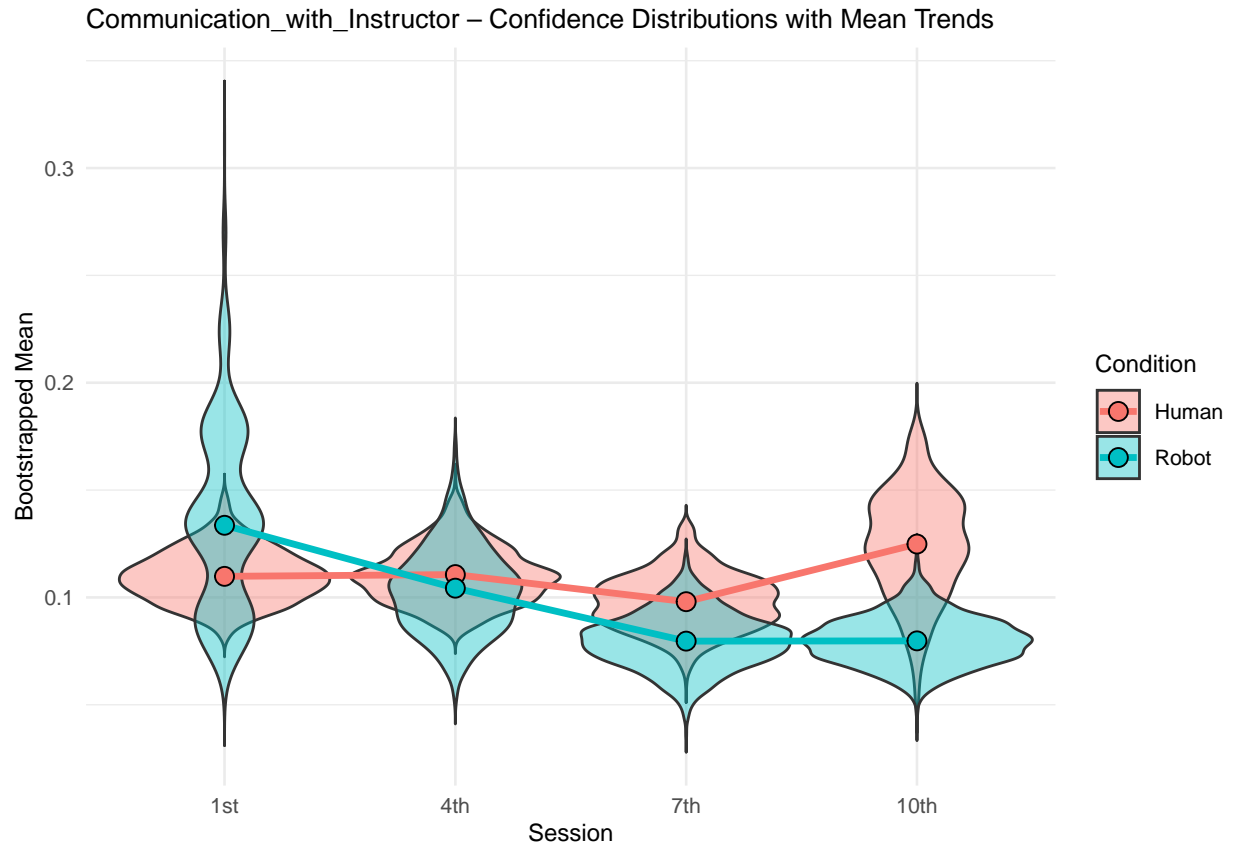


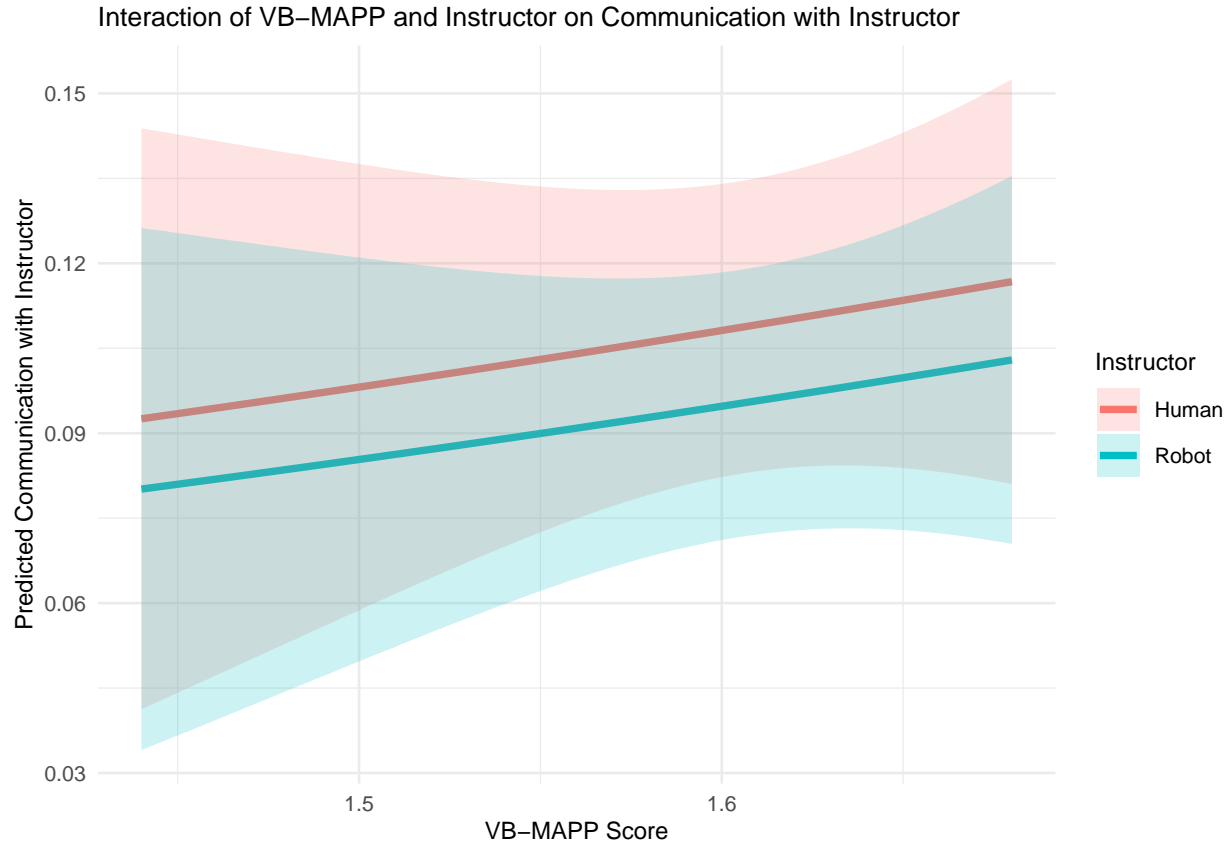
```
##
## =====
## Behavior: Affect_Negative
##
## Additive Model Summary:
## # A tibble: 4 x 6
##   term                estimate std.error statistic p.value stars
##   <chr>              <dbl>      <dbl>      <dbl>   <dbl> <chr>
## 1 (Intercept)      -6.42        2.73      -2.35   0.0187 "*"
## 2 ConditionRobot    0.200        0.289      0.693   0.489  ""
## 3 time_c           -0.0267       0.126     -0.212   0.832  ""
## 4 VBMAPP            1.01         1.67      0.604   0.546  ""
##
## Interaction Model Summary:
## # A tibble: 6 x 6
##   term                estimate std.error statistic p.value stars
##   <chr>              <dbl>      <dbl>      <dbl>   <dbl> <chr>
## 1 (Intercept)      -6.30        3.73     -1.69   0.0918 "."
## 2 ConditionRobot    0.0218       5.41     0.00403 0.997  ""
## 3 time_c           -0.120       0.183    -0.658   0.510  ""
## 4 VBMAPP            0.930       2.30     0.404   0.686  ""
## 5 ConditionRobot:time_c 0.175       0.251     0.699   0.485  ""
## 6 ConditionRobot:VBMAPP 0.110       3.36     0.0329  0.974  ""
```





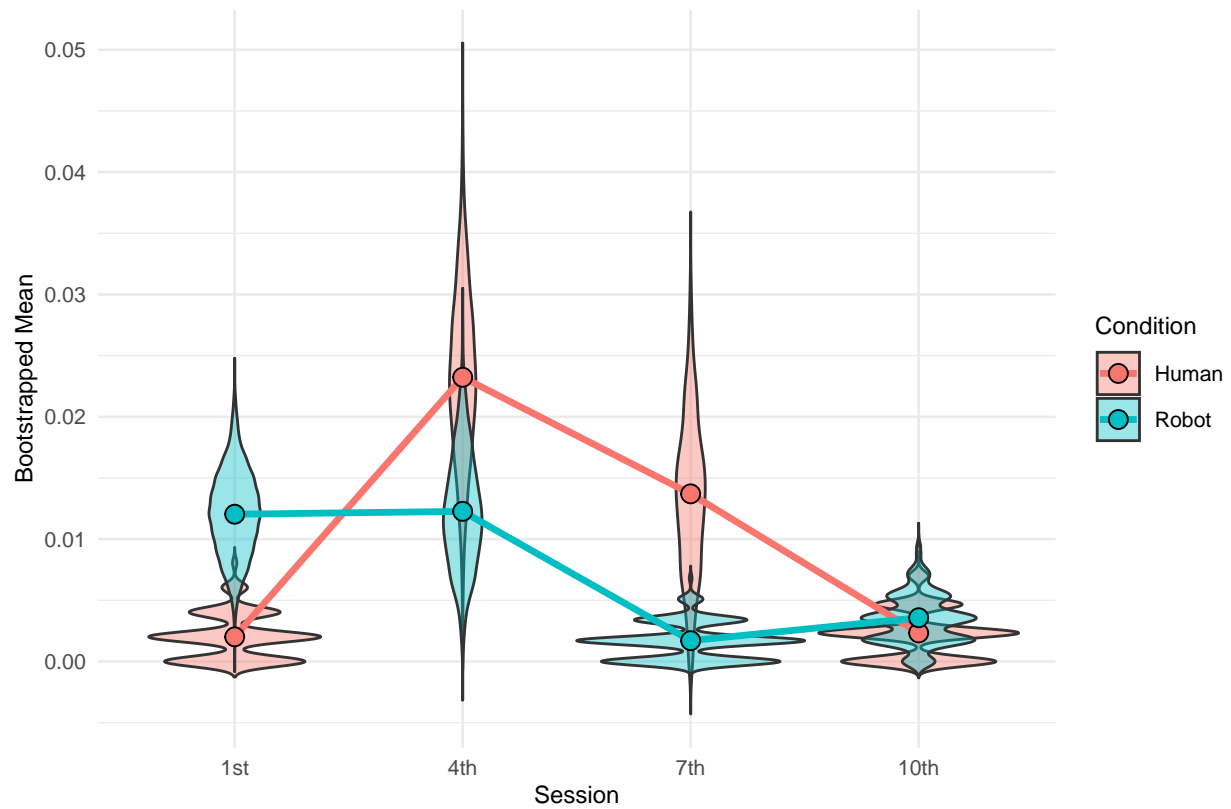
```
##
## =====
## Behavior: Communication_with_Instructor
##
## Additive Model Summary:
## # A tibble: 4 x 6
##   term          estimate std.error statistic p.value stars
##   <chr>          <dbl>    <dbl>    <dbl>   <dbl> <chr>
## 1 (Intercept)   -3.81      2.25     -1.69   0.0901 "."
## 2 ConditionRobot -0.136     0.131     -1.04   0.298  ""
## 3 time_c        -0.0790    0.0594     -1.33   0.183  ""
## 4 VBMAP          1.06      1.39      0.763   0.445  ""
##
## Interaction Model Summary:
## # A tibble: 6 x 6
##   term          estimate std.error statistic p.value stars
##   <chr>          <dbl>    <dbl>    <dbl>   <dbl> <chr>
## 1 (Intercept)   -3.84      2.65     -1.45   0.147  ""
## 2 ConditionRobot -0.254     2.54     -0.100   0.920  ""
## 3 time_c         0.00200   0.0797    0.0251   0.980  ""
## 4 VBMAP          1.08      1.64      0.659   0.510  ""
## 5 ConditionRobot:time_c -0.170    0.116     -1.46   0.143  ""
## 6 ConditionRobot:VBMAP 0.0668    1.57      0.0425   0.966  ""
```

