

Feelings_initial

2025-04-13

```
feelings_initial <- load("feelings_initial.RData")
ls()
```

```
## [1] "dat"                "feelings_initial" "Iaro_wide"        "Ineg_wide"
## [5] "Ipos_wide"
```

```
summary(feelings_initial)
```

```
##      Length      Class      Mode
##      4 character character
```

```
str(dat)
```

```
## 'data.frame':   16380 obs. of  9 variables:
## $ subj      : Factor w/ 156 levels "f001","f002",...: 1 1 1 1 1 1 1 1 1 1 ...
## $ trial.num: int   1 2 3 4 5 6 7 8 9 10 ...
## $ trial.val: Factor w/ 3 levels "neg","neu","pos": 3 1 1 3 3 2 2 1 1 3 ...
## $ sex       : Factor w/ 3 levels "male","female",...: 2 2 2 2 2 2 2 2 2 2 ...
## $ age       : int   19 19 19 19 19 19 19 19 19 19 ...
## $ ethn      : Factor w/ 7 levels "Asian or Pacific Islander",...: 1 1 1 1 1 1 1 1 1 1 ...
## $ Ineg      : num   1 4 2 1 1 1 1 3 5 1 ...
## $ Ipos      : num   3.69 1 1 1 4 ...
## $ Iaro      : num   2.86 3 2 2 3 ...
```

Descriptive statistics

```
summary(dat[, c("Ineg", "Ipos", "Iaro")])
```

	Ineg	Ipos	Iaro
## Min.	:1.000	Min. :1.000	Min. :1.000
## 1st Qu.:	:1.000	1st Qu.:1.000	1st Qu.:1.000
## Median :	:2.000	Median :2.000	Median :3.000
## Mean :	:3.075	Mean :3.066	Mean :3.265
## 3rd Qu.:	:5.000	3rd Qu.:5.000	3rd Qu.:5.000
## Max. :	:9.000	Max. :9.000	Max. :9.000

```
# identify NAs
colSums(is.na(dat))
```

```
##      subj trial.num trial.val      sex      age      ethn      Ineg      Ipos
##      0         0         0         0         0         0         0         0
##      Iaro
##      0
```

There are no NAs in the dataset.

```
# identify outliers using z-score

# Calculate Z-scores for Ineg, Ipos, and Iaro
dat$z_Ineg <- scale(dat$Ineg)
dat$z_Ipos <- scale(dat$Ipos)
dat$z_Iaro <- scale(dat$Iaro)

# Identify outliers (Z-score > 3 or < -3)
outliers_Ineg <- dat[abs(dat$z_Ineg) > 3, ]
outliers_Ineg
```

```
## [1] subj      trial.num trial.val sex      age      ethn      Ineg
## [8] Ipos      Iaro      z_Ineg    z_Ipos    z_Iaro
## <0 rows> (or 0-length row.names)
```

```
outliers_Ipos <- dat[abs(dat$z_Ipos) > 3, ]
outliers_Ipos
```

```
## [1] subj      trial.num trial.val sex      age      ethn      Ineg
## [8] Ipos      Iaro      z_Ineg    z_Ipos    z_Iaro
## <0 rows> (or 0-length row.names)
```

```
outliers_Iaro <- dat[abs(dat$z_Iaro) > 3, ]
outliers_Iaro
```

```
## [1] subj      trial.num trial.val sex      age      ethn      Ineg
## [8] Ipos      Iaro      z_Ineg    z_Ipos    z_Iaro
## <0 rows> (or 0-length row.names)
```

There are no outliers.

