STAT 512 Final Project

Effects of Brief Meditation on Mother Respiratory Sinus Arrhythmia

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Introduction

Background

This project is a sliver of my master's thesis, which I will defend in June 2020. We conducted a pilot study of a brief mindfulness induction (focused-attention meditation) on self- and co-regulation between parents and young children (ages 4.5 - 6.5) during a challenging dyadic task. My master's thesis investigates the effects of a meditation on parent autonomic nervous system activity during a challenging parenting moment and individual differences in such by prior contemplative experience and dispositional mindfulness.

Research Question

General: How does a mindfulness meditation affect parasympathetic nervous system activity in mothers during a subsequent challenging parent-child interaction?

Specific: How does the average change in respiratory sinus arrhythmia (response) in mothers (subject/block) differ by treatment group (meditation vs. podcast) across phases of a challenging parenting task (time period)?

Description

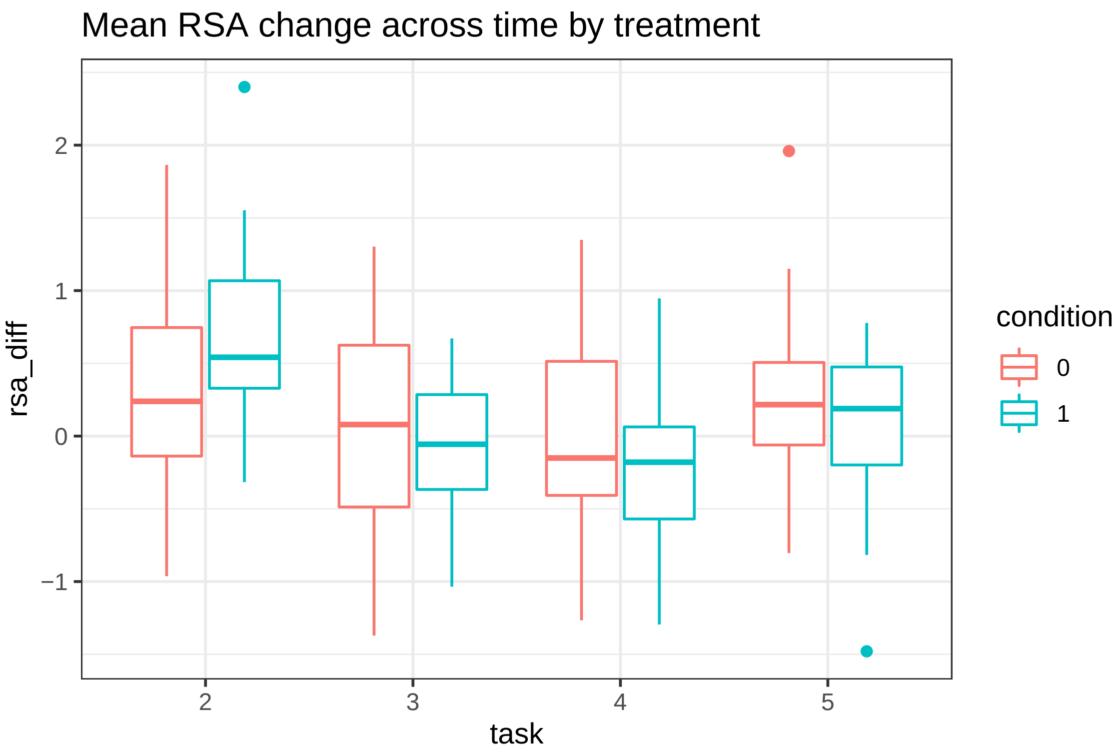
The observational/experimental unit is an individual parent.

For the purposes of this assignment, I only considered the subset of mothers (n = 40), but 27 fathers also participated in this study. The blocking variable was subject (unique mother identification as a factor).

