Does tACS affect the speed of decision-making in a foraging task?

```r
library(tidyverse)
```

```
## -- Attaching core tidyverse packages ------------------------ tidyverse 2.0.0 --
## v dplyr     1.2.0     v readr     2.1.6
## v forcats   1.0.1     v stringr   1.6.0
## v ggplot2   4.0.2     v tibble    3.3.1
## v lubridate 1.9.5     v tidyr     1.3.2
## v purrr     1.2.1
## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
## i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become errors
```

```r
library(brms)
```

```
## Loading required package: Rcpp
## Loading 'brms' package (version 2.23.0). Useful instructions
## can be found by typing help('brms'). A more detailed introduction
## to the package is available through vignette('brms_overview').
##
## Attaching package: 'brms'
##
## The following object is masked from 'package:stats':
##
##     ar
```

```r
library(bayesplot)
```

```
## This is bayesplot version 1.15.0
## - Online documentation and vignettes at mc-stan.org/bayesplot
## - bayesplot theme set to bayesplot::theme_default()
##    * Does _not_ affect other ggplot2 plots
##    * See ?bayesplot_theme_set for details on theme setting
##
## Attaching package: 'bayesplot'
##
## The following object is masked from 'package:brms':
##
##     rhat
```

```r
library(loo)
```

```
## This is loo version 2.9.0
## - Online documentation and vignettes at mc-stan.org/loo
## - As of v2.0.0 loo defaults to 1 core but we recommend using as many as possible. Use the 'cores' arg
```

```r
library(sjPlot)
```

```
##
## Attaching package: 'sjPlot'
##
## The following object is masked from 'package:ggplot2':
##
##     set_theme
```

```r
library(performance)

# Set options
options(mc.cores = parallel::detectCores())
rstan::rstan_options(auto_write = TRUE)
```

```r
df_p1 <- read.csv("/Users/debarpita/Desktop/arjun/trial_wise_dataset_post.csv")
df_p2 <- read.csv("/Users/debarpita/Desktop/arjun/trial_wise_dataset_pre.csv")
library(dplyr)
df <- bind_rows(df_p1, df_p2)
```

```r
cat(sprintf("Missing ReactionTime: %d (%.1f%%)\n",
            sum(is.na(df$ReactionTime)),
            100 * mean(is.na(df$ReactionTime))))
```

```
## Missing ReactionTime: 0 (0.0%)
```

```r
df <- df %>% filter(!is.na(ReactionTime))
```

```r
summary(df$ReactionTime)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.0000  0.4327  0.5227  0.5802  0.6507  5.2968
```

```r
# Remove extreme outliers (Turkey IQR rule)
Q1 <- quantile(df$ReactionTime, 0.25, na.rm = TRUE)
Q3 <- quantile(df$ReactionTime, 0.75, na.rm = TRUE)
IQR <- Q3 - Q1
df <- df %>%
  filter(ReactionTime >= Q1 - 1.5 * IQR,
         ReactionTime <= Q3 + 1.5 * IQR)

cat(sprintf("After outlier removal: %d observations\n", nrow(df)))
```

```
## After outlier removal: 5678 observations
```