Linear Mixed Effects Model: analyze data with repeated measures

- Each participant has multiple trials, so the trials within a participant are likely correlated
- Data is nested
- Each participant may have their own baseline level of emotional responses
- fixed effects (trial.val, sex, age, ethn) explain the variation between individuals
- random effects (1|subj) explain the correlation of repeated measures within individuals

How different trial types & demographics affect negative emotional response (Ineg)?

```
library(lme4)
```

```
## Loading required package: Matrix
```

```
# Mixed-effects model for predicting Ineg
```

```
model_ineg <- lmer(Ineg ~ trial.val + sex + age + ethn + (1|subj), data = dat)  
summary(model_ineg)
```

```
## Linear mixed model fit by REML ['lmerMod']
```

```
## Formula: Ineg ~ trial.val + sex + age + ethn + (1 | subj)
```

```
## Data: dat
```

```
##
```

```
## REML criterion at convergence: 58969.5
```

```
##
```

```
## Scaled residuals:
```

```
##      Min       1Q   Median       3Q      Max
```

```
## -3.9915 -0.5714 -0.0487  0.5031  5.6660
```

```
##
```

```
## Random effects:
```

```
## Groups Name Variance Std.Dev.
```

```
## subj (Intercept) 0.5259 0.7252
```

```
## Residual 2.0745 1.4403
```

```
## Number of obs: 16380, groups: subj, 156
```

```
##
```

```
## Fixed effects:
```

```
##
```

	Estimate	Std. Error
(Intercept)	5.218934	0.443816

trial.valneu	-4.076439	0.034381
--------------	-----------	----------

trial.valpos	-4.086175	0.024311
--------------	-----------	----------

sexfemale	0.317543	0.121858
-----------	----------	----------

sexother	-0.031652	0.747300
----------	-----------	----------

age	0.001809	0.021086
-----	----------	----------

ethnBlack/African American	-0.060943	0.237892
----------------------------	-----------	----------

ethnLatino/Hispanic	-0.317652	0.232008
---------------------	-----------	----------

ethnOther	0.138570	0.290750
-----------	----------	----------

ethnWhite/Caucasian	0.070420	0.155354
---------------------	----------	----------

ethnAmerican Indian/Native American or Alaskan Native	-0.692261	0.393608
---	-----------	----------

ethnDecline to state	-0.275510	0.543413
----------------------	-----------	----------

	t value	
--	---------	--

(Intercept)	11.759	
-------------	--------	--

trial.valneu	-118.566	
--------------	----------	--

trial.valpos	-168.079	
--------------	----------	--

sexfemale	2.606	
-----------	-------	--

sexother	-0.042	
----------	--------	--

age	0.086	
-----	-------	--

ethnBlack/African American	-0.256	
----------------------------	--------	--

ethnLatino/Hispanic	-1.369	
---------------------	--------	--

ethnOther	0.477	
-----------	-------	--

ethnWhite/Caucasian	0.453	
---------------------	-------	--

ethnAmerican Indian/Native American or Alaskan Native	-1.759	
---	--------	--

ethnDecline to state	-0.507	
----------------------	--------	--

```
##
```

```
## Correlation of Fixed Effects:
##          (Intr) trl.vln trl.vlp sexfml sexthr age    etB/AA ethL/H ethnOt
## trial.valne -0.019
## trial.valps -0.027  0.354
## sexfemale   -0.197  0.000   0.000
## sexother    -0.070  0.000   0.000   0.084
## age         -0.941  0.000   0.000   0.021  0.059
## ethnBlck/AA -0.026  0.000   0.000   0.072 -0.002 -0.149
## ethnLtn/Hsp  0.065  0.000   0.000   0.072 -0.008 -0.250  0.334
## ethnOther   -0.081  0.000   0.000  -0.044 -0.006 -0.038  0.234  0.244
## ethnWht/Ccs -0.091  0.000   0.000   0.107 -0.062 -0.171  0.468  0.496  0.357
## ethAI/NAoAN -0.141  0.000   0.000   0.123  0.012  0.029  0.176  0.178  0.134
## ethnDclntst -0.067  0.000   0.000   0.144  0.010 -0.027  0.139  0.145  0.096
##          ethW/C eIAoAN
## trial.valne
## trial.valps
## sexfemale
## sexother
## age
## ethnBlck/AA
## ethnLtn/Hsp
## ethnOther
## ethnWht/Ccs
## ethAI/NAoAN  0.271
## ethnDclntst  0.211  0.092
```