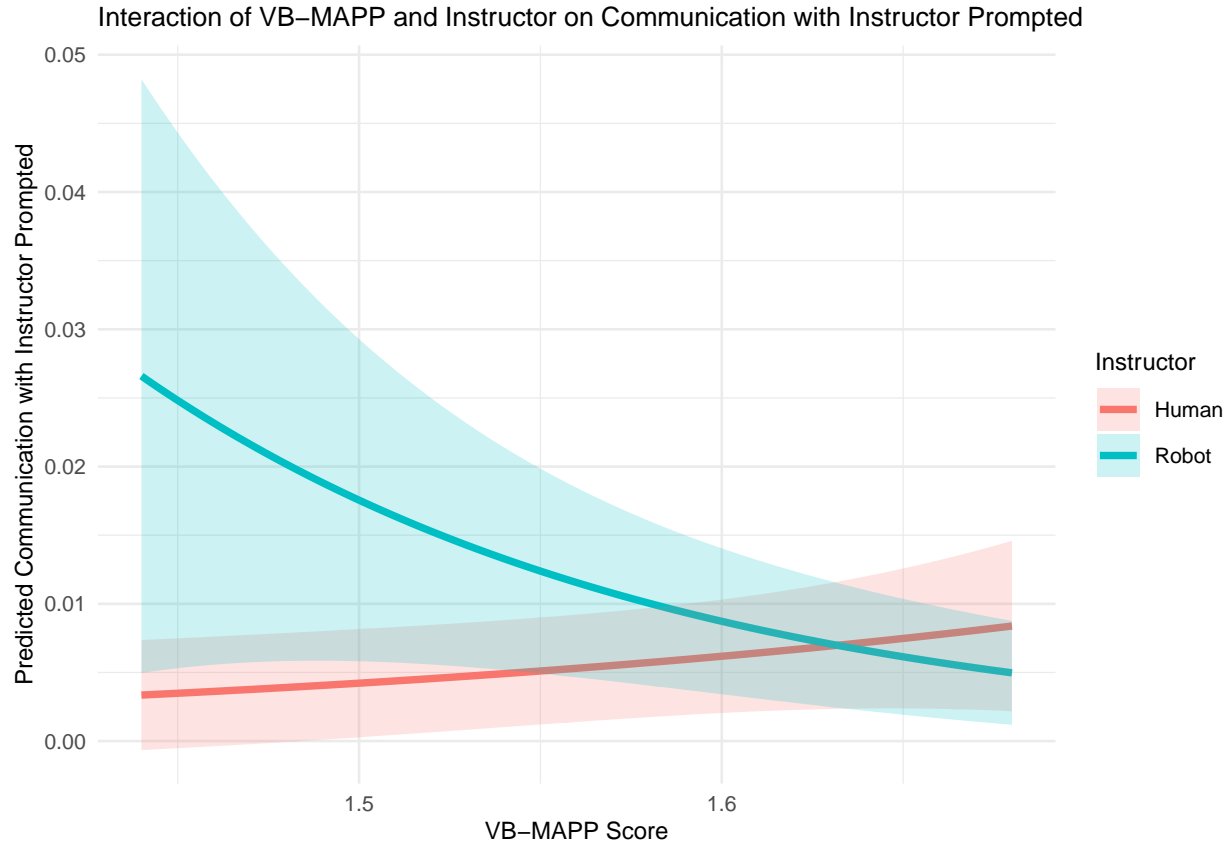




```
##
## =====
## Behavior: Communication_with_Instructor_Prompted
##
## Additive Model Summary:
## # A tibble: 4 x 6
##   term                estimate std.error statistic p.value stars
##   <chr>              <dbl>    <dbl>    <dbl>    <dbl> <chr>
## 1 (Intercept)       -2.70      3.05     -0.884    0.377 ""
## 2 ConditionRobot     0.239     0.313     0.762    0.446 ""
## 3 time_c            -0.178     0.124    -1.44    0.150 ""
## 4 VBMAP              -1.36     1.94     -0.702    0.482 ""
##
## Interaction Model Summary:
## # A tibble: 6 x 6
##   term                estimate std.error statistic p.value stars
##   <chr>              <dbl>    <dbl>    <dbl>    <dbl> <chr>
## 1 (Intercept)       -11.2      4.62     -2.43    0.0152 "*"
## 2 ConditionRobot     17.8      5.88      3.03    0.00246 "***"
## 3 time_c            -0.0287    0.153    -0.187    0.851 ""
## 4 VBMAP              3.84      2.85      1.35    0.178 ""
## 5 ConditionRobot:time_c -0.337    0.242    -1.39    0.163 ""
## 6 ConditionRobot:VBMAP -10.9     3.66     -2.99    0.00283 "***"
```

Communication\_with\_Instructor\_Prompted – Confidence Distributions with Mean Trends

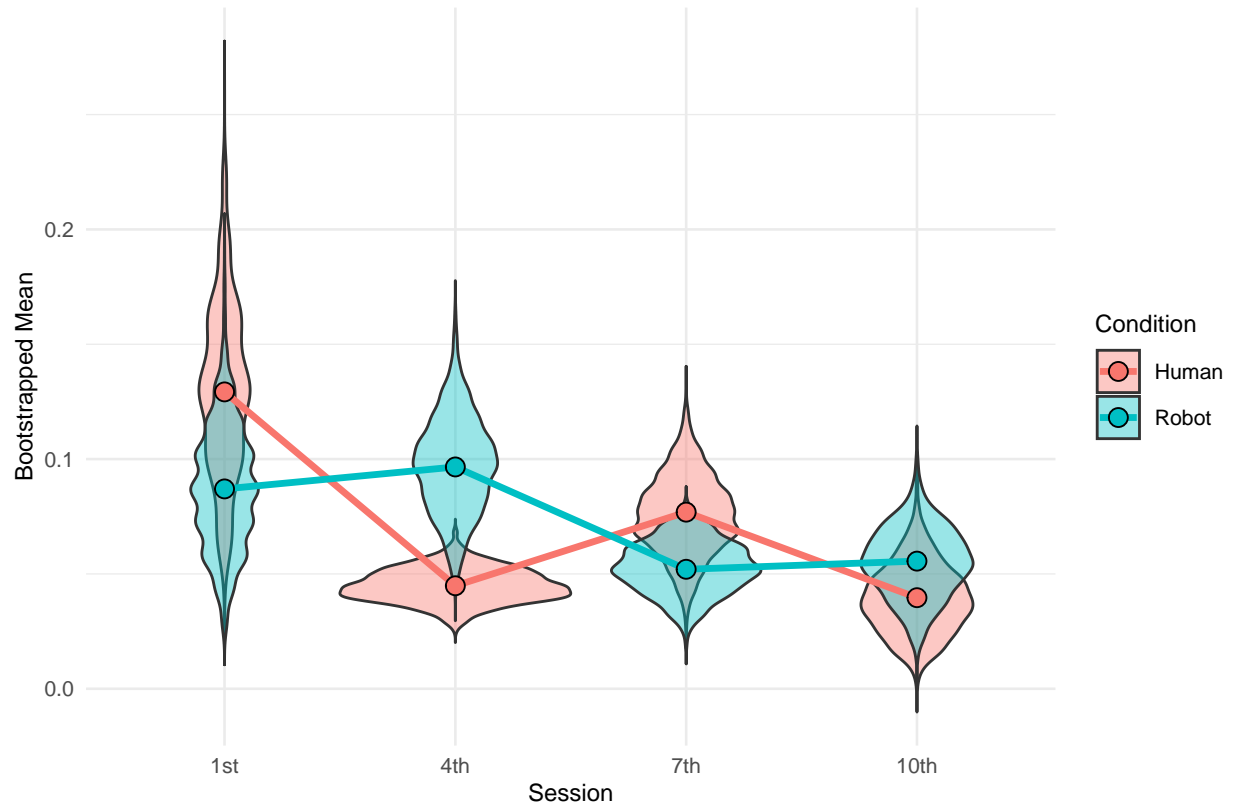


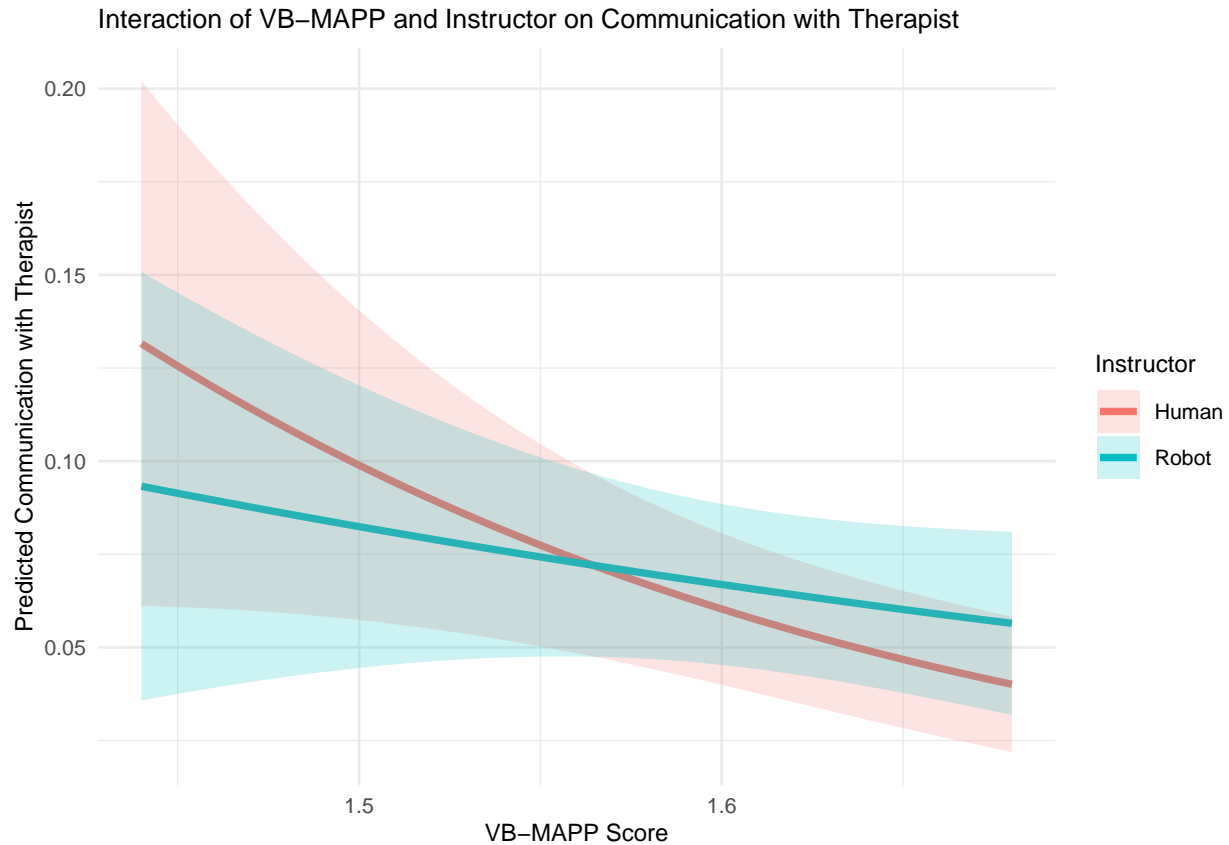


```
##
## =====
## Behavior: Communication_with_Therapist
##
## Additive Model Summary:
## # A tibble: 4 x 6
##   term                estimate std.error statistic    p.value stars
##   <chr>              <dbl>    <dbl>    <dbl>    <dbl> <chr>
## 1 (Intercept)        3.57      2.04      1.75  0.0805    "."
## 2 ConditionRobot     0.0322    0.226    0.143  0.887     ""
## 3 time_c             -0.450    0.113   -3.97  0.0000705 "***"
## 4 VBMAP              -3.92     1.27   -3.07  0.00211   "**"
##
## Interaction Model Summary:
## # A tibble: 6 x 6
##   term                estimate std.error statistic    p.value stars
##   <chr>              <dbl>    <dbl>    <dbl>    <dbl> <chr>
## 1 (Intercept)        5.84      2.75      2.13  0.0334    "*"
## 2 ConditionRobot     -4.87      3.85     -1.26  0.207     ""
## 3 time_c             -0.544    0.142     -3.83  0.000126 "***"
## 4 VBMAP              -5.37      1.73     -3.11  0.00186   "**"
## 5 ConditionRobot:time_c  0.208    0.187      1.11  0.266     ""
## 6 ConditionRobot:VBMAP  3.11      2.41      1.29  0.197     ""
```