original was 6016

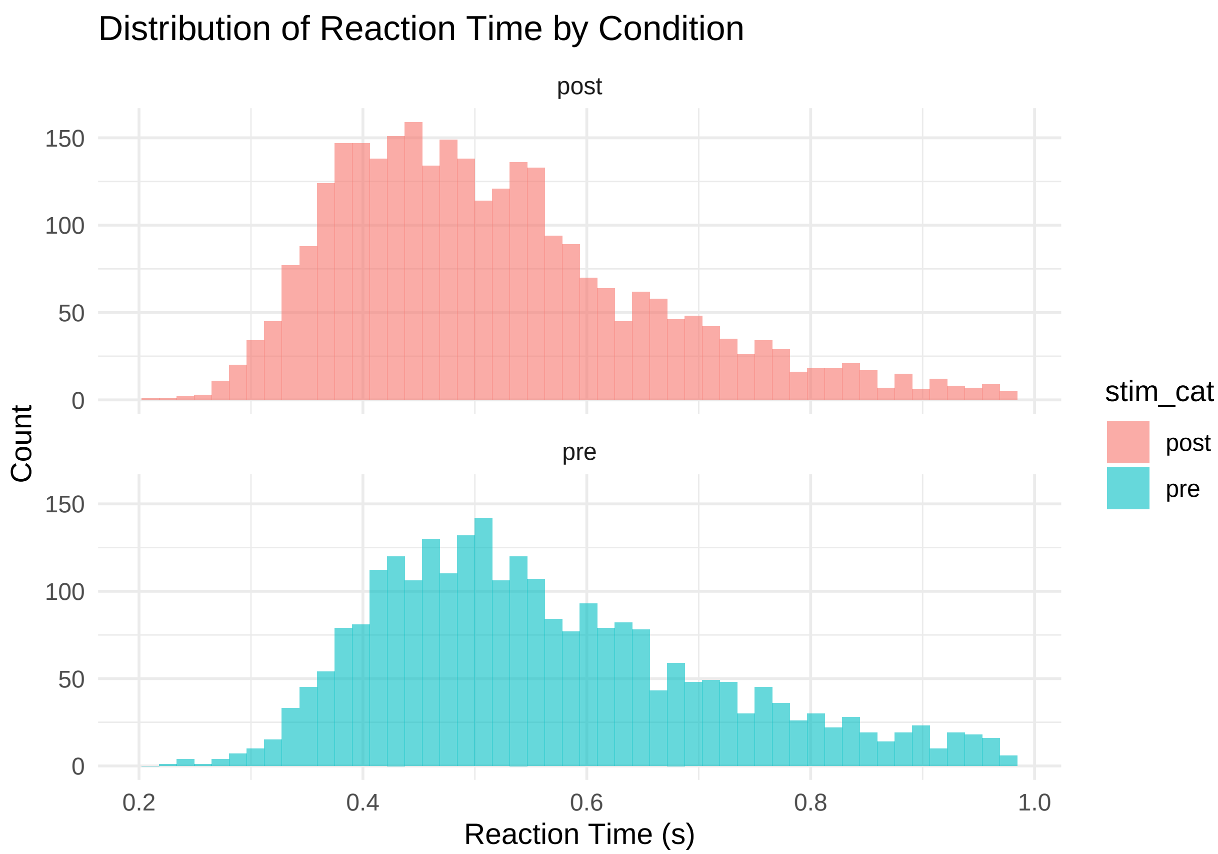
```r
# Log-transform ReactionTime
df <- df %>%
  mutate(log_ReactionTime = log(ReactionTime + 1e-6))

# Create trial number
```

```r
df <- df %>%
  group_by(Participant_ID, stim_cat) %>%
  mutate(trial_number = row_number()) %>%
  ungroup()

# Z-score predictors
df <- df %>%
  mutate(
    trial_number_z = scale(trial_number)[,1],
    AvgRewardRate_z = scale(AvgRewardRate)[,1],
    trait_anxiety_score_z = scale(trait_anxiety_score)[,1]
  )
```

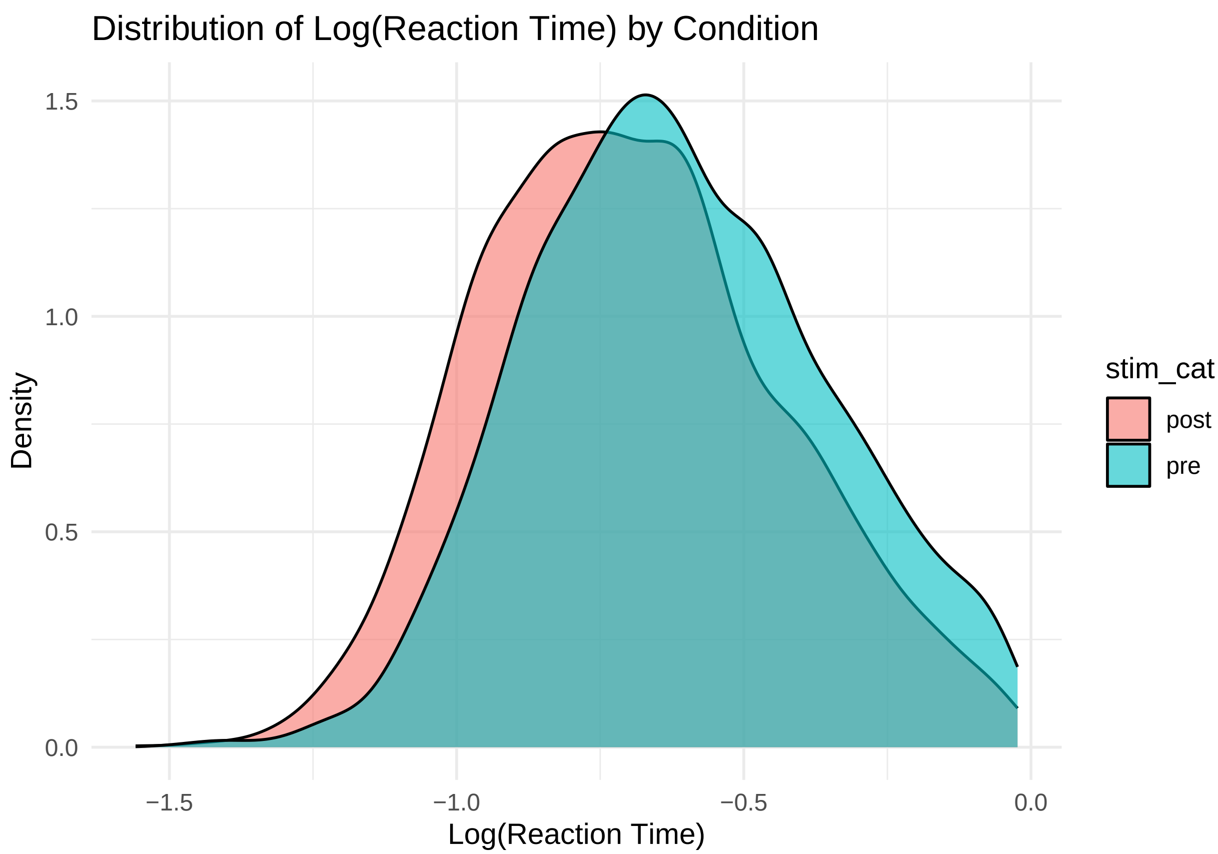
```r
df <- df %>%
  group_by(Participant_ID, stim_cat, env) %>%
  mutate(AvgRewardRate_before = lag(AvgRewardRate)) %>%
  ungroup() %>%
  filter(!is.na(AvgRewardRate_before))
```

```r
df <- df %>%
  mutate(
    AvgRewardRate_before_z = scale(AvgRewardRate_before)[,1]
  )
```

```r
# Distribution of ReactionTime
p1 <- ggplot(df, aes(x = ReactionTime, fill = stim_cat)) +
  geom_histogram(bins = 50, alpha = 0.6, position = "identity") +
  facet_wrap(~stim_cat, ncol = 1) +
  theme_minimal() +
  labs(title = "Distribution of Reaction Time by Condition",
       x = "Reaction Time (s)", y = "Count")

print(p1)
```