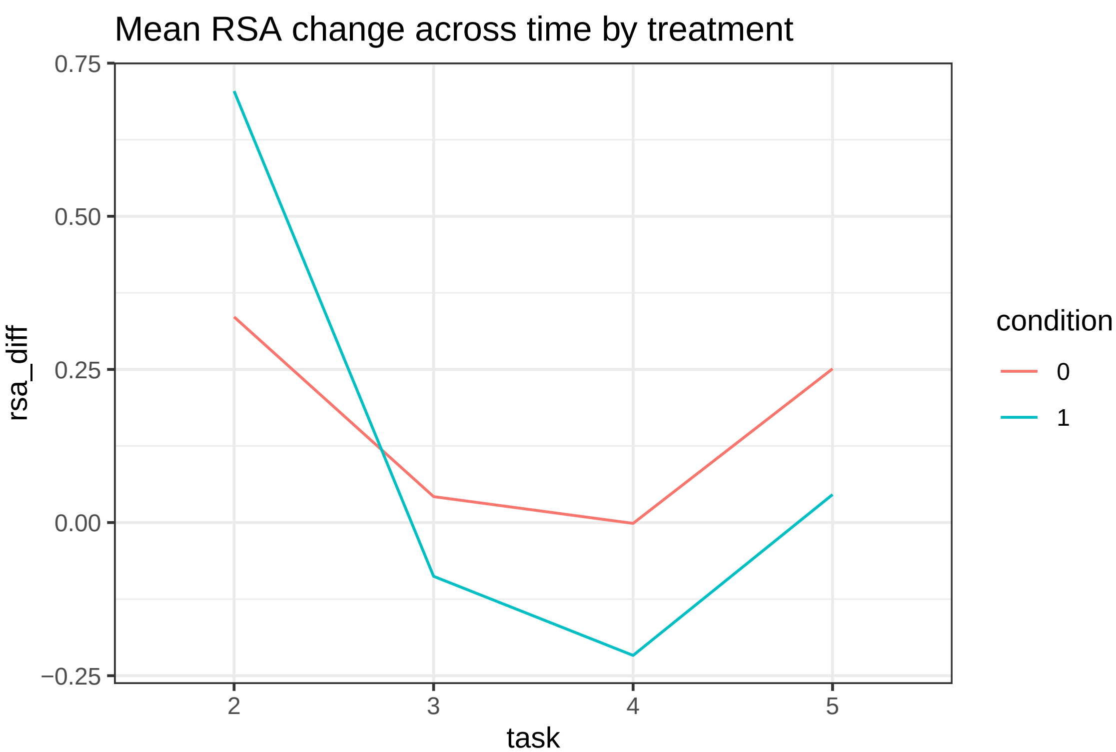
The response variable was the average change in respiratory sinus arrhythmia (RSA), which is a noninvasive indicator of parasympathetic nervous system activity. RSA was a continuous variable but will be calculated as a difference score from baseline.

The predictor variables were audio recording as treatment (between-subjects factor) and protocol task as time period (within-subjects factor). Treatment was a categorical variable with two levels: control (0) and experimental (1). Mothers were randomly assigned to a group, balancing for child gender, child age, parent gender, parent mental health, and family strengthening activities. The experimental group listened to a focused-attention meditation, whereas the control group listened to an educational podcast about the benefits of sleep for the same duration. Time period was a categorical variable with 5 levels: 3-minute resting period; 5.5-minute audio treatment; 4-minute dyadic challenge (part 1); 3-minute dyadic stressor (part 2); 3-minute dyadic recovery (part 3). After the response was calculated as a difference score from baseline/resting period, only the latter 4 levels remained.

Summary



Mean RSA change across time by treatment
2
1
0
−1
rsa_diff
2
3
4
5
task
condition
0
1



Mean RSA change across time by treatment
0.75
0.50
0.25
0.00
−0.25
rsa_diff
2
3
4
5
task
condition
0
1

Pre-analysis assumptions

Outliers

There are no extreme outlying scores of RSA, based on inter-quartile calculations.

Normality

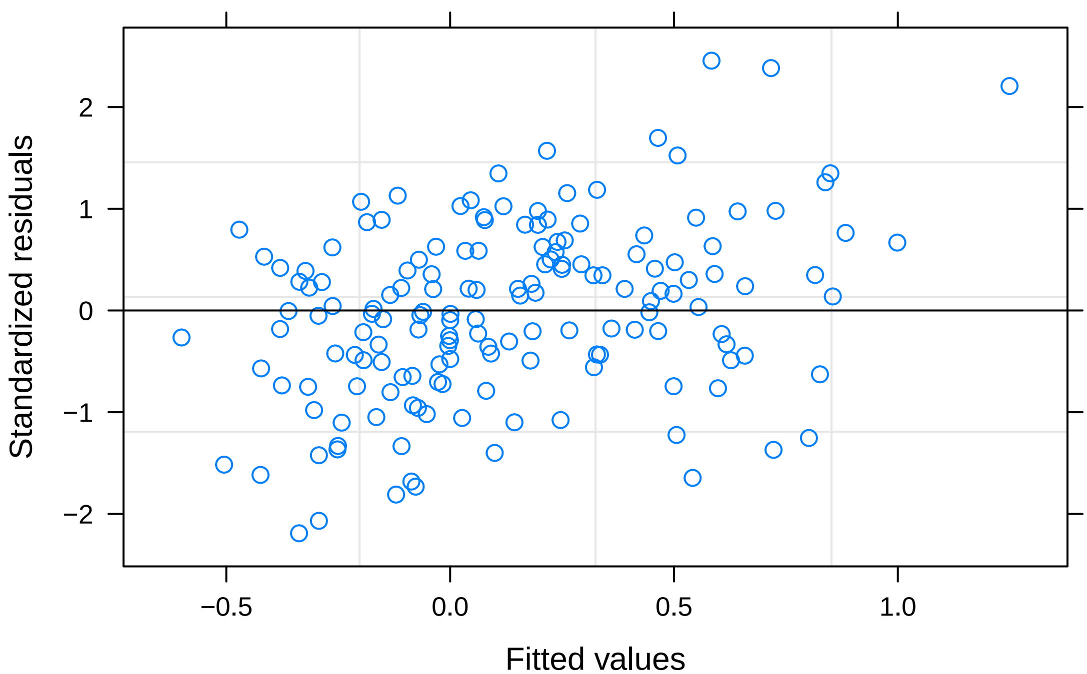
Based on the Shapiro-Wilk test, the residuals of the difference scores for RSA by time period (task) and treatment group (condition) are normally distributed.