Communication\_with\_Therapist – Confidence Distributions with Mean Trends

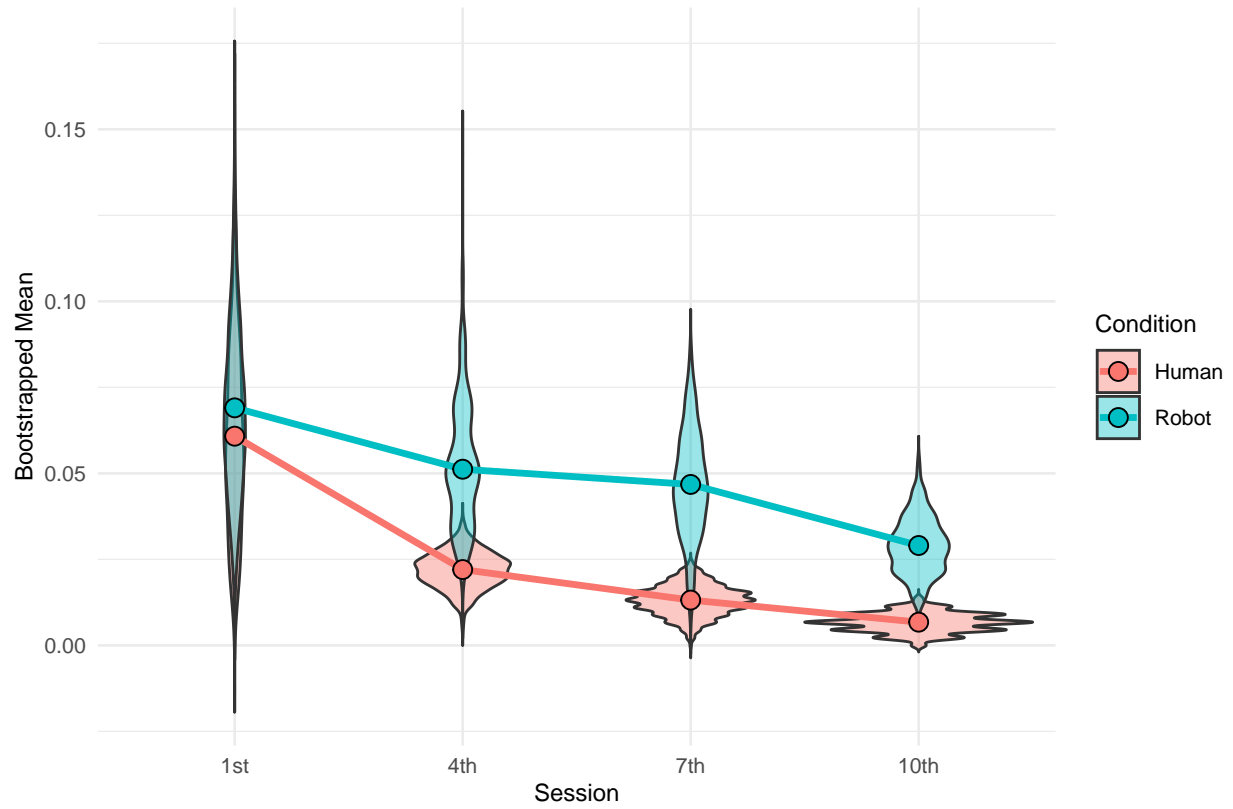




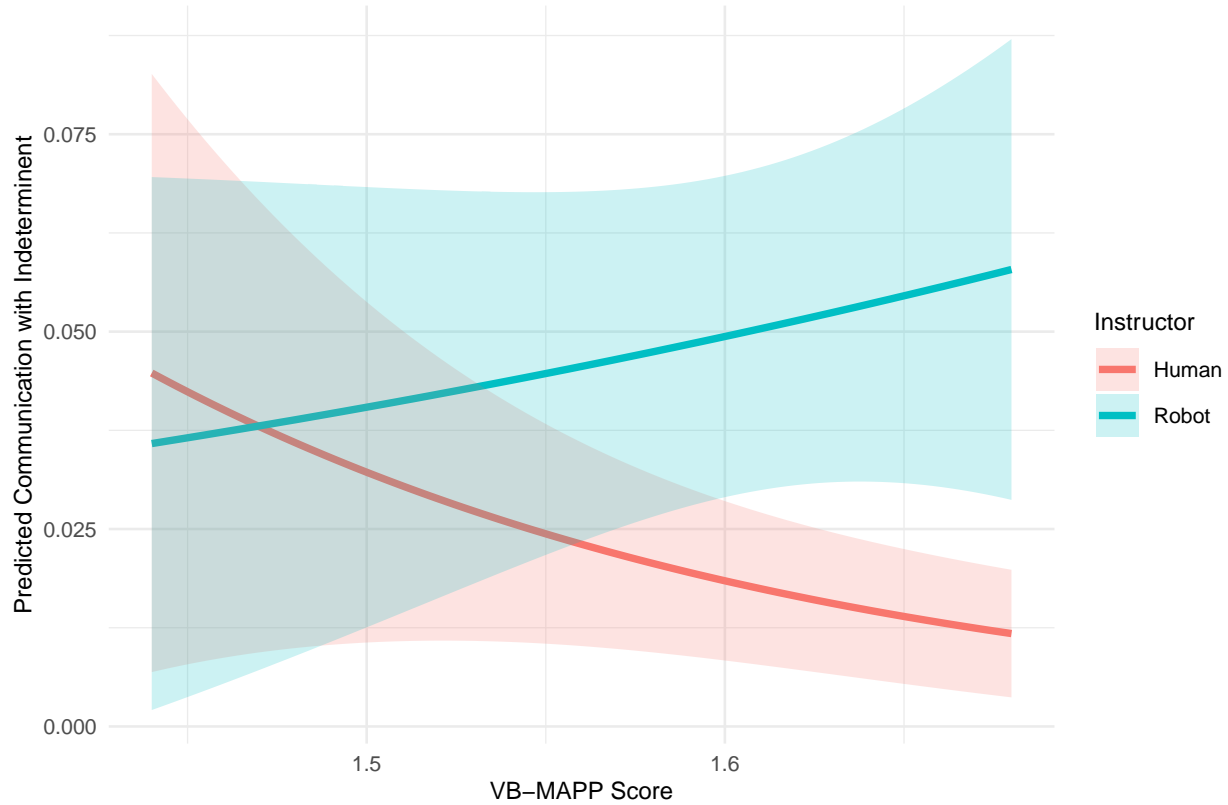
```
##
## =====
## Behavior: Communication_with_Indeterminent
##
## Additive Model Summary:
## # A tibble: 4 x 6
##   term                estimate std.error statistic  p.value stars
##   <chr>              <dbl>    <dbl>    <dbl>    <dbl> <chr>
## 1 (Intercept)       -1.96      3.09     -0.634  0.526   ""
## 2 ConditionRobot      1.05      0.294     3.58  0.000337 "***"
## 3 time_c            -0.226     0.122    -1.85  0.0638   "."
## 4 VBMAP              -1.24      1.89     -0.658  0.510   ""
##
## Interaction Model Summary:
## # A tibble: 6 x 6
##   term                estimate std.error statistic  p.value stars
##   <chr>              <dbl>    <dbl>    <dbl>    <dbl> <chr>
## 1 (Intercept)         5.16      3.75      1.37  0.169   ""
## 2 ConditionRobot     -11.5      5.25     -2.19  0.0289  "*"
## 3 time_c             -0.273     0.171    -1.59  0.111   ""
## 4 VBMAP              -5.71      2.36     -2.42  0.0153  "*"
## 5 ConditionRobot:time_c 0.0424    0.235     0.180  0.857   ""
## 6 ConditionRobot:VBMAP  7.80      3.26      2.39  0.0168  "*"

```

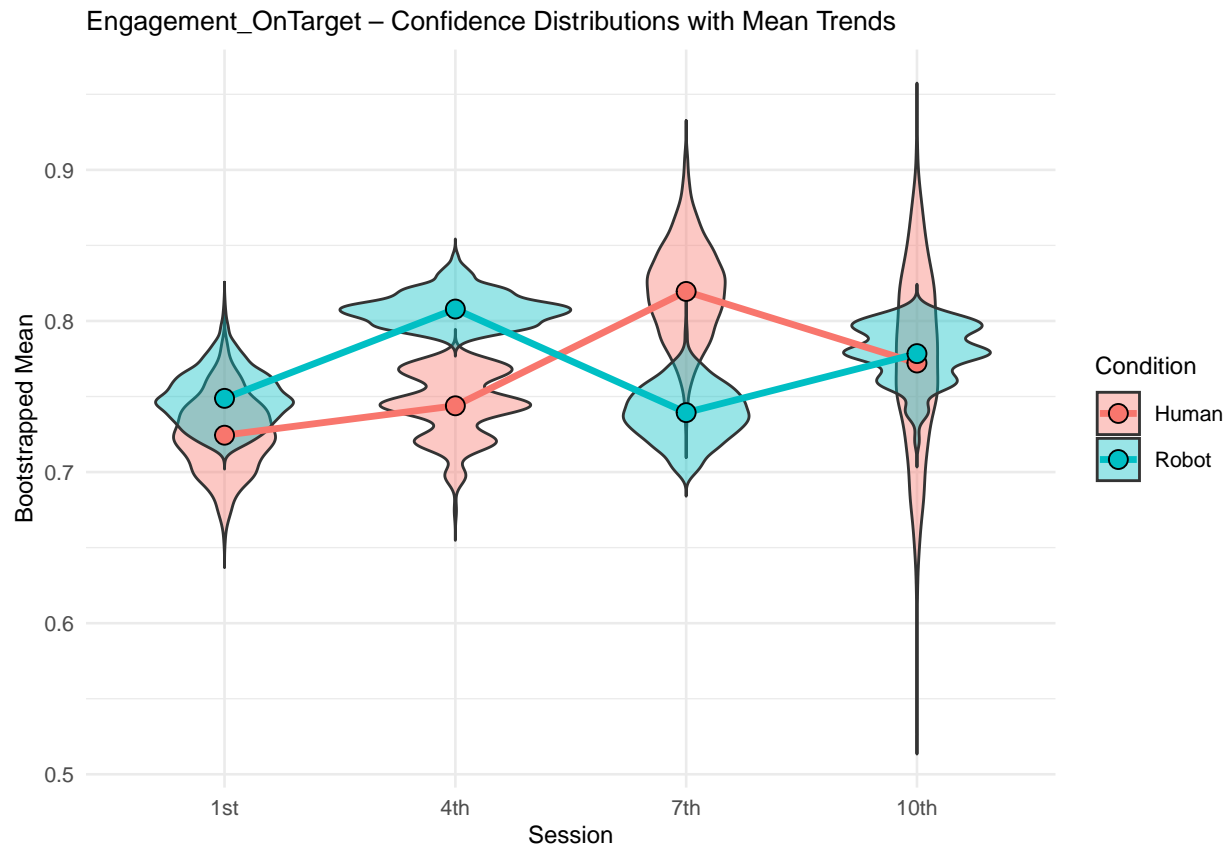
Communication\_with\_Indeterminent – Confidence Distributions with Mean Trends