- Random effects: each participant has a different baseline emotional response
 - (1|subj): represents the random effect
 - * each participant (subj) has a different baseline deviation (intercept).
 - * This accounts for the correlation between multiple trial results from the same participant
- REML score (residual maximum likelihood estimate): assess the model fit
- Fixed Effects:
 - Intercept: Negative trial
 - trial.valneu (Neutral trial): Estimate = -4.08, t = -118.57, a very significant negative value.
 - * Compared to the baseline (negative trial), the neutral trial significantly decreases negative emotions (Ineg)
 - trial.valpos (Positive trial): Estimate = -4.09, t = -168.08, also significant.
 - * the positive trial also significantly decreases negative emotions compared to the negative trial
 - sexfemale: Estimate = 0.317543, t = 2.606.
 - * Females have significantly higher negative emotional responses (Ineg) compared to males
 - The effects of age and ethnicity are small and not significant

How different trial types & demographics affect positive emotional response (Ipos)?

```
# Mixed-effects model for predicting Ipos
model_ipos <- lmer(Ipos ~ trial.val + sex + age + ethn + (1|subj), data = dat)
summary(model_ipos)
```

```

## Linear mixed model fit by REML ['lmerMod']
## Formula: Ipos ~ trial.val + sex + age + ethn + (1 | subj)
## Data: dat
##
## REML criterion at convergence: 60034.7
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -3.8302 -0.5834 -0.0294  0.5335  5.4659
##
## Random effects:
## Groups Name Variance Std.Dev.
## subj (Intercept) 0.5687 0.7541
## Residual 2.2138 1.4879
## Number of obs: 16380, groups: subj, 156
##
## Fixed effects:
##
## Estimate Std. Error
## (Intercept) 0.71768 0.46141
## trial.valneu 0.33658 0.03552
## trial.valpos 4.03432 0.02511
## sexfemale 0.20020 0.12669
## sexother -1.13135 0.77693
## age 0.02213 0.02192
## ethnBlack/African American 0.08731 0.24732
## ethnLatino/Hispanic -0.33718 0.24121
## ethnOther -0.01740 0.30228
## ethnWhite/Caucasian 0.13375 0.16151
## ethnAmerican Indian/Native American or Alaskan Native -0.93997 0.40921
## ethnDecline to state -0.33289 0.56496
## t value
## (Intercept) 1.555
## trial.valneu 9.477
## trial.valpos 160.642
## sexfemale 1.580
## sexother -1.456
## age 1.010
## ethnBlack/African American 0.353
## ethnLatino/Hispanic -1.398
## ethnOther -0.058
## ethnWhite/Caucasian 0.828
## ethnAmerican Indian/Native American or Alaskan Native -2.297
## ethnDecline to state -0.589
##
## Correlation of Fixed Effects:
## (Intr) trl.vln trl.vlp sexfml sexthr age etB/AA ethL/H ethnOt
## trial.valne -0.019
## trial.valps -0.027 0.354
## sexfemale -0.197 0.000 0.000
## sexother -0.070 0.000 0.000 0.084
## age -0.941 0.000 0.000 0.021 0.059
## ethnBlck/AA -0.026 0.000 0.000 0.072 -0.002 -0.149
## ethnLtn/Hsp 0.065 0.000 0.000 0.072 -0.008 -0.250 0.334
## ethnOther -0.081 0.000 0.000 -0.044 -0.006 -0.038 0.234 0.244

```

```
## ethnWht/Ccs -0.091  0.000  0.000  0.107 -0.062 -0.171  0.468  0.496  0.357
## ethAI/NAoAN -0.141  0.000  0.000  0.123  0.012  0.029  0.176  0.178  0.134
## ethnDclntst -0.067  0.000  0.000  0.144  0.010 -0.027  0.139  0.145  0.096
##          ethW/C eIAoAN
## trial.valne
## trial.valps
## sexfemale
## sexother
## age
## ethnBlck/AA
## ethnLtn/Hsp
## ethnOther
## ethnWht/Ccs
## ethAI/NAoAN  0.271
## ethnDclntst  0.211  0.092
```