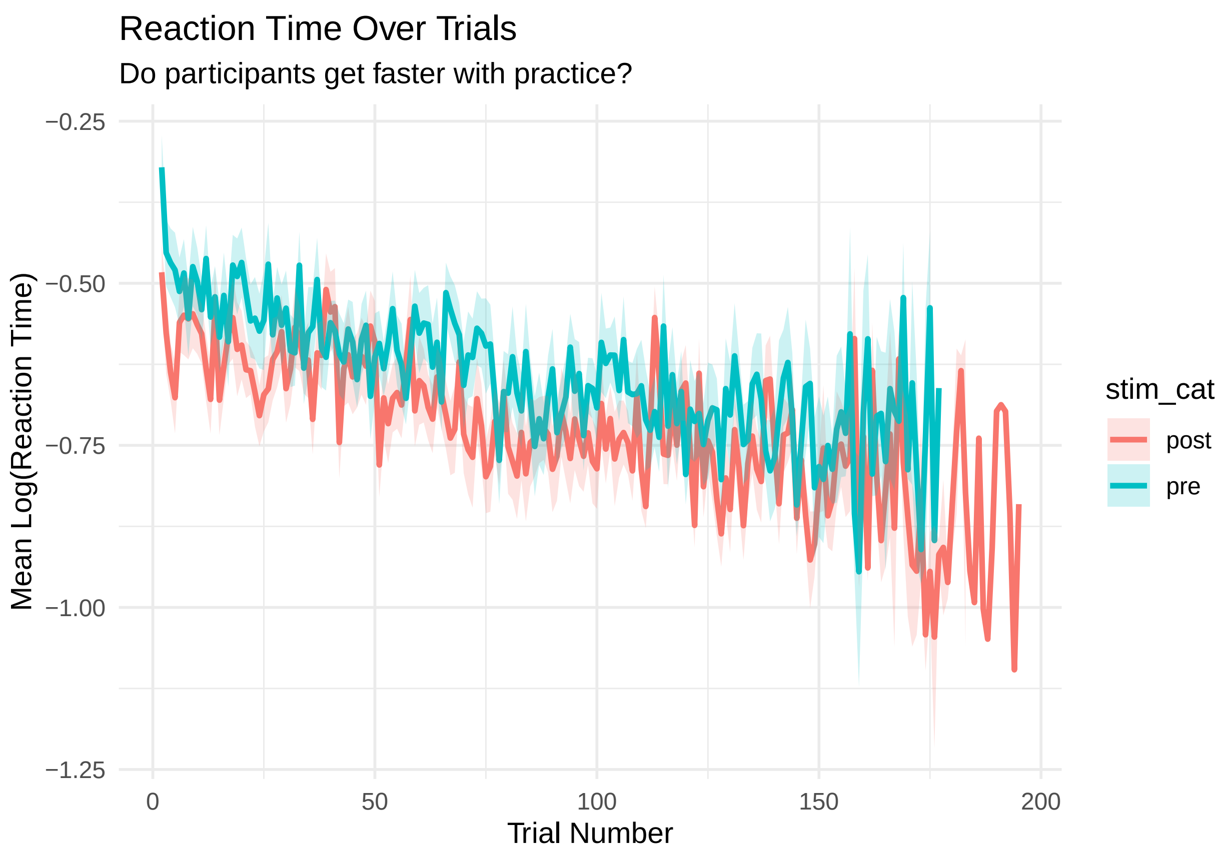



```
# Log-transformed
p2 <- ggplot(df, aes(x = log_ReactionTime, fill = stim_cat)) +
  geom_density(alpha = 0.6) +
  theme_minimal() +
  labs(title = "Distribution of Log(Reaction Time) by Condition",
       x = "Log(Reaction Time)", y = "Density")

print(p2)
```




```r
# Reaction time over trials
df_summary <- df %>%
  group_by(stim_cat, trial_number) %>%
  summarise(
    mean_RT = mean(log_ReactionTime, na.rm = TRUE),
    se_RT = sd(log_ReactionTime, na.rm = TRUE) / sqrt(n()),
    .groups = "drop"
  )

ggplot(df_summary, aes(x = trial_number, y = mean_RT, color = stim_cat)) +
  geom_line(size = 1) +
  geom_ribbon(aes(ymin = mean_RT - se_RT, ymax = mean_RT + se_RT, fill = stim_cat),
              alpha = 0.2, color = NA) +
  theme_minimal() +
  labs(title = "Reaction Time Over Trials",
       x = "Trial Number", y = "Mean Log(Reaction Time)",
       subtitle = "Do participants get faster with practice?")
```