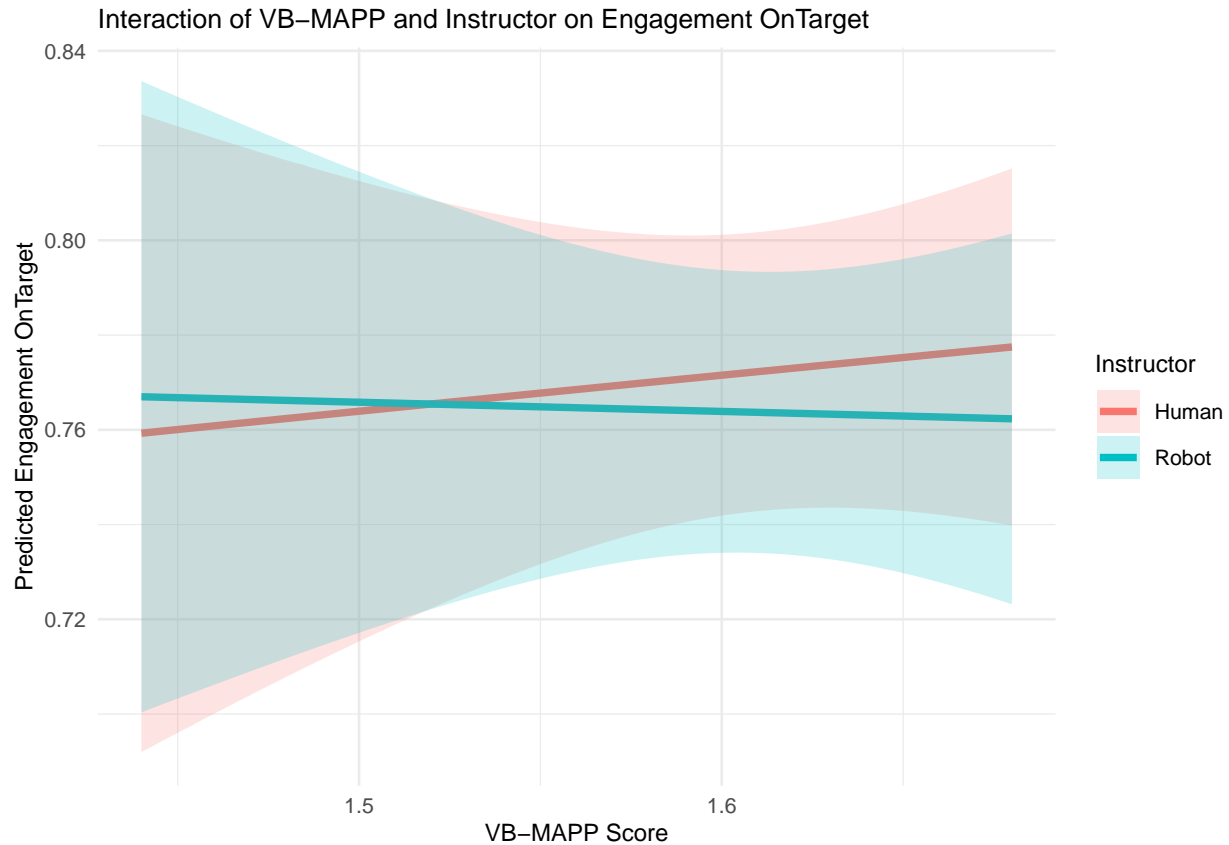


Interaction of VB-MAPP and Instructor on Communication with Indeterminant

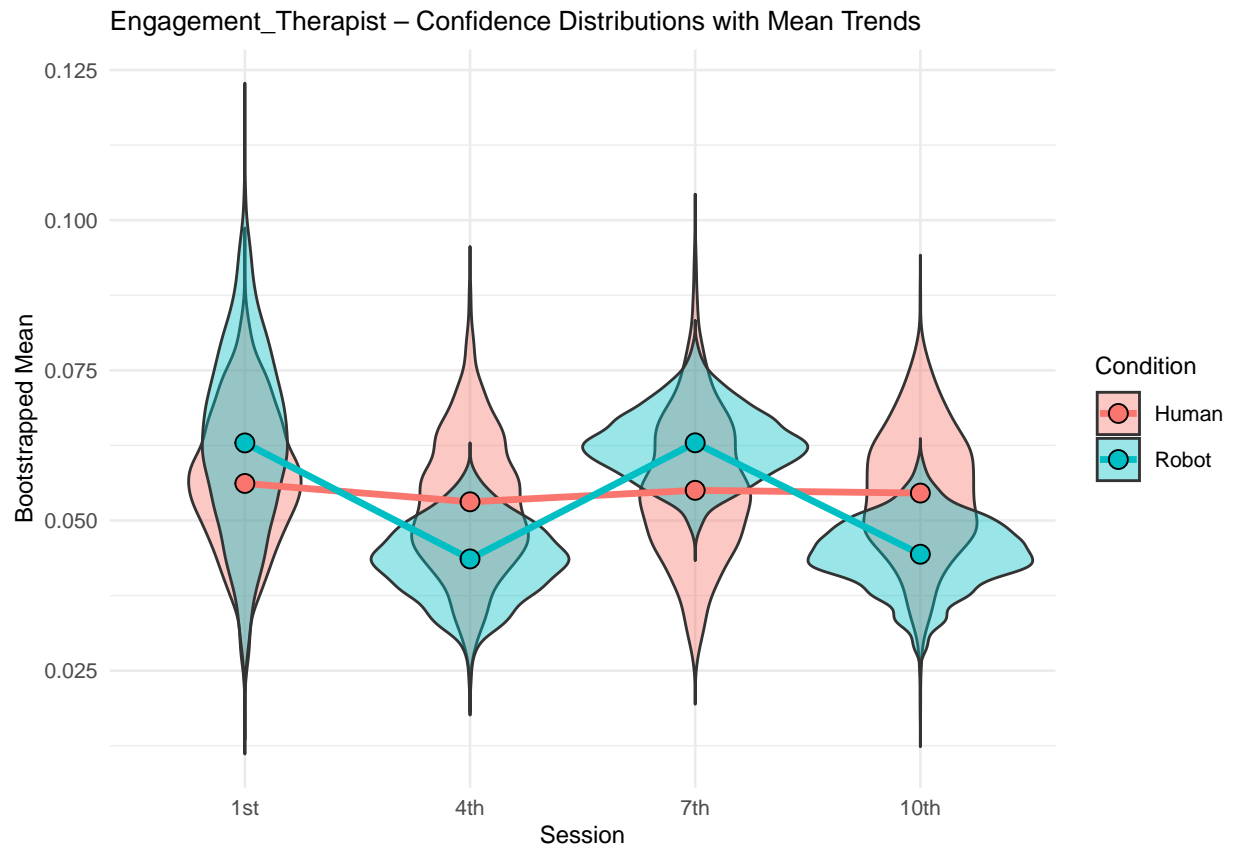


```
##
## =====
## Behavior: Engagement_OnTarget
##
## Additive Model Summary:
## # A tibble: 4 x 6
##   term                estimate std.error statistic p.value stars
##   <chr>              <dbl>      <dbl>      <dbl>   <dbl> <chr>
## 1 (Intercept)        0.907        1.17        0.777   0.437 ""
## 2 ConditionRobot    -0.0382       0.122       -0.315   0.753 ""
## 3 time_c             0.0895       0.0551       1.63    0.104 ""
## 4 VBMAP              0.191        0.723       0.264   0.792 ""
##
## Interaction Model Summary:
## # A tibble: 6 x 6
##   term                estimate std.error statistic p.value stars
##   <chr>              <dbl>      <dbl>      <dbl>   <dbl> <chr>
## 1 (Intercept)        0.535        1.60        0.334   0.738 ""
## 2 ConditionRobot      0.812        2.28        0.356   0.722 ""
## 3 time_c              0.172        0.0773      2.23    0.0261 "*"
## 4 VBMAP               0.426        0.994       0.429   0.668 ""
## 5 ConditionRobot:time_c -0.162       0.108      -1.51    0.132 ""
## 6 ConditionRobot:VBMAP -0.534       1.42       -0.377   0.706 ""
```

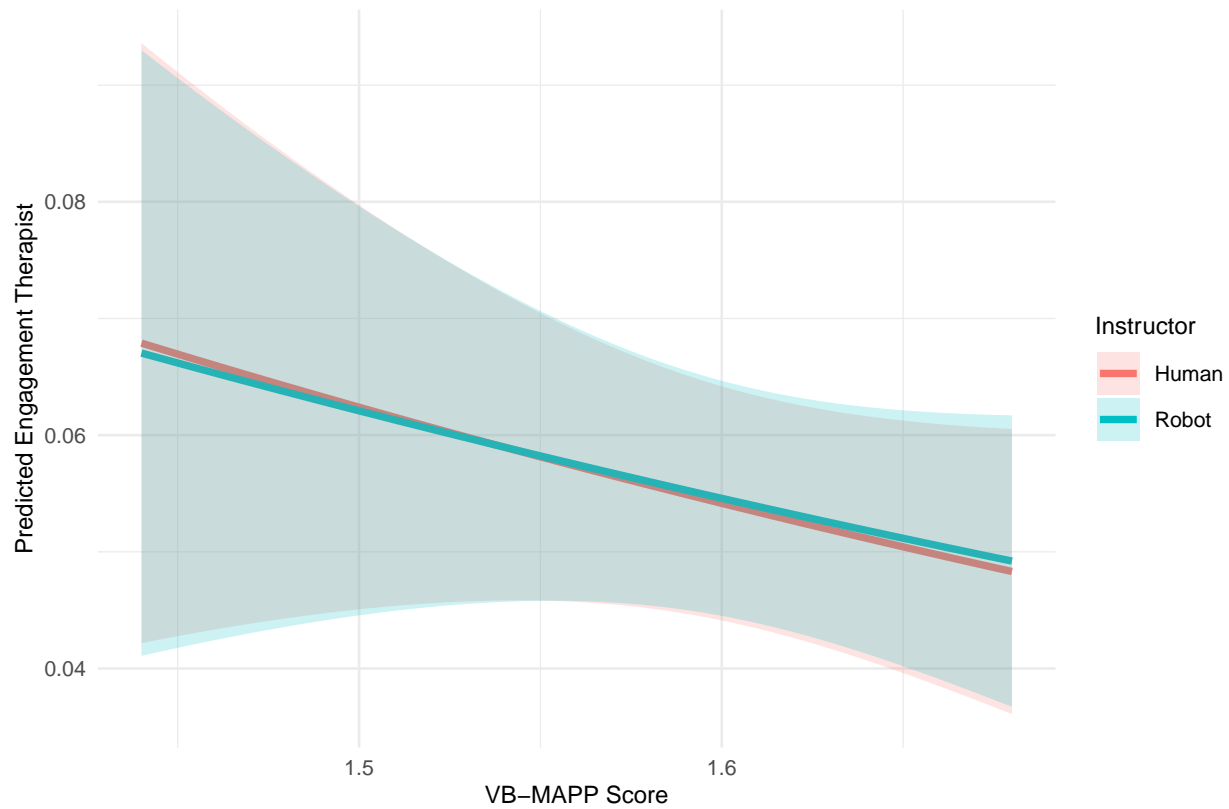




```
##
## =====
## Behavior: Engagement_Therapist
##
## Additive Model Summary:
## # A tibble: 4 x 6
##   term                estimate std.error statistic p.value stars
##   <chr>              <dbl>      <dbl>      <dbl>   <dbl> <chr>
## 1 (Intercept)      -0.560        1.31     -0.428   0.669   ""
## 2 ConditionRobot    0.00880        0.137      0.0640   0.949   ""
## 3 time_c           -0.0160        0.0615    -0.260   0.795   ""
## 4 VBMAP           -1.44         0.815     -1.77    0.0775  "."
##
## Interaction Model Summary:
## # A tibble: 6 x 6
##   term                estimate std.error statistic p.value stars
##   <chr>              <dbl>      <dbl>      <dbl>   <dbl> <chr>
## 1 (Intercept)      -0.454        1.82     -0.249   0.803   ""
## 2 ConditionRobot    -0.211        2.61     -0.0807  0.936   ""
## 3 time_c           -0.00490       0.0876    -0.0559  0.955   ""
## 4 VBMAP            -1.50         1.14     -1.32    0.186   ""
## 5 ConditionRobot:time_c -0.0219      0.123     -0.178   0.858   ""
## 6 ConditionRobot:VBMAP  0.137        1.63      0.0840  0.933   ""
```