Analysis

Analysis was executed in R version 3.6.2 (2019-12-12), using the `nlme` and `emmeans` packages. A balanced two-factor (two-way) repeated measures analysis of variance (ANOVA) was performed to evaluate the effect of treatment across time on mean change in RSA. In order to account for intra-individual variability in RSA, I first calculated a difference score for each individual based on the baseline/resting average RSA. This difference score was then used as the response variable in the model. Fixed effects included treatment (experimental vs. control), time period (audio, 3-part parent-child task), and a $treatment * time$ interaction. Subject (individual mother) was included as a random effect to account for repeated measures.

First, the assumption of compound symmetry was investigated. Three models were fit to be compared using AIC: basic, unstructured covariance, and autogressive covariance approaches. According to AIC, the model with autoregressive covariance fits the data most appropriately.

```
##                 df      AIC
## model1_basic    10 297.8500
## model2_corsymm  16 298.2902
## model3_corar1   11 292.7178
```



The assumption of normally distributed residuals seems to be met.

Results

```
##                 numDF denDF   F-value p-value
## (Intercept)         1   114  2.959085  0.0881
## task                3   114 15.902412  <.0001
## condition           1    38  0.085335  0.7718
## task:condition      3   114  3.481452  0.0183
```

```
## $emmeans
## task = 2:
##  condition   emmean    SE df lower.CL upper.CL
##  0          0.33570 0.139 38   0.0535   0.6179
##  1          0.70441 0.139 38   0.4222   0.9866
##
## task = 3:
##  condition   emmean    SE df lower.CL upper.CL
##  0          0.04235 0.139 38  -0.2398   0.3245
##  1         -0.08774 0.139 38  -0.3699   0.1944
##
## task = 4:
##  condition   emmean    SE df lower.CL upper.CL
##  0         -0.00135 0.139 38  -0.2835   0.2808
##  1         -0.21687 0.139 38  -0.4990   0.0653
##
## task = 5:
##  condition   emmean    SE df lower.CL upper.CL
##  0          0.25109 0.139 38  -0.0311   0.5333
##  1          0.04572 0.139 38  -0.2364   0.3279
##
## d.f. method: containment
## Confidence level used: 0.95
##
## $contrasts
## task = 2:
##  contrast estimate    SE df t.ratio p.value
##  0 - 1      -0.369 0.197 38 -1.871  0.0691
##
## task = 3:
##  contrast estimate    SE df t.ratio p.value
##  0 - 1       0.130 0.197 38  0.660  0.5133
##
## task = 4:
##  contrast estimate    SE df t.ratio p.value
##  0 - 1       0.216 0.197 38  1.093  0.2811
##
## task = 5:
##  contrast estimate    SE df t.ratio p.value
##  0 - 1       0.205 0.197 38  1.042  0.3041
```

Conclusions

There was a statistically significant effect of time period on change in RSA, $F(3, 114) = 15.9$, $p < .0001$, meaning that RSA change values significantly differed in some way between time periods. The effect of condition on change in RSA was not significant, $F(1, 38) = 0.09$, $p = 0.77$. There was a statistically significant interaction between treatment and time on change in RSA, $F(3, 114) = 3.48$, $p = 0.02$. Therefore, the effect of treatment was analyzed at each time point. Based on pairwise comparisons, there were no statistically significant differences in RSA change between condition at each time point.

The results do not indicate significant differences in RSA change in mothers by treatment across phases of a challenging parent-child task. Based on this analysis, there is no evidence to suggest that the brief mindfulness meditation had an effect on mothers' parasympathetic nervous system activity during a challenging parenting moment.