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

## Warning: Removed 14 rows containing missing values or values outside the scale range
## (`geom_ribbon()`).
```



Model 1: Baseline tACS Effect Does tACS change the baseline speed of decision-making? log(ReactionTime) ~ stim_cat + trial_number + (1|Participant_ID)

```
model1 <- brm(
  log_ReactionTime ~ stim_cat + trial_number_z + (1 | Participant_ID),
  data = df,
  family = gaussian(),
  chains = 4,
  iter = 3000,
  warmup = 1000,
  cores = 4,
  seed = 123,
  file = "model1_RT_baseline"
)
```

```
summary(model1)
```

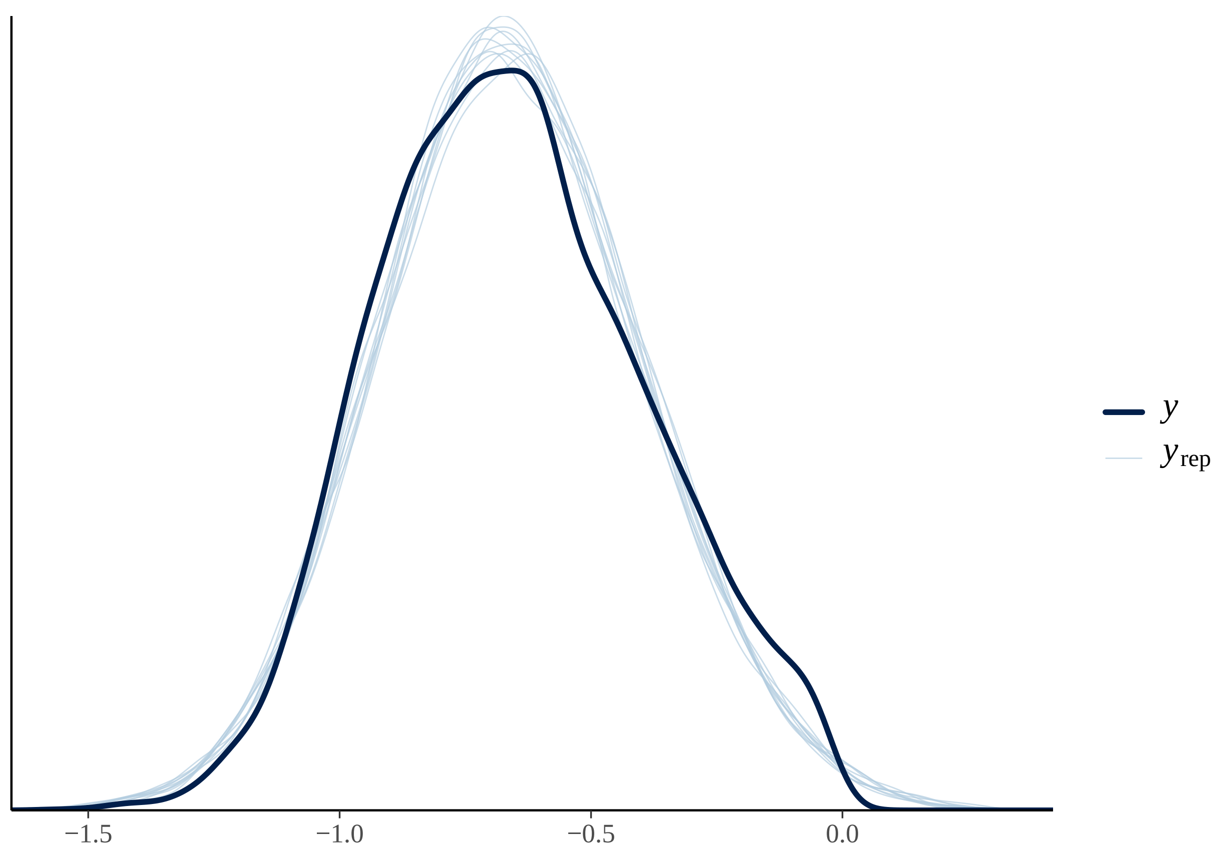
```
##  Family: gaussian
##   Links: mu = identity
## Formula: log_ReactionTime ~ stim_cat + trial_number_z + (1 | Participant_ID)
##    Data: df (Number of observations: 5678)
##   Draws: 4 chains, each with iter = 3000; warmup = 1000; thin = 1;
##          total post-warmup draws = 8000
##
## Multilevel Hyperparameters:
## ~Participant_ID (Number of levels: 21)
```