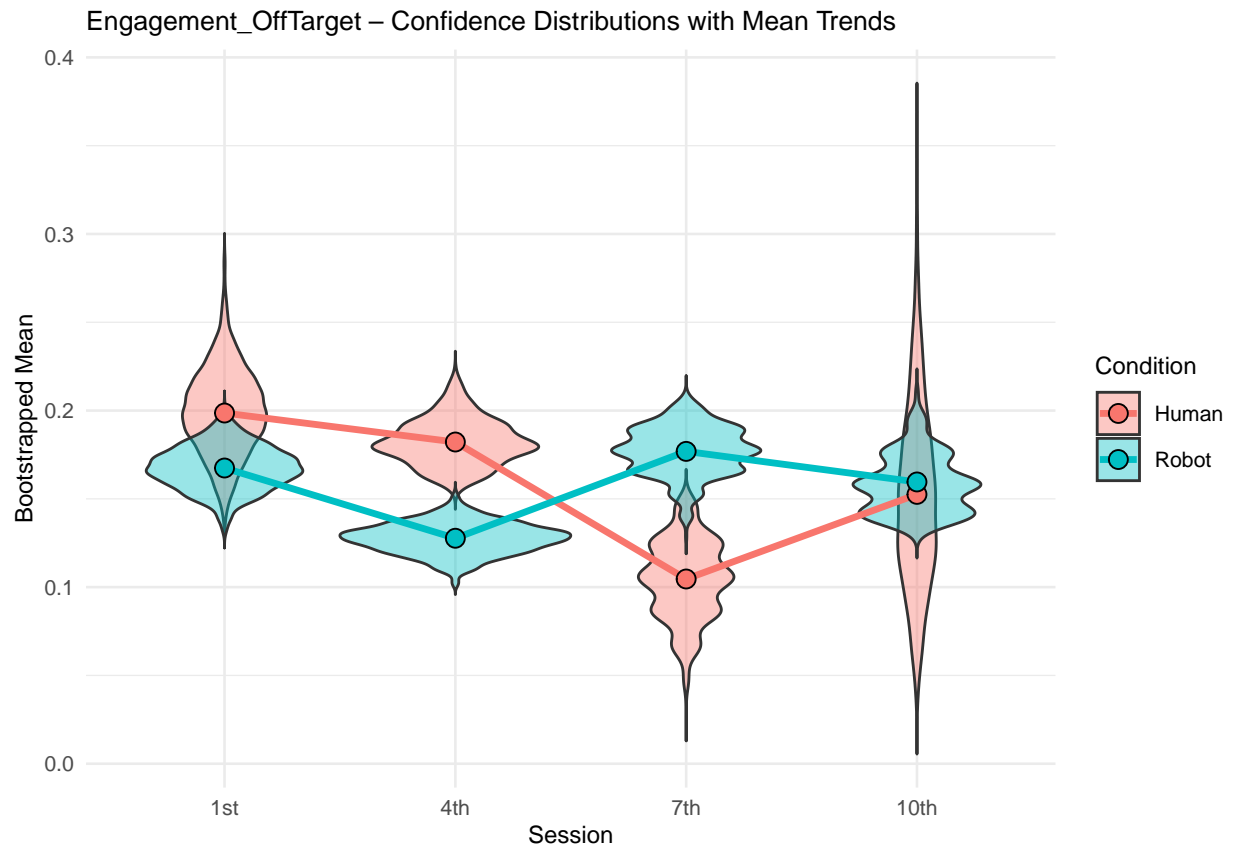


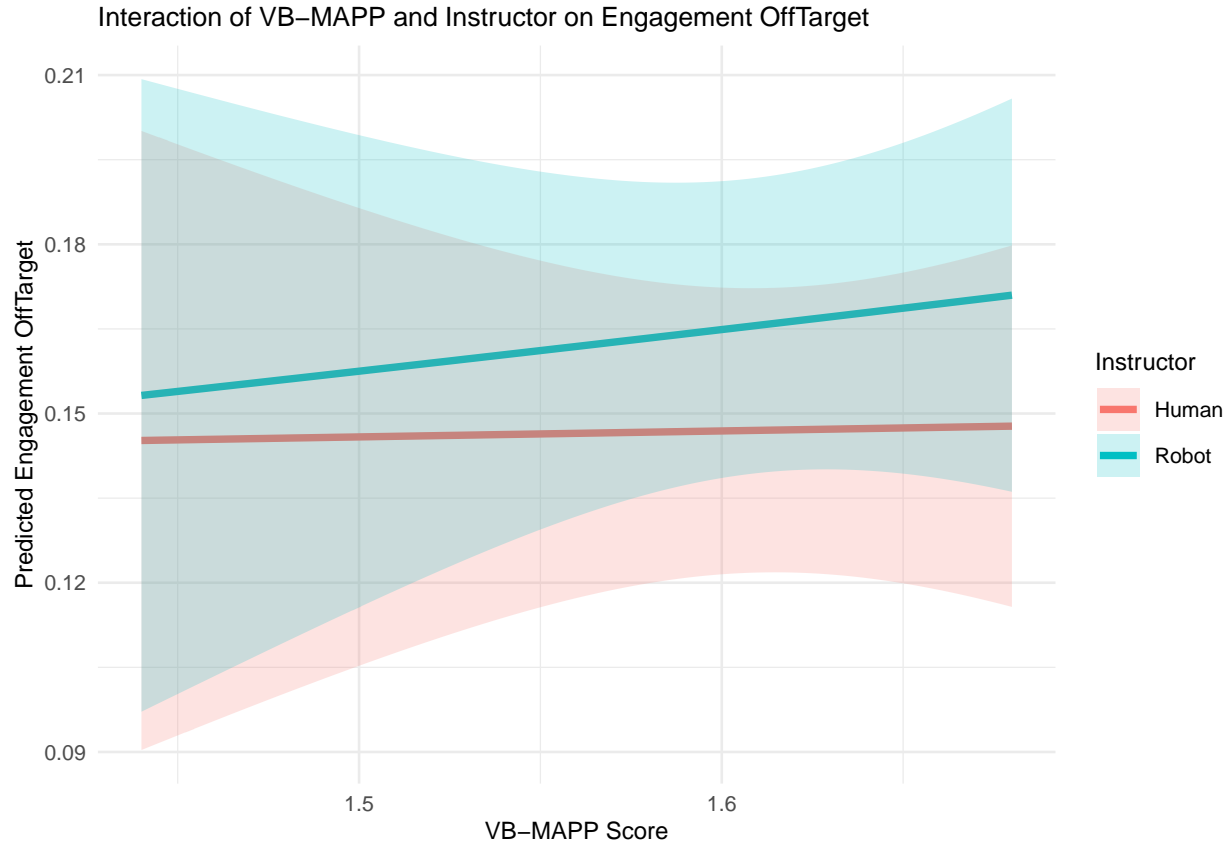
Interaction of VB-MAPP and Instructor on Engagement Therapist



```
##
## =====
## Behavior: Engagement_OffTarget
##
## Additive Model Summary:
## # A tibble: 4 x 6
##   term                estimate std.error statistic p.value stars
##   <chr>              <dbl>      <dbl>      <dbl>   <dbl> <chr>
## 1 (Intercept)       -2.13        1.39      -1.53    0.125 ""
## 2 ConditionRobot     0.114        0.145       0.790    0.430 ""
## 3 time_c            -0.120        0.0663     -1.81    0.0702 "."
## 4 VBMAP              0.247        0.860       0.287    0.774 ""
##
## Interaction Model Summary:
## # A tibble: 6 x 6
##   term                estimate std.error statistic p.value stars
##   <chr>              <dbl>      <dbl>      <dbl>   <dbl> <chr>
## 1 (Intercept)       -1.89        1.89      -1.00    0.315 ""
## 2 ConditionRobot    -0.601        2.66      -0.226    0.821 ""
## 3 time_c           -0.269        0.0925     -2.91    0.00362 "***"
## 4 VBMAP             0.0847        1.17       0.0724    0.942 ""
## 5 ConditionRobot:time_c 0.284        0.127       2.24    0.0250 "* "
## 6 ConditionRobot:VBMAP 0.461        1.65       0.280    0.779 ""
```

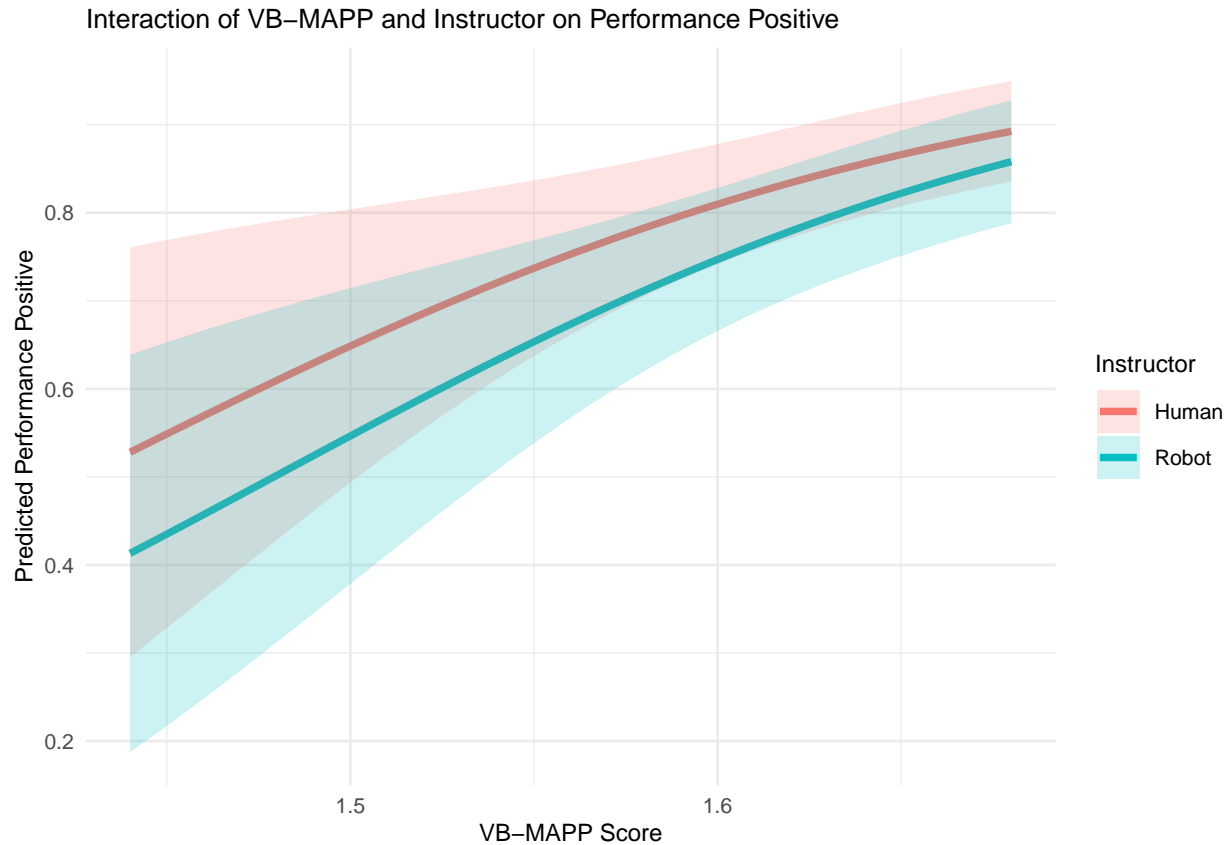






```
##
## =====
## Behavior: Performance_Positive
##
## Additive Model Summary:
## # A tibble: 4 x 6
##   term                estimate std.error statistic  p.value stars
##   <chr>              <dbl>    <dbl>    <dbl>    <dbl> <chr>
## 1 (Intercept)      -12.4      3.91     -3.18  0.00148 ***
## 2 ConditionRobot   -0.374    0.161     -2.32  0.0201  "*"
## 3 time_c           0.0378   0.0730     0.517  0.605   ""
## 4 VBMAP            8.67      2.43      3.57  0.000364 ***
##
## Interaction Model Summary:
## # A tibble: 6 x 6
##   term                estimate std.error statistic  p.value stars
##   <chr>              <dbl>    <dbl>    <dbl>    <dbl> <chr>
## 1 (Intercept)      -11.9      4.16     -2.87  0.00414 ***
## 2 ConditionRobot   -1.34      2.77     -0.482  0.630   ""
## 3 time_c           0.0276   0.106     0.261  0.794   ""
## 4 VBMAP            8.35      2.59      3.22  0.00126 ***
## 5 ConditionRobot:time_c 0.0190   0.144     0.132  0.895   ""
## 6 ConditionRobot:VBMAP 0.606     1.74      0.348  0.728   ""
```





## 2.2 Results: Additive Model Comparison Between Human and Robot Instructors

To evaluate the effect of instructor type on children's learning behaviors, we fitted additive generalized linear mixed models (GLMMs) with `Condition` (Human vs. Robot) as a fixed effect, controlling for session time (`time_c`) and individual skill level (VB-MAPP). A random intercept for `Subject` accounted for repeated measures. All dependent variables were modeled with a beta distribution to account for their bounded, proportional nature. Below we report the estimated effect of the Robot condition (`ConditionRobot`) relative to the Human condition for each behavioral outcome.

First, let's take a look at the hexagonal plots from each metric:

```
if (!requireNamespace("fmsb", quietly = TRUE)) install.packages("fmsb")
library(fmsb)
library(dplyr)
library(tidyr)

# Load data
df <- read.csv("~/GitHub/Circle-Time-Data-Analyses/CircleTimeData-VBMAPP.csv")
df$Condition <- factor(df$Condition, levels = c(1, 2), labels = c("Human", "Robot"))

# List of variables to plot
metrics <- c(
  "Affect_Positive", "Affect_Negative",
  "Communication_with_Instructor", "Communication_with_Instructor_Prompted",
```

```

"Communication_with_Therapist", "Communication_with_Indeterminent",
"Engagement_OnTarget", "Engagement_Therapist", "Engagement_OffTarget",
"Performance_Positive"
)

# Loop through each metric
for (metric in metrics) {
  # Compute average by Subject and Condition
  avg_df <- df %>%
    group_by(Subject, Condition) %>%
    summarise(value = mean(.data[[metric]], na.rm = TRUE), .groups = "drop") %>%
    pivot_wider(names_from = Condition, values_from = value)

  # Skip if incomplete
  if (any(!c("Human", "Robot") %in% colnames(avg_df))) next

  # Sort for consistency
  avg_df <- avg_df[order(avg_df$Subject), ]
  human <- avg_df$Human
  robot <- avg_df$Robot
  subjects <- avg_df$Subject

  # Create radar data frame
  data <- as.data.frame(rbind(
    rep(1, length(human)),
    rep(0, length(human)),
    human,
    robot
  ))
  colnames(data) <- subjects
  rownames(data) <- c("Max", "Min", "Human", "Robot")

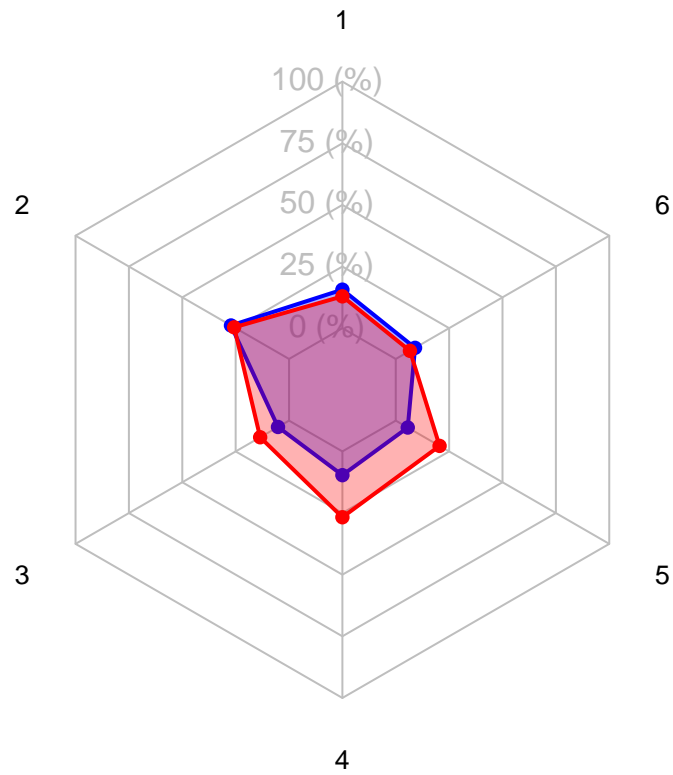
  # Adjust title font size
  oldpar <- par(no.readonly = TRUE)
  par(cex.main = 0.9)

  # Plot
  radarchart(data,
    axistype = 1,
    pcol = c("blue", "red"),
    pfccl = c(rgb(0, 0, 1, 0.3), rgb(1, 0, 0, 0.3)),
    plwd = 2,
    plty = 1,
    cglcol = "grey",
    cglty = 1,
    axislabcol = "grey",
    vlce = 0.8,
    title = paste(metric, "by Participant: Human (blue) vs. Robot (red)")
  )

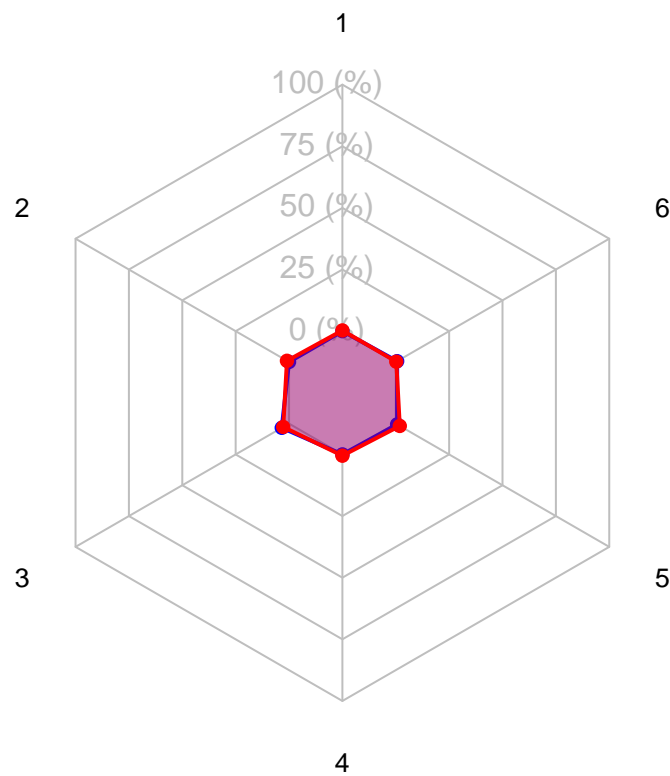
  par(oldpar)
}