- Intercept (negative trial): estimate = 0.72, t-value = 1.56. The effect of negative trial on positive emotions (Ipos) is small.
- trial.valneu: estimate = 0.34, t-value = 9.48. Compared to valneg, the neutral trial significantly increases positive emotions (Ipos).
- trial.valpos: estimate = 4.03, t-value = 160.64. Compared to valneg, the positive trial largely increases positive emotions (Ipos), and the effect is extremely significant.
- sexfemale: estimate = 0.20, t = 1.58. Females tend to have slightly higher positive emotional responses than males.
- ethnAmerican Indian/Native American or Alaskan Native: estimate = -0.94, t = -2.30. This ethnicity tends to have significantly lower positive emotional responses compared to the reference group.
- trial.valneu and trial.valpos have a correlation of 0.354, showing that the effects of neutral and positive trials are somewhat related.

How different trial types & demographics affect arousal emotional response (Iaro)?

```
# Mixed-effects model for predicting Iaro
model_aro <- lmer(Iaro ~ trial.val + sex + age + ethn + (1|subj), data = dat)
summary(model_aro)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: Iaro ~ trial.val + sex + age + ethn + (1 | subj)
## Data: dat
##
## REML criterion at convergence: 59841.3
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -4.4843 -0.6288 -0.1072  0.5760  4.8022
##
## Random effects:
## Groups Name Variance Std.Dev.
## subj (Intercept) 1.593 1.262
## Residual 2.168 1.472
## Number of obs: 16380, groups: subj, 156
##
```

```

## Fixed effects:
##
##               Estimate Std. Error
## (Intercept)      2.92802    0.76311
## trial.valneu     -2.25913    0.03515
## trial.valpos     -0.30058    0.02485
## sexfemale         0.22642    0.20959
## sexother        -1.53358    1.28529
## age               0.02904    0.03627
## ethnBlack/African American  0.22313    0.40915
## ethnLatino/Hispanic  0.12385    0.39903
## ethnOther         0.52839    0.50007
## ethnWhite/Caucasian  0.06932    0.26720
## ethnAmerican Indian/Native American or Alaskan Native -0.85245    0.67697
## ethnDecline to state  0.07313    0.93462
##
##               t value
## (Intercept)       3.837
## trial.valneu     -64.279
## trial.valpos     -12.095
## sexfemale         1.080
## sexother        -1.193
## age               0.801
## ethnBlack/African American  0.545
## ethnLatino/Hispanic  0.310
## ethnOther         1.057
## ethnWhite/Caucasian  0.259
## ethnAmerican Indian/Native American or Alaskan Native -1.259
## ethnDecline to state  0.078
##
## Correlation of Fixed Effects:
##      (Intr) trl.vln trl.vlp sexfml sexthr age  etB/AA ethL/H ethnOt
## trial.valne -0.012
## trial.valps -0.016  0.354
## sexfemale   -0.197  0.000  0.000
## sexother    -0.070  0.000  0.000  0.084
## age         -0.942  0.000  0.000  0.021  0.059
## ethnBlck/AA -0.026  0.000  0.000  0.072 -0.002 -0.149
## ethnLtn/Hsp  0.065  0.000  0.000  0.072 -0.008 -0.250  0.334
## ethnOther    -0.081  0.000  0.000 -0.044 -0.006 -0.038  0.234  0.244
## ethnWht/Ccs  -0.091  0.000  0.000  0.107 -0.062 -0.171  0.468  0.496  0.357
## ethAI/NAoAN -0.141  0.000  0.000  0.123  0.012  0.029  0.176  0.178  0.134
## ethnDclntst -0.067  0.000  0.000  0.144  0.010 -0.027  0.139  0.145  0.096
##      ethW/C eIAoAN
## trial.valne
## trial.valps
## sexfemale
## sexother
## age
## ethnBlck/AA
## ethnLtn/Hsp
## ethnOther
## ethnWht/Ccs
## ethAI/NAoAN  0.271
## ethnDclntst  0.211  0.092

```

- Intercept (negative trial): estimate = 2.93, t-value = 3.84. The effect of negative trial on arousal (Iaro) is moderate.
- `trial.valneu`: estimate -2.26, t-value = -64.28. Compared to `valneg`, the neutral trial significantly decreases arousal (Iaro), which can be expected.
- `trial.valpos`: estimate = -0.30, t-value = -12.10. Compared to `valneg`, the positive trial also significantly decreases arousal (Iaro), but the effect is small.
- Other fixed effects are not significant.