```
##                Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## sd(Intercept)     0.15      0.03     0.11     0.21 1.01      610     1391
##
## Regression Coefficients:
##                 Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## Intercept          -0.67      0.04    -0.74    -0.60 1.00      463      501
## stim_catpre         0.08      0.01     0.07     0.09 1.00     3884     3957
## trial_number_z     -0.04      0.00    -0.05    -0.03 1.00     4809     5007
##
## Further Distributional Parameters:
##       Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## sigma     0.22      0.00     0.21     0.22 1.00     3314     4137
##
## Draws were sampled using sampling(NUTS). For each parameter, Bulk_ESS
## and Tail_ESS are effective sample size measures, and Rhat is the potential
## scale reduction factor on split chains (at convergence, Rhat = 1).
```

beta_stim_catpre > 0: Pre-stimulation decisions are SLOWER -> confidencce doesnt include 0 beta_trial_number < 0: Decisions get FASTER over time (learning/practice effect)

```r
pp_check(model1)
```

```
## Using 10 posterior draws for ppc type 'dens_overlay' by default.
```



Model 2: Reward Context Effect Does environmental richness (average reward rate) speed up or slow down decisions? log(ReactionTime) ~ AvgRewardRate_before + trial_number + (1|Participant_ID)

```r
model2 <- brm(
  log_ReactionTime ~ AvgRewardRate_before_z + trial_number_z + (1 | Participant_ID),
  data = df,
  family = gaussian(),
  chains = 4,
  iter = 3000,
  warmup = 1000,
  cores = 4,
  seed = 123
)
```

```
## Compiling Stan program...
```

```
## Trying to compile a simple C file
```

```
## Running /Library/Frameworks/R.framework/Resources/bin/R CMD SHLIB foo.c
## using C compiler: 'Apple clang version 17.0.0 (clang-1700.6.3.2)'
## using SDK: 'MacOSX26.2.sdk'
## clang -arch arm64 -std=gnu2x -I"/Library/Frameworks/R.framework/Resources/include" -DNDEBUG   -I"/Li
## In file included from <built-in>:1:
## In file included from /Library/Frameworks/R.framework/Versions/4.5-arm64/Resources/library/StanHeade
## In file included from /Library/Frameworks/R.framework/Versions/4.5-arm64/Resources/library/RcppEigen
## In file included from /Library/Frameworks/R.framework/Versions/4.5-arm64/Resources/library/RcppEigen
## /Library/Frameworks/R.framework/Versions/4.5-arm64/Resources/library/RcppEigen/include/Eigen/src/Cor
##   679 | #include <cmath>
##       |          ^~~~~~~
## 1 error generated.
## make: *** [foo.o] Error 1
```

```
## Start sampling
```

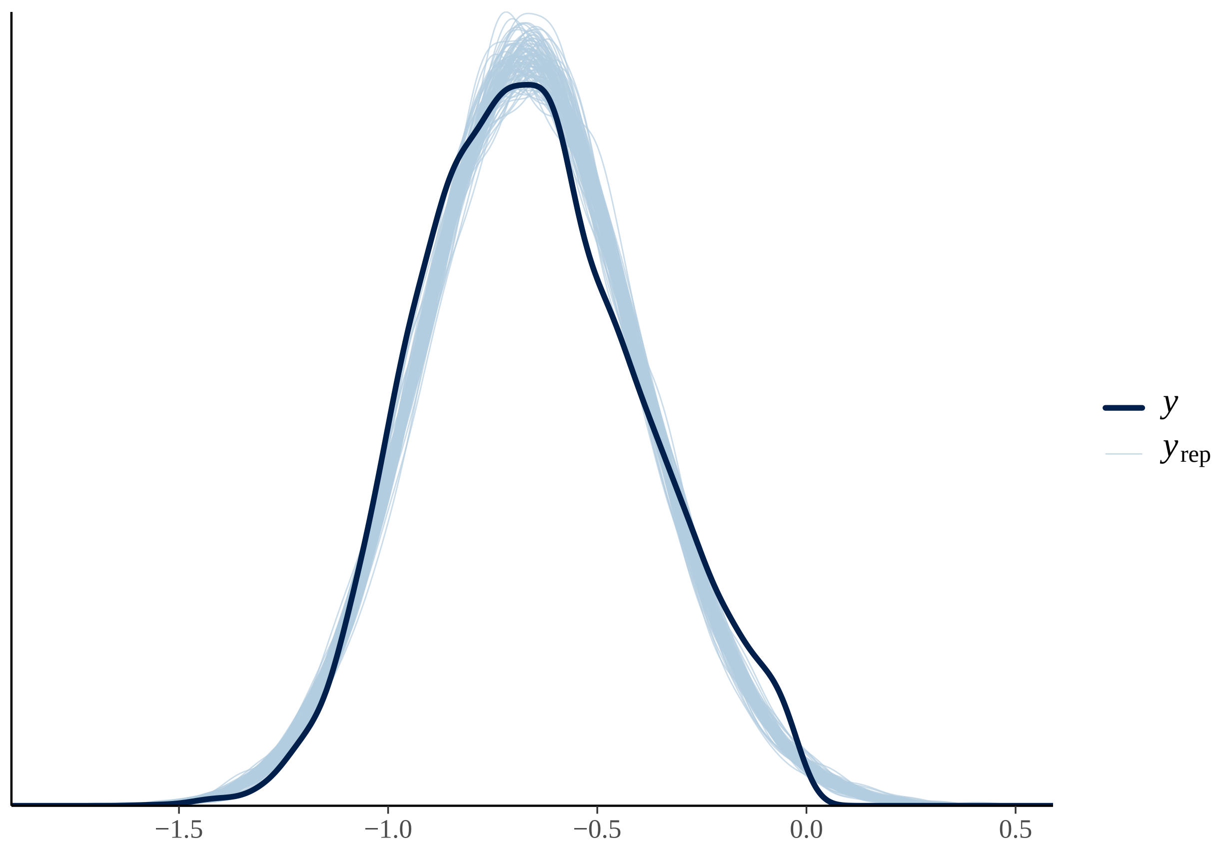
```r
summary(model2)
```