```

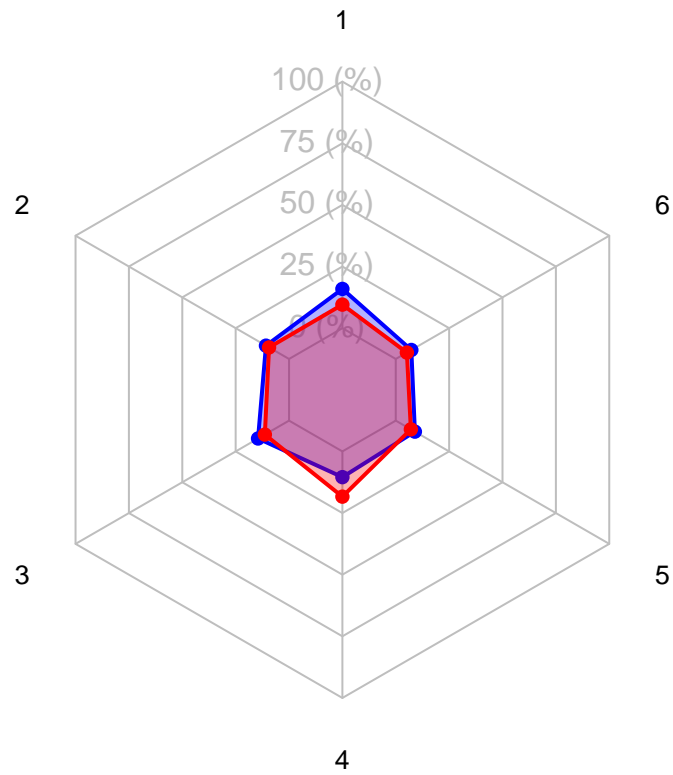
**Affect\_Positive by Participant: Human (blue) vs. Robot (red)**



Affect\_Negative by Participant: Human (blue) vs. Robot (red)

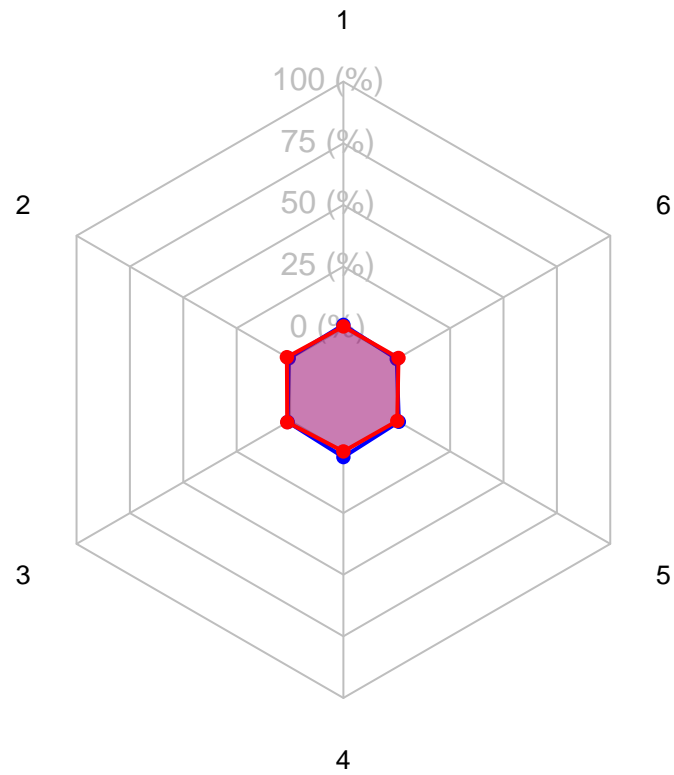


**Communication\_with\_Instructor by Participant: Human (blue) vs. Robot (red)**

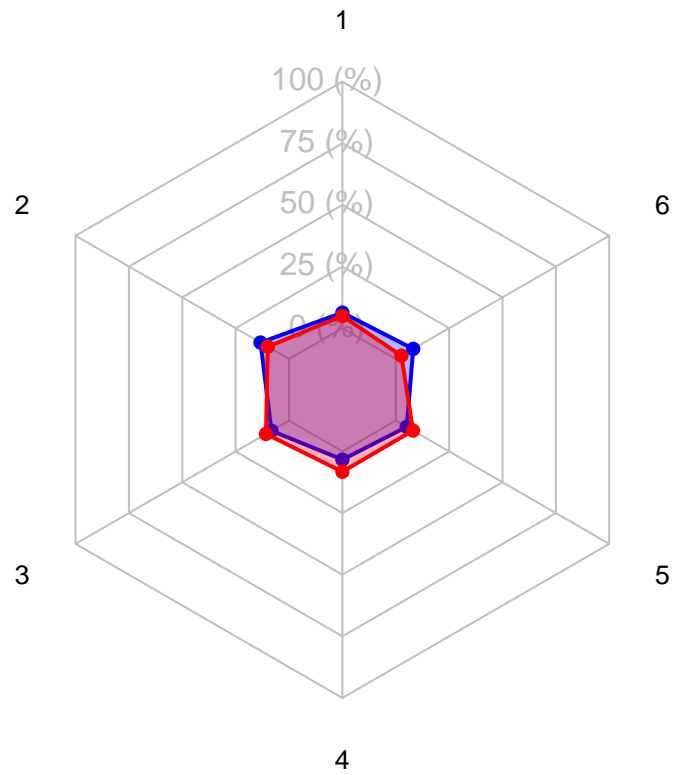




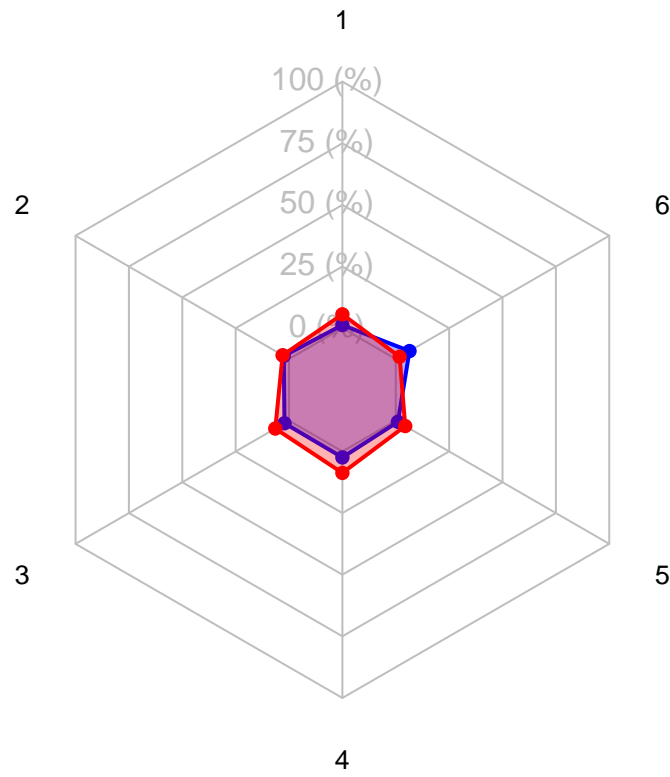
**Communication\_with\_Instructor\_Prompted by Participant: Human (blue) vs. Robot**



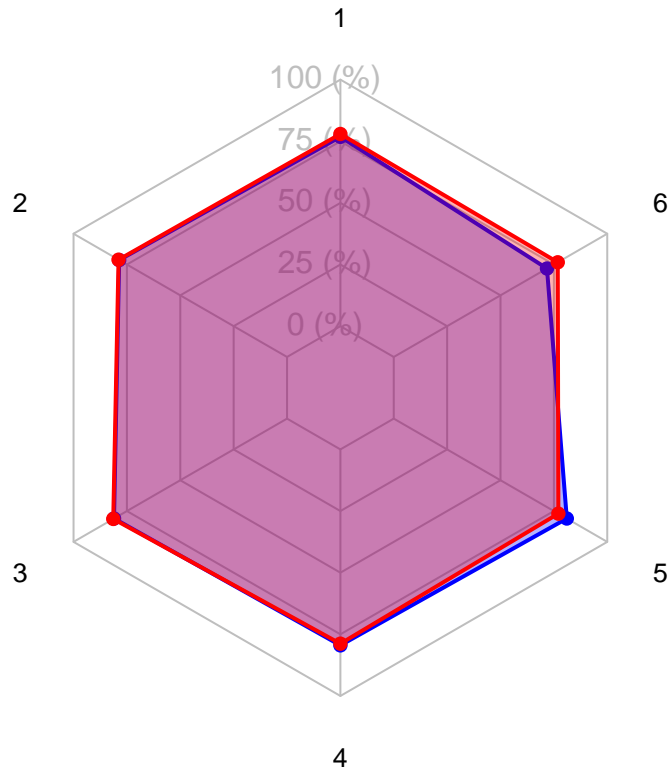
**Communication\_with\_Therapist by Participant: Human (blue) vs. Robot (red)**



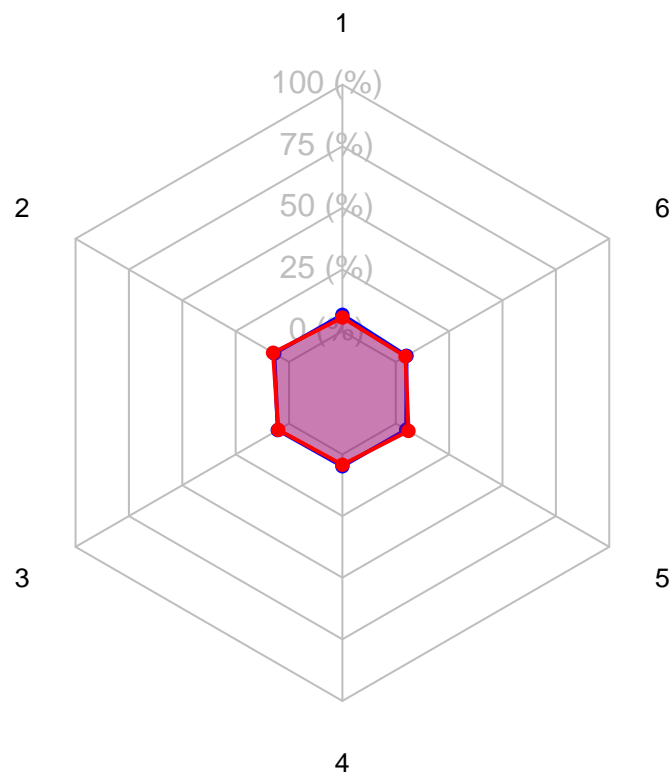
Communication\_with\_Indeterminent by Participant: Human (blue) vs. Robot (re



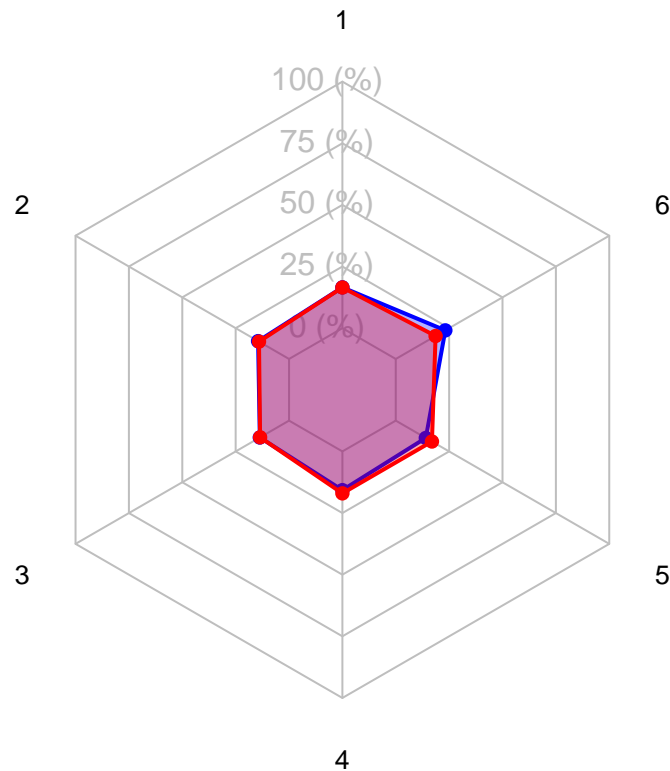
Engagement\_OnTarget by Participant: Human (blue) vs. Robot (red)



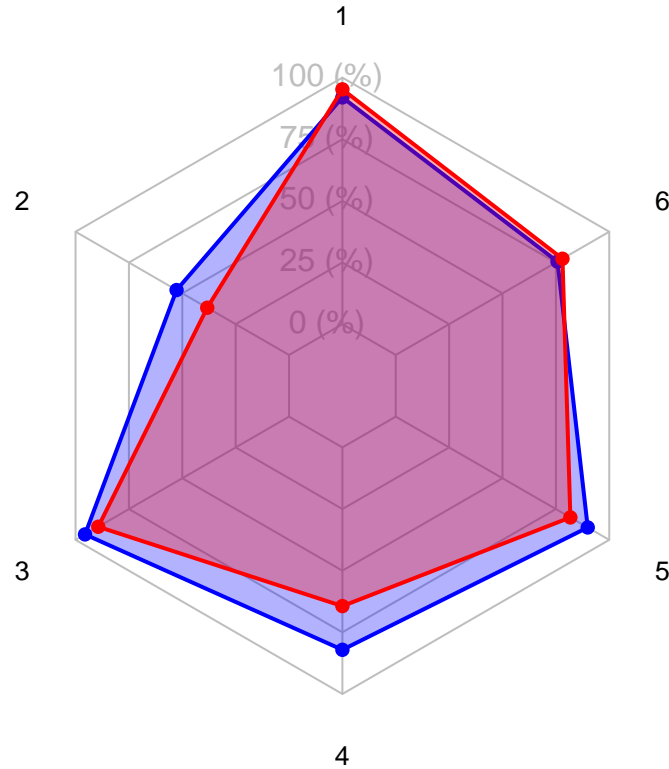
Engagement\_Therapist by Participant: Human (blue) vs. Robot (red)