Autoregressive Modeling

Assign 1 overall inertia score for pos, neg, and aro for each participant:

```
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(purrr)
library(broom)

# Create a function to return inertia (lag-1 beta value)
get_inertia <- function(x) {
  # Create lagged data
  lag_x <- dplyr::lag(x)
  df <- data.frame(current = x, lagged = lag_x)
  df <- na.omit(df)

  # Linear regression: current ~ lagged
  model <- lm(current ~ lagged, data = df)
  coef(model)["lagged"]
}

# find inertia scores for the 3 emotions for each participant
overall_inertia <- dat %>%
  group_by(subj) %>%
  summarise(
    pos_inertia = get_inertia(Ipos),
    neg_inertia = get_inertia(Ineg),
    aro_inertia = get_inertia(Iaro)
  )
overall_inertia

## # A tibble: 156 x 4
```



```
##      subj pos_inertia neg_inertia aro_inertia
##      <fct>      <dbl>      <dbl>      <dbl>
##  1 f001      -0.0956      -0.149      -0.139
##  2 f002       0.0187       0.0682       0.0974
##  3 f003      -0.0855      -0.143       0.0149
##  4 f004       0.0648      -0.0705       0.0150
##  5 f005      -0.0433      -0.0918      -0.0962
##  6 f006      -0.0750       0.160       0.175
##  7 f007       0.0834       0.0245       0.190
##  8 f008      -0.0125      -0.0254       0.00949
##  9 f009       0.0162       0.0865      -0.136
## 10 f010       0.164       0.110       0.0143
## # i 146 more rows
```

For each of the 3 emotional reactions (pos, neg, aro), assign 1 inertia score for each of the 3 trial type (pos, neg, neu)

```
library(tidyr)
```

```
##
## Attaching package: 'tidyr'
```

```
## The following objects are masked from 'package:Matrix':
##
##      expand, pack, unpack
```

```
# For each subj x trial.val x emotion
inertia_long <- dat %>%
  group_by(subj, trial.val) %>%
  summarise(
    pos_inertia = get_inertia(Ipos),
    neg_inertia = get_inertia(Ineg),
    aro_inertia = get_inertia(Iaro),
    .groups = "drop"
  )

# Reshape into wide format: 1 row per participant, 9 inertia scores
inertia_wide <- inertia_long %>%
  pivot_wider(
    names_from = trial.val,
    values_from = c(pos_inertia, neg_inertia, aro_inertia),
    names_glue = "{.value}_{trial.val}"
  )

inertia_wide
```

```
## # A tibble: 156 x 10
##      subj pos_inertia_neg pos_inertia_neu pos_inertia_pos neg_inertia_neg
##      <fct>      <dbl>      <dbl>      <dbl>      <dbl>
##  1 f001      -0.0233       NA       0.0214      -0.203
##  2 f002      -0.0233      -0.115     -0.00418     0.376
##  3 f003       0.131      -0.0939     -0.127     -0.106
```

```
## 4 f004      -0.0732      -0.0111      0.196      0.0689
## 5 f005       0.223      -0.0769      0.0571      0.107
## 6 f006      -0.0883      -0.161      0.239      0.416
## 7 f007      -0.0233      -0.0888      0.0636      0.191
## 8 f008       0.0422      -0.247      0.0363     -0.174
## 9 f009      -0.0560      0.0590      0.0652      0.0603
## 10 f010     -0.0233      0.0577      0.199      0.220
## # i 146 more rows
## # i 5 more variables: neg_inertia_neu <dbl>, neg_inertia_pos <dbl>,
## #   aro_inertia_neg <dbl>, aro_inertia_neu <dbl>, aro_inertia_pos <dbl>
```

```
# Find the reason of NAs
```

```
# Whether there's not enough data for each subj × trial.val group?
```

```
dat %>%
  group_by(subj, trial.val) %>%
  summarise(n = n()) %>%
  filter(n < 5)
```

```
## 'summarise()' has grouped output by 'subj'. You can override using the
## '.groups' argument.
```

```
## # A tibble: 0 x 3
## # Groups:   subj [0]
## # i 3 variables: subj <fct>, trial.val <fct>, n <int>
```

```
# Whether some emotion ratings for certain trial type are always the same?
```

```
dat %>%
  group_by(subj, trial.val) %>%
  summarise(
    Ineg_var = var(Ineg),
    Ipos_var = var(Ipos),
    Iaro_var = var(Iaro)
  ) %>%
  filter(Ineg_var == 0 | Ipos_var == 0 | Iaro_var == 0)
```

```
## 'summarise()' has grouped output by 'subj'. You can override using the
## '.groups' argument.
```

```
## # A tibble: 106 x 5
## # Groups:   subj [80]
##   subj trial.val Ineg_var Ipos_var Iaro_var
##   <fct> <fct>      <dbl>   <dbl>   <dbl>
## 1 f001 neu         0      0.267  0.352
## 2 f001 pos         0      1.61   1.08
## 3 f002 neu         0      1.26   1.35
## 4 f002 pos         0      1.51   1.14
## 5 f005 neu         0      0.267  0.0667
## 6 f007 neu         0      0.0663  0
## 7 f007 pos         0      0.786  0.382
```

```
## 8 f013 neu 0 0.0659 0
## 9 f019 neu 0.124 4.92 0
## 10 f020 neu 0 2.52 1.55
## # i 96 more rows
```