```
##  Family: gaussian
##   Links: mu = identity
## Formula: log_ReactionTime ~ AvgRewardRate_before_z + trial_number_z + (1 | Participant_ID)
##    Data: df (Number of observations: 5594)
##   Draws: 4 chains, each with iter = 3000; warmup = 1000; thin = 1;
##          total post-warmup draws = 8000
##
## Multilevel Hyperparameters:
## ~Participant_ID (Number of levels: 21)
##               Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## sd(Intercept)     0.14      0.02     0.10     0.20 1.00      792     1500
##
## Regression Coefficients:
##                        Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS
## Intercept                 -0.63      0.03    -0.70    -0.57 1.00      517
## AvgRewardRate_before_z    -0.04      0.00    -0.05    -0.03 1.00     5068
## trial_number_z            -0.04      0.00    -0.05    -0.03 1.00     5174
##                        Tail_ESS
## Intercept                   893
```

```
## AvgRewardRate_before_z     4995
## trial_number_z             4857
##
## Further Distributional Parameters:
##       Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## sigma     0.22      0.00     0.21     0.22 1.00     2996     3778
##
## Draws were sampled using sampling(NUTS). For each parameter, Bulk_ESS
## and Tail_ESS are effective sample size measures, and Rhat is the potential
## scale reduction factor on split chains (at convergence, Rhat = 1).
```

beta_AvgRewardRate_before < 0: Richer environments → FASTER decisions and ci doesnt include 0

```
pp_check(model2, ndraws = 100)
```



Model 3: (Stimulation × Reward Context) Does tACS change how reward context affects decision speed? log(ReactionTime) ~ stim_cat * AvgRewardRatebefore + trial_number + (1|Participant_ID)‘

```
model3 <- brm(
  log_ReactionTime ~ stim_cat * AvgRewardRate_before_z + trial_number_z +
                     (1 | Participant_ID),
  data = df,
  family = gaussian(),
  chains = 4,
  iter = 3000,
  warmup = 1000,
```