**Engagement\_OffTarget by Participant: Human (blue) vs. Robot (red)**



### Performance\_Positive by Participant: Human (blue) vs. Robot (red)



#### 2.2.1 Affect

- **Positive Affect** was significantly higher during robot-led instruction compared to human-led instruction:  
 $= 0.435, SE = 0.151, z = 2.89, p = 0.0039$   
 This suggests that children expressed more positive emotional behaviors (e.g., smiling, clapping) during robot sessions.
- **Negative Affect** did not differ significantly between conditions:  
 $= 0.200, SE = 0.289, z = 0.69, p = 0.489$

#### 2.2.2 Communication

- **Communication with Instructor** showed no significant difference between conditions:  
 $= -0.136, SE = 0.131, z = -1.04, p = 0.298$

- **Instructor-Prompted Communication** was also not significantly affected:  
 $= 0.239, SE = 0.313, z = 0.76, p = 0.446$
- **Communication with Therapist or Peers** remained similar across conditions:  
 $= 0.032, SE = 0.226, z = 0.14, p = 0.887$
- **Indeterminate Communication** (where the communication partner was unclear) was significantly higher under the robot condition:  
 $= 1.05, SE = 0.294, z = 3.58, p = 0.0003$   
 This may reflect increased ambiguity in children’s social orientation during robot-led sessions.

### 2.2.3 Engagement

- **On-Target Engagement** (attention to instructor or screen) did not differ significantly:  
 $= -0.038, SE = 0.122, z = -0.32, p = 0.753$
- **Engagement with Therapist or Peers** showed no condition effect:  
 $= 0.009, SE = 0.137, z = 0.06, p = 0.949$
- **Off-Target Engagement** (distraction or disengagement) also did not differ:  
 $= 0.114, SE = 0.145, z = 0.79, p = 0.430$

### 2.2.4 Performance

- **Positive Performance** was significantly lower in the robot condition:  
 $= -0.374, SE = 0.161, z = -2.32, p = 0.020$   
 This indicates children demonstrated fewer correct task responses during robot-led sessions, after adjusting for time and VB-MAPP scores.

---

### 2.2.5 Summary

In summary, the robot instructor was associated with **greater positive affect** but **lower task performance**. Communication directed to unknown partners was significantly more frequent in robot-led sessions, suggesting possible issues with clarity or focus. Engagement and most communication behaviors did not significantly differ between conditions. These findings highlight the **potential emotional benefits** of social robot instruction, while also identifying **critical areas—especially performance—that warrant refinement** in robot-mediated pedagogy.

## 2.3 Interaction Effects: Moderator Influence of Time and VB-MAPP on Robot-Led Instruction

To explore whether the effect of robot-led instruction varied across time or with the learner’s developmental profile, we modeled interaction terms between `ConditionRobot` and two continuous covariates: `time_c` (centered session time) and `VBMAP` (individual skill level). Below we interpret these moderation effects for each behavioral outcome.



### 2.3.1 Affect

- **Positive Affect**

- The interaction between **ConditionRobot** and **VB-MAPP** was significant:  
= 4.22,  $SE = 1.48$ ,  $z = 2.86$ ,  $p = 0.0043$   
This suggests that the advantage of robot instruction in eliciting positive affect increased with higher VB-MAPP scores.
- No significant moderation by time was observed:  
= -0.070,  $SE = 0.121$ ,  $z = -0.57$ ,  $p = 0.566$

- **Negative Affect**

- Neither time nor VB-MAPP significantly moderated the robot condition's effect:  
*Time interaction:* = 0.175,  $p = 0.485$   
*VB-MAPP interaction:* = 0.110,  $p = 0.974$

### 2.3.2 Communication

- **With Instructor**

- No significant moderation by time ( = -0.170,  $p = 0.143$ ) or VB-MAPP ( = 0.067,  $p = 0.966$ )

- **Instructor-Prompted**

- VB-MAPP significantly moderated the effect of robot instruction:  
= -10.9,  $SE = 3.66$ ,  $z = -2.99$ ,  $p = 0.0028$   
This negative interaction indicates that children with higher VB-MAPP scores showed fewer prompted communications under the robot condition.
- Time was not a significant moderator: = -0.337,  $p = 0.163$

- **With Therapist/Peers**

- No significant moderation by time or VB-MAPP:  
*Time:* = 0.208,  $p = 0.266$   
*VB-MAPP:* = 3.11,  $p = 0.197$

- **Indeterminate**

- Both moderators were significant:
  - \* *VB-MAPP interaction:* = 7.80,  $SE = 3.26$ ,  $z = 2.39$ ,  $p = 0.0168$   
This suggests the ambiguity in children's social orientation during robot instruction increased with VB-MAPP score.
  - \* *Time interaction was not significant:* = 0.042,  $p = 0.857$

### 2.3.3 Engagement

- **On Target**

- No significant moderation by VB-MAPP: = -0.534,  $p = 0.706$
- Time showed a non-significant trend: = -0.162,  $p = 0.132$

- **With Therapist/Peers**

- Neither moderator had a significant effect:  
*Time:* = -0.022,  $p = 0.858$   
*VB-MAPP:* = 0.137,  $p = 0.933$

- **Off Target**

- Time significantly moderated the robot effect:  
 $= 0.284, SE = 0.127, z = 2.24, p = 0.0250$   
This implies that robot-led instruction was associated with increased off-target engagement as time progressed.
- No significant interaction with VB-MAPP:  $= 0.461, p = 0.779$

### 2.3.4 Performance

- **Positive Performance**

- No significant moderation by either variable:  
*Time:*  $= 0.019, p = 0.895$   
*VB-MAPP:*  $= 0.606, p = 0.728$

### 2.3.5 Summary of Interaction Effects

Learning Behavior	VB-MAPP Moderation	Time Moderation	Interpretation
<b>Affect_Positive</b>	$p = 0.0043$		Robot effect stronger for children with higher VB-MAPP
<b>Affect_Negative</b>			No differential effect
<b>Comm_Instructor</b>			No moderation observed
<b>Comm_Prompted</b>	$p = 0.0028$		Fewer prompted responses from higher-skilled children under robot condition
<b>Comm_Therapist/Peers</b>			No differential effect
<b>Comm_Indeterminate</b>	$p = 0.0168$		More ambiguous social behaviors with robot, especially for higher VB-MAPP
<b>Engagement_OnTarget</b>		(trend)	No clear pattern
<b>Engagement_Therapist/Peers</b>			No differential effect
<b>Engagement_OffTarget</b>		$p = 0.025$	Robot instruction led to more off-task behaviors over time
<b>Performance_Positive</b>			No significant moderation

Overall, robot-led instruction was **more emotionally engaging for higher-performing children**, but it also led to **more ambiguous and off-task behaviors**, especially as sessions progressed. These nuanced findings underscore the importance of **personalizing robotic instruction** based on learner profile and session context.

## 2.4 Predictive Role of Learning Behaviors on Performance in Human vs. Robot-Led Circle Time

### 2.4.1 Overview

This section explores how various learning behaviors predict children’s **positive performance** during circle-time sessions, separately under **Human** and **Robot** instruction conditions. Using Generalized Linear Mixed Models (GLMMs) with beta regression, we analyzed each behavioral predictor while controlling for children’s VB-MAPP developmental levels and session time.

### 2.4.2 Modeling Approach

For each learning behavior, we modeled:

```
Performance_Positive ~ Behavior + VBMAPP + time_c + (1 | Subject)
```

```
## Performance_Positive ~ Behavior + VBMAPP + time_c + (1 | Subject)
```

This was done independently for the **Robot** and **Human** groups using the `glmmTMB` package in R. The response variable was beta-transformed for appropriate modeling. `###` How does each learning behavior predict performance under the robot condition only? `##`

```
# Create time_c before subsetting
df$time_c <- scale(df$time, center = TRUE, scale = FALSE)

# Subset robot condition
robot_df <- df %>% filter(Condition == "Robot")

# Beta transformation for Performance_Positive
n <- nrow(robot_df)
robot_df$Performance_Positive <- (robot_df$Performance_Positive * (n - 1) + 0.5) / n

# Define predictors (excluding Performance variables)
predictors <- c(
  "Affect_Positive", "Affect_Negative",
  "Communication_with_Instructor", "Communication_with_Instructor_Prompted",
  "Communication_with_Therapist", "Communication_with_Indeterminent",
  "Engagement_OnTarget", "Engagement_Therapist", "Engagement_OffTarget"
)

# Response variable
response <- "Performance_Positive"

# Loop through predictors to model their effect on performance
for (pred in predictors) {
  cat("\n=====n")
  cat("Predictor:", pred, "=>", response, "\n")

  # Define formula
  form <- as.formula(paste(response, "~", pred, "+ VBMAPP + time_c + (1 | Subject)"))

  # Fit model
  model <- glmmTMB(form, data = robot_df, family = beta_family())

  # Tidy output
  results <- broom.mixed::tidy(model, effects = "fixed")
  results$stars <- sapply(results$p.value, sig_stars)

  # Display summary
  print(results[, c("term", "estimate", "std.error", "statistic", "p.value", "stars")])
}
```

```
##
```

```

## =====
## Predictor: Affect_Positive => Performance_Positive
## # A tibble: 4 x 6
##   term          estimate std.error statistic  p.value stars
##   <chr>          <dbl>    <dbl>    <dbl>    <dbl> <chr>
## 1 (Intercept)   -11.3      3.36    -3.37  0.000748  "****"
## 2 Affect_Positive -2.92     2.08    -1.40  0.160      ""
## 3 VBMAPPP        8.07     2.04     3.96  0.0000754  "****"
## 4 time_c        -0.0300    0.126   -0.238  0.812      ""
##
## =====
## Predictor: Affect_Negative => Performance_Positive
## # A tibble: 4 x 6
##   term          estimate std.error statistic  p.value stars
##   <chr>          <dbl>    <dbl>    <dbl>    <dbl> <chr>
## 1 (Intercept)   -12.9      4.72    -2.73  0.00635  "***"
## 2 Affect_Negative -4.02     7.46    -0.538  0.590      ""
## 3 VBMAPPP        8.76     2.94     2.98  0.00287  "***"
## 4 time_c         0.0606    0.122    0.498  0.619      ""
##
## =====
## Predictor: Communication_with_Instructor => Performance_Positive
## # A tibble: 4 x 6
##   term          estimate std.error statistic  p.value stars
##   <chr>          <dbl>    <dbl>    <dbl>    <dbl> <chr>
## 1 (Intercept)   -13.4      3.85    -3.48  0.000498  "****"
## 2 Communication_with_Instructor -4.74     2.11    -2.25  0.0246    "*"
## 3 VBMAPPP        9.35     2.41     3.88  0.000104  "****"
## 4 time_c        -0.0510    0.117   -0.437  0.662      ""
##
## =====
## Predictor: Communication_with_Instructor_Prompted => Performance_Positive
## # A tibble: 4 x 6
##   term          estimate std.error statistic  p.value stars
##   <chr>          <dbl>    <dbl>    <dbl>    <dbl> <chr>
## 1 (Intercept)   -13.3      4.72    -2.82  0.00487  "****"
## 2 Communication_with_Instructor_Prom~ 6.12     23.2     0.264  0.792      ""
## 3 VBMAPPP        8.96     2.90     3.09  0.00201  "****"
## 4 time_c         0.0597    0.141    0.423  0.673      ""
##
## =====
## Predictor: Communication_with_Therapist => Performance_Positive
## # A tibble: 4 x 6
##   term          estimate std.error statistic  p.value stars
##   <chr>          <dbl>    <dbl>    <dbl>    <dbl> <chr>
## 1 (Intercept)   -12.3      4.56    -2.69  0.00713  "****"
## 2 Communication_with_Therapist -3.46     2.72    -1.27  0.202      ""
## 3 VBMAPPP        8.53     2.83     3.01  0.00260  "****"
## 4 time_c        -0.0290    0.123   -0.236  0.813      ""
##
## =====
## Predictor: Communication_with_Indeterminent => Performance_Positive
## # A tibble: 4 x 6
##   term          estimate std.error statistic  p.value stars