- The reason of NAs is not due to insufficient data for each $\text{subj} \times \text{trial.val}$ group
- NAs are also not likely to be caused by zero-variance of some emotion inertia ratings, since NAs from `inertia_wide` are more than the number of $\text{Var} = 0$.

```
# Merge all inertia scores (by subj)
inertia_all <- overall_inertia %>%
  left_join(inertia_wide, by = "subj")
inertia_all
```

```
## # A tibble: 156 x 13
##   subj pos_inertia neg_inertia aro_inertia pos_inertia_neg pos_inertia_neu
##   <fct>      <dbl>      <dbl>      <dbl>      <dbl>      <dbl>
## 1 f001    -0.0956    -0.149    -0.139    -0.0233      NA
## 2 f002     0.0187     0.0682     0.0974    -0.0233    -0.115
## 3 f003    -0.0855    -0.143     0.0149     0.131    -0.0939
## 4 f004     0.0648    -0.0705     0.0150    -0.0732    -0.0111
## 5 f005    -0.0433    -0.0918    -0.0962     0.223    -0.0769
## 6 f006    -0.0750     0.160     0.175    -0.0883    -0.161
## 7 f007     0.0834     0.0245     0.190    -0.0233    -0.0888
## 8 f008    -0.0125    -0.0254     0.00949    0.0422    -0.247
## 9 f009     0.0162     0.0865    -0.136    -0.0560     0.0590
## 10 f010     0.164     0.110     0.0143    -0.0233     0.0577
## # i 146 more rows
## # i 7 more variables: pos_inertia_pos <dbl>, neg_inertia_neg <dbl>,
## #   neg_inertia_neu <dbl>, neg_inertia_pos <dbl>, aro_inertia_neg <dbl>,
## #   aro_inertia_neu <dbl>, aro_inertia_pos <dbl>
```