```r
  cores = 4,
  seed = 123,
  file = "model3_RT_interaction"
)
```

```r
summary(model3)
```

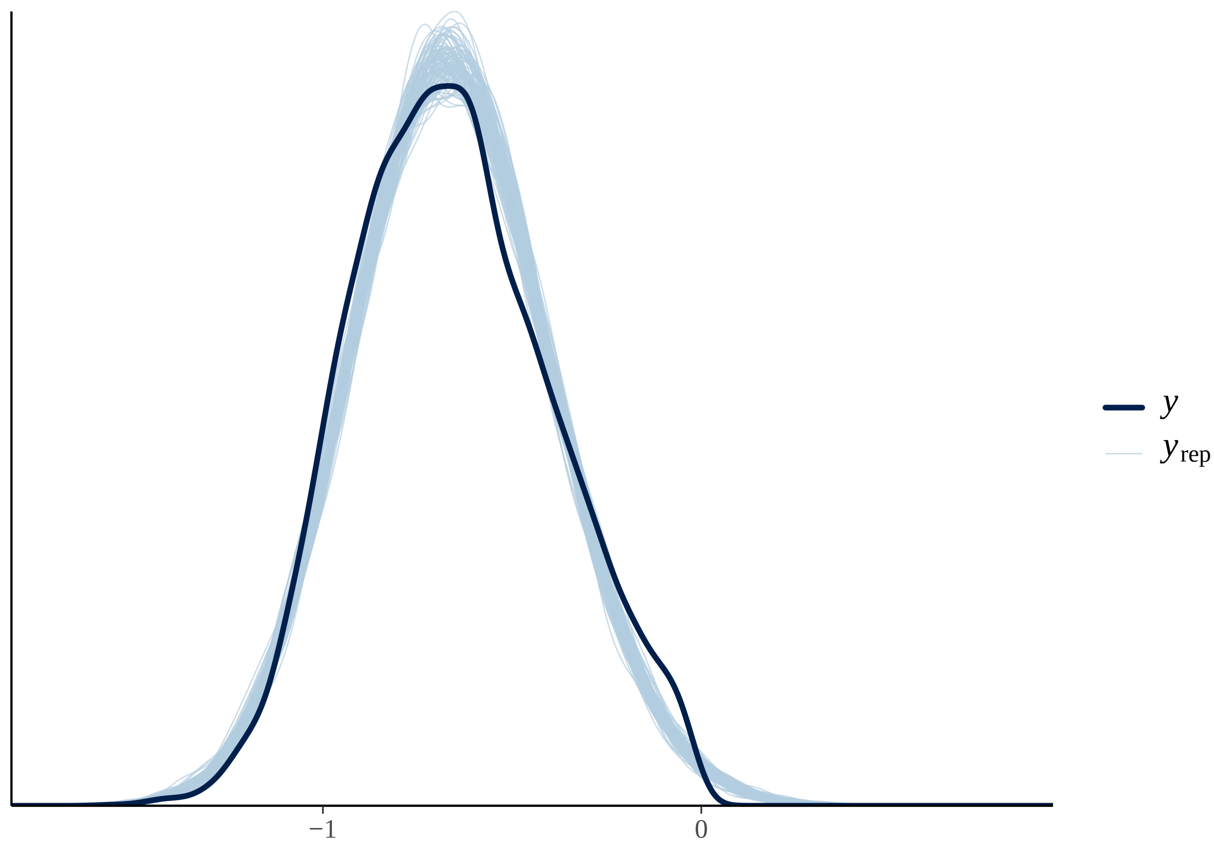
```
##  Family: gaussian
##   Links: mu = identity
## Formula: log_ReactionTime ~ stim_cat * AvgRewardRate_before_z + trial_number_z + (1 | Participant_ID)
##    Data: df (Number of observations: 5594)
##   Draws: 4 chains, each with iter = 3000; warmup = 1000; thin = 1;
##          total post-warmup draws = 8000
##
## Multilevel Hyperparameters:
## ~Participant_ID (Number of levels: 21)
##               Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## sd(Intercept)     0.15      0.03     0.11     0.20 1.01     1046     2078
##
## Regression Coefficients:
##                                 Estimate Est.Error l-95% CI u-95% CI Rhat
## Intercept                          -0.66      0.03    -0.72    -0.59 1.01
## stim_catpre                        -0.00      0.02    -0.04     0.03 1.00
## AvgRewardRate_before_z             -0.01      0.01    -0.03     0.00 1.00
## trial_number_z                     -0.04      0.00    -0.05    -0.03 1.00
## stim_catpre:AvgRewardRate_before_z    -0.06      0.02    -0.09    -0.03 1.00
##                                 Bulk_ESS Tail_ESS
## Intercept                            855     1049
## stim_catpre                         3239     3757
## AvgRewardRate_before_z              3844     4416
## trial_number_z                      5232     5494
## stim_catpre:AvgRewardRate_before_z     3356     3853
##
## Further Distributional Parameters:
##       Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## sigma     0.22      0.00     0.21     0.22 1.00     4407     4516
##
## Draws were sampled using sampling(NUTS). For each parameter, Bulk_ESS
## and Tail_ESS are effective sample size measures, and Rhat is the potential
## scale reduction factor on split chains (at convergence, Rhat = 1).
```

beta_interaction < 0: Pre-stim shows STRONGER speeding effect in rich environments

```r
ce <- conditional_effects(model3,
                          effects = "AvgRewardRate_before_z:stim_cat")

p <- plot(ce, plot = FALSE)[[1]] +
  labs(title = "Interaction: Reward Context × Stimulation",
       subtitle = "How does reward richness affect decision speed in each condition?",
       x = "Average Reward Rate (z-scored)",
       y = "Handling Time") +
  theme_minimal()
```

```r
print(p)
```


```r
pp_check(model3, ndraws = 100)
```



Model 4: Adding Anxiety Does trait anxiety modulate the effects of tACS on decision speed? log(ReactionTime) ~ stim_cat * AvgRewardRatebefore + trait_anxiety + trial_number + (1|Participant_ID)‘