```

```
##   <chr>                                <dbl>    <dbl>    <dbl>    <dbl> <chr>
## 1 (Intercept)                        -13.8      4.64     -2.98  0.00285 "***"
## 2 Communication_with_Indeterminent    -4.40      3.08     -1.43  0.153   ""
## 3 VBMAPP                             9.48       2.91      3.26  0.00111 "***"
## 4 time_c                             -0.0265    0.118     -0.224 0.823   ""
##
## =====
## Predictor: Engagement_OnTarget => Performance_Positive
## # A tibble: 4 x 6
##   term                estimate std.error statistic p.value stars
##   <chr>              <dbl>    <dbl>    <dbl>    <dbl> <chr>
## 1 (Intercept)      -12.8      5.03     -2.54  0.0110  "*"
## 2 Engagement_OnTarget -0.0813   2.62     -0.0310 0.975   ""
## 3 VBMAPP            8.71      2.86      3.05  0.00231 "***"
## 4 time_c            0.0381    0.113     0.336  0.737   ""
##
## =====
## Predictor: Engagement_Therapist => Performance_Positive
## # A tibble: 4 x 6
##   term                estimate std.error statistic p.value stars
##   <chr>              <dbl>    <dbl>    <dbl>    <dbl> <chr>
## 1 (Intercept)      -12.7      4.72     -2.69  0.00720 "***"
## 2 Engagement_Therapist -0.750    5.31     -0.141 0.888   ""
## 3 VBMAPP            8.64      2.90      2.98  0.00292 "***"
## 4 time_c            0.0340    0.116     0.292  0.770   ""
##
## =====
## Predictor: Engagement_OffTarget => Performance_Positive
## # A tibble: 4 x 6
##   term                estimate std.error statistic p.value stars
##   <chr>              <dbl>    <dbl>    <dbl>    <dbl> <chr>
## 1 (Intercept)      -12.9      4.63     -2.79  0.00535 "***"
## 2 Engagement_OffTarget  0.820    3.68      0.223  0.824   ""
## 3 VBMAPP            8.66      2.89      2.99  0.00275 "***"
## 4 time_c            0.0352    0.114     0.310  0.756   ""
```

### 2.4.3 How does each learning behavior predict performance under the human condition only?

```
# Subset data to human-only condition
human_df <- df %>% filter(Condition == "Human")

# Beta-safe transformation of Performance_Positive
n_human <- nrow(human_df)
human_df$Performance_Positive <- (human_df$Performance_Positive * (n_human - 1) + 0.5) / n_human

# Define predictors (excluding Performance variables)
predictors <- c(
  "Affect_Positive", "Affect_Negative",
  "Communication_with_Instructor", "Communication_with_Instructor_Prompted",
  "Communication_with_Therapist", "Communication_with_Indeterminent",
  "Engagement_OnTarget", "Engagement_Therapist", "Engagement_OffTarget"
```

```

)

# Response variable
response <- "Performance_Positive"

# Loop through predictors to model their effect on performance
for (pred in predictors) {
  cat("\n===== \n")
  cat("Predictor:", pred, "=>", response, "\n")

  # Define formula
  form <- as.formula(paste(response, "~", pred, "+ VBMAPP + time_c + (1 | Subject)"))

  # Fit model
  model <- glmmTMB(form, data = human_df, family = beta_family())

  # Tidy output
  results <- broom.mixed::tidy(model, effects = "fixed")
  results$stars <- sapply(results$p.value, sig_stars)

  # Display summary
  print(results[, c("term", "estimate", "std.error", "statistic", "p.value", "stars")])
}

```

```

##
## =====
## Predictor: Affect_Positive => Performance_Positive
## # A tibble: 4 x 6
##   term          estimate std.error statistic p.value stars
##   <chr>          <dbl>    <dbl>    <dbl>   <dbl> <chr>
## 1 (Intercept)   -11.5      4.41     -2.62   0.00882 ***
## 2 Affect_Positive -0.390    2.34     -0.166  0.868   ""
## 3 VBMAPP         8.17      2.63      3.11   0.00189 ***
## 4 time_c         0.00174   0.0964    0.0181  0.986   ""
##
## =====
## Predictor: Affect_Negative => Performance_Positive
## # A tibble: 4 x 6
##   term          estimate std.error statistic p.value stars
##   <chr>          <dbl>    <dbl>    <dbl>   <dbl> <chr>
## 1 (Intercept)   -11.3      1.76     -6.45  1.14e-10 ***
## 2 Affect_Negative 21.3      8.22      2.60  9.42e- 3 ***
## 3 VBMAPP         7.90      1.11      7.09  1.35e-12 ***
## 4 time_c         0.0448    0.0933    0.480  6.31e- 1 ""
##
## =====
## Predictor: Communication_with_Instructor => Performance_Positive
## # A tibble: 4 x 6
##   term          estimate std.error statistic p.value stars
##   <chr>          <dbl>    <dbl>    <dbl>   <dbl> <chr>
## 1 (Intercept)   -11.9      2.38     -5.00  0.000000580 ***
## 2 Communication_with_Instructor  5.72      2.57      2.23  0.0261   "*"
## 3 VBMAPP         7.97      1.51      5.28  0.000000126 ***

```

```

## 4 time_c          -0.00378    0.0899   -0.0421 0.966      ""
##
## =====
## Predictor: Communication_with_Instructor_Prompted => Performance_Positive
## # A tibble: 4 x 6
##   term                estimate std.error statistic p.value stars
##   <chr>                <dbl>    <dbl>    <dbl>    <dbl> <chr>
## 1 (Intercept)        -11.8      3.34     -3.53  4.20e-4  "***"
## 2 Communication_with_Instructor_Prom~    5.96    7.73      0.771  4.40e-1  ""
## 3 VBMAPP              8.27     2.09      3.96  7.61e-5  "***"
## 4 time_c              0.0208    0.0876    0.237  8.12e-1  ""
##
## =====
## Predictor: Communication_with_Therapist => Performance_Positive
## # A tibble: 4 x 6
##   term                estimate std.error statistic  p.value stars
##   <chr>                <dbl>    <dbl>    <dbl>    <dbl> <chr>
## 1 (Intercept)        -10.3     3.59     -2.87  0.00416  "**"
## 2 Communication_with_Therapist   -2.90    1.66     -1.75  0.0808  "."
## 3 VBMAPP              7.51     2.21      3.39  0.000699 "***"
## 4 time_c             -0.0865    0.0997    -0.868  0.386   ""
##
## =====
## Predictor: Communication_with_Indeterminent => Performance_Positive
## # A tibble: 4 x 6
##   term                estimate std.error statistic  p.value stars
##   <chr>                <dbl>    <dbl>    <dbl>    <dbl> <chr>
## 1 (Intercept)        -12.0     3.16     -3.80  0.000143 "***"
## 2 Communication_with_Indeterminent  -0.220    2.58     -0.0855 0.932   ""
## 3 VBMAPP              8.46     1.97      4.29  0.0000180 "***"
## 4 time_c              0.00269    0.104     0.0258 0.979   ""
##
## =====
## Predictor: Engagement_OnTarget => Performance_Positive
## # A tibble: 4 x 6
##   term                estimate std.error statistic  p.value stars
##   <chr>                <dbl>    <dbl>    <dbl>    <dbl> <chr>
## 1 (Intercept)        -13.3     3.17     -4.20  0.0000261 "***"
## 2 Engagement_OnTarget    1.77    0.970      1.82  0.0680   "."
## 3 VBMAPP              8.41     1.93      4.35  0.0000137 "***"
## 4 time_c             -0.0156    0.0842    -0.186 0.853   ""
##
## =====
## Predictor: Engagement_Therapist => Performance_Positive
## # A tibble: 4 x 6
##   term                estimate std.error statistic  p.value stars
##   <chr>                <dbl>    <dbl>    <dbl>    <dbl> <chr>
## 1 (Intercept)        -12.0     3.22     -3.72  0.000196 "***"
## 2 Engagement_Therapist  -0.553    4.01     -0.138 0.890   ""
## 3 VBMAPP              8.44     1.99      4.24  0.0000221 "***"
## 4 time_c              0.00517    0.0913    0.0566 0.955   ""
##
## =====
## Predictor: Engagement_OffTarget => Performance_Positive

```

```
## # A tibble: 4 x 6
##   term                estimate std.error statistic    p.value stars
##   <chr>              <dbl>    <dbl>    <dbl>    <dbl> <chr>
## 1 (Intercept)      -11.8      3.07     -3.82  0.000131  "****"
## 2 Engagement_OffTarget -2.19     1.07     -2.05  0.0402    "*"
## 3 VBMAPP             8.51     1.92      4.44  0.00000891 "****"
## 4 time_c            -0.0121   0.0825    -0.147 0.883     ""
```

## 2.4.4 Summary of Results

### 2.4.4.1 Table 1. Predictive Effects of Learning Behaviors on Performance (Robot Condition)

Predictor	Estimate	Std. Error	z-value	p-value	Significance
Affect_Positive	-3.09	2.13	-1.45	0.148	
Affect_Negative	-4.11	7.72	-0.53	0.594	
Communication_with_Instructor	-4.91	2.19	-2.25	0.0247	*
Communication_with_Instructor_Prompt	6.32	23.9	0.26	0.792	
Communication_with_Therapist	-3.60	2.81	-1.28	0.200	
Communication_with_Indeterminent	-4.52	3.19	-1.42	0.156	
Engagement_OnTarget	-0.07	2.71	-0.03	0.979	
Engagement_Therapist	-0.83	5.49	-0.15	0.880	
Engagement_OffTarget	0.85	3.80	0.22	0.824	

### 2.4.4.2 Interpretation – Robot Condition

- **Only one behavior**, *Communication\_with\_Instructor*, significantly predicted performance ( $p = 0.025$ ). Interestingly, the relationship was **negative**, suggesting that more communication with the robot instructor might be linked to **lower** performance. This could be due to the child's reliance on prompts or social behavior not aligning with task success.
- All other behaviors were not significantly predictive of performance in the robot-led sessions, indicating either weaker or non-existent associations in this context.

### 2.4.4.3 Table 2. Predictive Effects of Learning Behaviors on Performance (Human Condition)

Predictor	Estimate	Std. Error	z-value	p-value	Significance
Affect_Positive	-0.43	2.42	-0.18	0.860	
Affect_Negative	22.0	8.45	2.60	0.009	**
Communication_with_Instructor	5.89	2.64	2.23	0.026	*
Communication_with_Instructor_Prompt	6.42	7.97	0.77	0.443	
Communication_with_Therapist	-3.00	1.71	-1.75	0.080	.
Communication_with_Indeterminent	-0.22	2.65	-0.08	0.934	
Engagement_OnTarget	1.83	1.00	1.82	0.068	.
Engagement_Therapist	-0.57	4.13	-0.14	0.891	
Engagement_OffTarget	-2.25	1.10	-2.05	0.040	*



Predictor	Estimate	Std. Error	z-value	p-value	Significance
-----------	----------	------------	---------	---------	--------------

#### 2.4.4.4 Interpretation – Human Condition

- **Affect\_Negative** had a **strong positive association** with performance ( $p < 0.01$ ). This counterintuitive finding may suggest that children expressing frustration or difficulty were **engaging with the task**, potentially improving with guidance.
- **Communication\_with\_Instructor** was also positively predictive ( $p = 0.026$ ), contrasting with its negative effect under the robot condition. This may highlight the natural fluidity and effectiveness of human-led interactions.
- **Engagement\_OffTarget** significantly predicted **lower** performance ( $p = 0.040$ ), as expected.
- Marginal trends were observed for **Engagement\_OnTarget** ( $p = 0.068$ ) and **Communication\_with\_Therapist** ( $p = 0.080$ ), suggesting potential relevance with larger samples.

#### 2.4.5 Comparative Insights

- **Communication\_with\_Instructor** showed opposite effects:
  - **Negative** under robot instruction ( $p = 0.025$ )
  - **Positive** under human instruction ( $p = 0.026$ )
 This suggests that while human instructors likely foster meaningful instructional interactions, interactions with the robot may signal confusion, prompting, or a lack of task engagement.
- **Affect\_Negative** was **positively predictive** of performance only under the **human** condition. This may reflect effective human responses to emotional cues, adjusting support to improve performance.
- None of the **Engagement metrics** significantly predicted performance in robot-led sessions. However, **Engagement\_OffTarget** was **negatively associated** with performance under human instruction ( $p = 0.040$ ), aligning with expectations.
- Across all models, **VB-MAPP score** was a **strong and consistent positive predictor** of performance ( $p < 0.01$ ), validating the role of developmental ability.

## 3 Conclusion

This study investigated the comparative efficacy of human- versus robot-led group instruction during Circle Time sessions for children with Autism Spectrum Disorder (ASD), using a within-subject longitudinal design. Behavioral data were analyzed across affect, communication, engagement, and task performance dimensions using generalized linear mixed models with beta regression.

Our findings demonstrate that robot-led instruction elicited significantly greater positive affect in children compared to human-led sessions, especially among participants with higher VB-MAPP scores. However, this affective advantage was not mirrored in performance outcomes; children exhibited significantly lower task performance under robot instruction. Notably, robot sessions were also associated with increased communication directed to indeterminate partners and more off-task engagement over time, suggesting possible challenges in maintaining instructional clarity and behavioral focus.

Behavioral predictors of performance diverged markedly between conditions. While communication with the human instructor positively predicted task success, the same behavior under robot instruction was negatively associated with performance—potentially reflecting less effective pedagogical interactions or misaligned social contingencies. Engagement metrics did not significantly predict performance under the robot condition, reinforcing the limited instructional efficacy of the robot in its current design.

These findings highlight the dual role of social robots as emotionally engaging but pedagogically limited agents in early autism interventions. The elevated positive affect may partly reflect a novelty effect, particularly among higher-functioning children, yet this affective engagement did not sustain or enhance learning outcomes. As such, future work should explore adaptive robot behaviors that integrate emotional responsiveness with task-contingent feedback and clearer instructional scaffolding. Designing robot-mediated group instruction that balances engagement with effectiveness is critical for supporting inclusive learning environments for neurodiverse populations.