Appendix

```r
# set global options for figures, code, warnings, and messages
knitr::opts_chunk$set(fig.width = 6,
                      fig.height = 4,
                      fig.path = "figs/",
                      echo = FALSE,
                      warning = FALSE,
                      message = FALSE)
# load packages
library(tidyverse)
library(rstatix)
library(nlme)
library(emmeans)
# read in treatment assignment data and filter to mothers only
trt_audio <- readr::read_csv("data/audio_parent.csv") %>%
  dplyr::filter(individual == 1)
# filter to baseline rsa for each person
rsa_base <- readr::read_csv("data/hrv_parent_valid.csv") %>%
  dplyr::select(family, individual, task, rsa_mean_task) %>%
  dplyr::filter(individual == 1,
                task == 1) %>%
  dplyr::distinct() %>%
  dplyr::select(-individual, -task) %>%
  dplyr::rename(rsa_baseline = rsa_mean_task)
# prepare all data for summaries and models
rsa_trt_data <- readr::read_csv("data/hrv_parent_valid.csv") %>%
  dplyr::select(family, individual, task, rsa_mean_task) %>%
  dplyr::filter(individual == 1) %>%
  dplyr::distinct() %>%
  dplyr::left_join(rsa_base, by = "family") %>%
  dplyr::full_join(trt_audio, by = c("family", "individual")) %>%
  dplyr::select(-individual) %>%
  dplyr::group_by(family) %>%
  dplyr::mutate(rsa_diff = rsa_mean_task - rsa_baseline) %>%
  dplyr::filter(task != 1) %>%
  dplyr::ungroup() %>%
  rstatix::convert_as_factor(family, task, condition) %>%
  dplyr::rename(mother_id = family)
# rstatix sum stats
rsa_trt_data %>%
  dplyr::select(-rsa_mean_task, -rsa_baseline) %>%
  dplyr::group_by(task, condition) %>%
  rstatix::get_summary_stats() %>%
  dplyr::ungroup()
# boxplot of mean rsa diff by time and trt
rsa_trt_data %>%
  ggplot(aes(x = task, y = rsa_diff, color = condition)) +
  geom_boxplot() +
  theme_bw() +
  ggtitle("Mean RSA change across time by treatment")
# line plot mean rsa diff score by time and trt
rsa_trt_data %>%
```

```r
  ggplot(aes(x = task, y = rsa_diff)) +
  stat_summary(aes(group = condition, color = condition),
               geom = "line",
               fun = mean) +
  theme_bw() +
  ggtitle("Mean RSA change across time by treatment")
# check for outliers
rsa_trt_data %>%
  dplyr::group_by(condition, task) %>%
  rstatix::identify_outliers(rsa_diff)
# check normality of residuals for outcome
rsa_trt_data %>%
  dplyr::group_by(condition, task) %>%
  rstatix::shapiro_test(rsa_diff)
# MODEL 1: basic/corCompSymm: covariance same across period on same subject
options(contrasts = c("contr.sum", "contr.poly"))
model1_basic <- nlme::lme(rsa_diff ~ task*condition,
                                     random = ~1 | mother_id,
                                     data = rsa_trt_data)
summary(model1_basic)
nlme::anova.lme(model1_basic, type = "marginal")
emmeans::emmeans(model1_basic, dunnett ~ task|condition)
emmeans::emmeans(model1_basic, pairwise ~ task|condition)
# MODEL 2: corSymm: unstructured covariance; correlations allowed to differ
options(contrasts = c("contr.sum", "contr.poly"))
model2_corsymm <- nlme::lme(rsa_diff ~ task*condition,
                            random = ~1|mother_id,
                            correlation = corSymm(form = ~1|mother_id),
                            data = rsa_trt_data)
summary(model2_corsymm)
nlme::getVarCov(model2_corsymm, individual = 1, type = "marginal")
# MODEL 3: corAR1: autoregressive covariance; assumes covariance decreases
# exp; assumes equal time spacing (violated with different task lengths?)
options(contrasts = c("contr.sum", "contr.poly"))
model3_corar1 <- nlme::lme(rsa_diff ~ task*condition,
                           random = ~1|mother_id,
                           correlation = corAR1(form = ~1|mother_id),
                           data = rsa_trt_data)
summary(model3_corar1)
nlme::anova.lme(model3_corar1, type = "marginal")
emmeans::emmeans(model3_corar1, dunnett ~ task|condition)
emmeans::emmeans(model3_corar1, pairwise ~ condition|task)
AIC(model1_basic, model2_corsymm, model3_corar1)
# diagnostic plot for model 3: autoregressive covariance structure
plot(model3_corar1)
# repeated measures with diff score using other package
model4_diff <- lme4::lmer(rsa_diff ~ condition*task + (1|mother_id),
                          data = rsa_trt_data)
summary(model4_diff)
anova(model4_diff, ddf = "Kenward-Roger")
emmeans::emmeans(model4_diff, pairwise ~ condition|task)
nlme::anova.lme(model3_corar1, type = "marginal")
emmeans::emmeans(model3_corar1, pairwise ~ condition|task)
```