```
model4 <- brm(
  log_ReactionTime ~ stim_cat * AvgRewardRate_before_z + trait_anxiety_score_z +
                     trial_number_z + (1 | Participant_ID),
  data = df,
  family = gaussian(),
  chains = 4,
  iter = 3000,
  warmup = 1000,
  cores = 4,
  seed = 123,
  file = "model4_RT_anxiety"
)
```

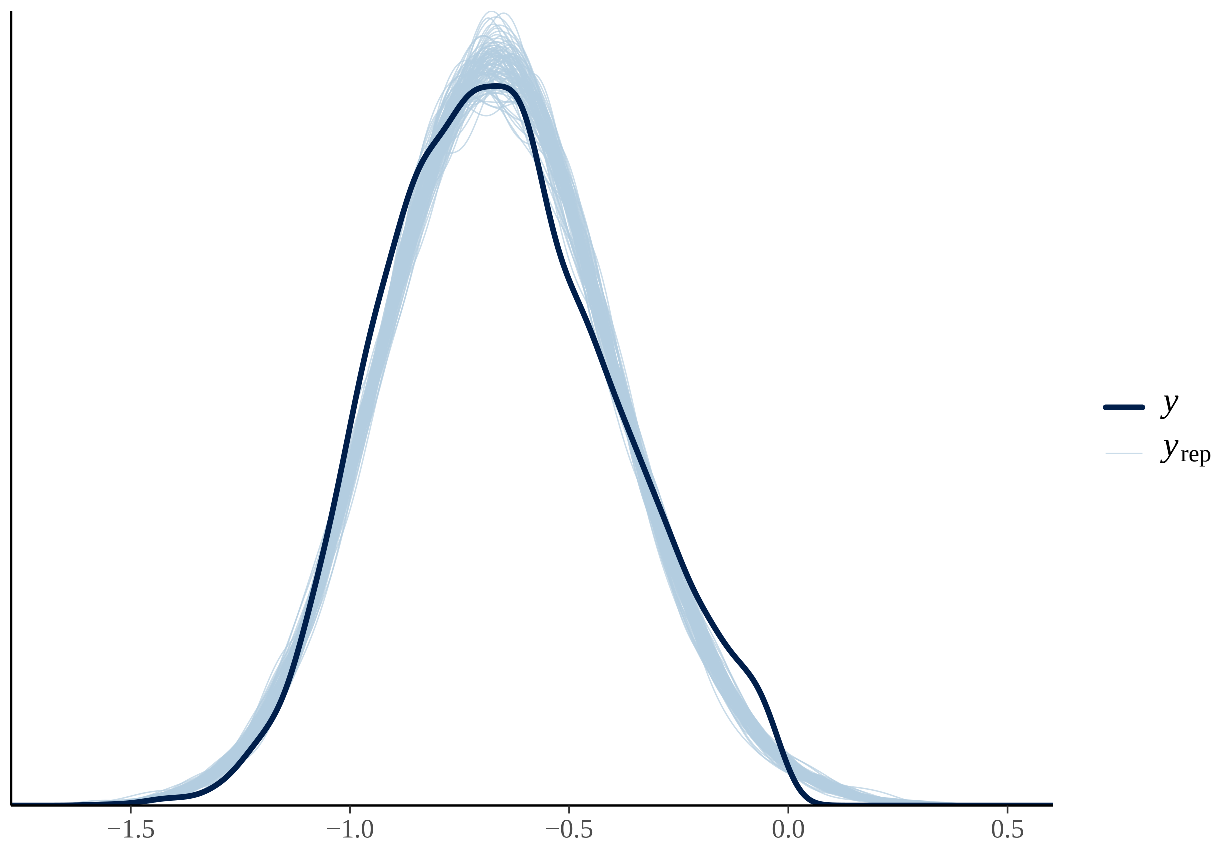
```
summary(model4)
```

```
##  Family: gaussian
##   Links: mu = identity
## Formula: log_ReactionTime ~ stim_cat * AvgRewardRate_before_z + trait_anxiety_score_z + trial_number
##    Data: df (Number of observations: 5594)
##   Draws: 4 chains, each with iter = 3000; warmup = 1000; thin = 1;
##          total post-warmup draws = 8000
##
```

```
## Multilevel Hyperparameters:
## ~Participant_ID (Number of levels: 21)
##               Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## sd(Intercept)     0.15      0.03     0.11     0.21 1.00     1628     2708
##
## Regression Coefficients:
##                                   Estimate Est.Error l-95% CI u-95% CI Rhat
## Intercept                            -0.66      0.03    -0.73    -0.59 1.01
## stim_catpre                          -0.00      0.02    -0.04     0.03 1.00
## AvgRewardRate_before_z               -0.01      0.01    -0.03     0.00 1.00
## trait_anxiety_score_z                -0.03      0.03    -0.09     0.03 1.00
## trial_number_z                       -0.04      0.00    -0.05    -0.03 1.00
## stim_catpre:AvgRewardRate_before_z    -0.06      0.02    -0.09    -0.03 1.00
##                                   Bulk_ESS Tail_ESS
## Intercept                             1659     2376
## stim_catpre                           5011     4430
## AvgRewardRate_before_z                5845     4496
## trait_anxiety_score_z                 1598     2664
## trial_number_z                        7069     5422
## stim_catpre:AvgRewardRate_before_z     5304     4940
##
## Further Distributional Parameters:
##       Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## sigma     0.22      0.00     0.21     0.22 1.00     6568     3923
##
## Draws were sampled using sampling(NUTS). For each parameter, Bulk_ESS
## and Tail_ESS are effective sample size measures, and Rhat is the potential
## scale reduction factor on split chains (at convergence, Rhat = 1).
```

beta_anxiety < 0: Higher anxiety $\rightarrow$ FASTER decisions but ci includes 0

```
pp_check(model4, ndraws = 100)
```



y
y rep
−1.5
−1.0
−0.5
0.0
0.5