```
library(ggplot2)
library(dplyr)
library(tidyr)
library(e1071) # for skewness
library(psych) # for describe()
```

```
##
## Attaching package: 'psych'
```

```
## The following objects are masked from 'package:ggplot2':
##
##   %>%, alpha
```

```
# Convert to inertia_long format
inertia_long <- inertia_all %>%
  pivot_longer(-subj, names_to = "inertia_type", values_to = "inertia")

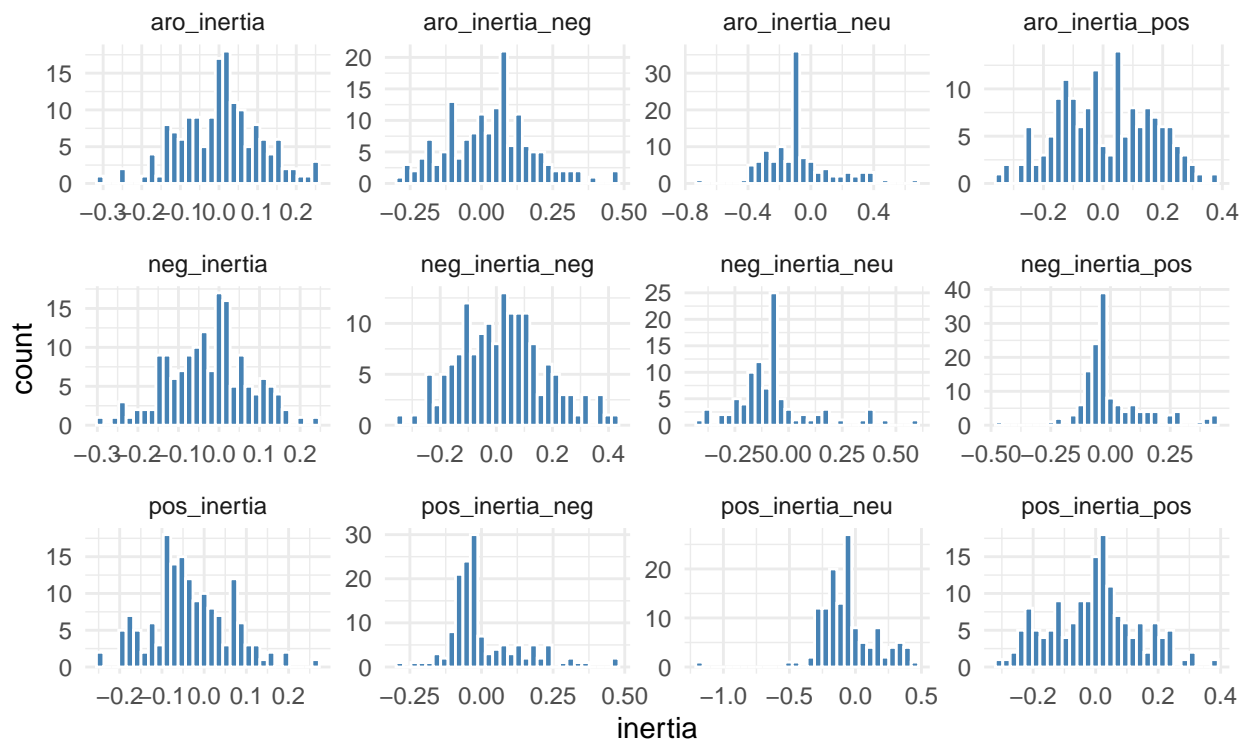
# Distribution & Skewness
inertia_long %>%
  group_by(inertia_type) %>%
```

```
mutate(
  skew = skewness(inertia, na.rm = TRUE),
  normality_p = shapiro.test(inertia)$p.value
) %>%
ggplot(aes(x = inertia)) +
geom_histogram(bins = 30, fill = "steelblue", color = "white") +
facet_wrap(~ inertia_type, scales = "free") +
theme_minimal() +
labs(title = "Histogram of Inertia Scores across Participants",
      subtitle = "Check for skewness & normality visually")
```

```
## Warning: Removed 159 rows containing non-finite outside the scale range
## ('stat_bin()').
```

Histogram of Inertia Scores across Participants

Check for skewness & normality visually



```
# describe_stats for all 3 + 9 = 12 types of inertia
describe_stats <- inertia_long %>%
  group_by(inertia_type) %>%
  summarise(
    n = sum(!is.na(inertia)),
    sd = sd(inertia, na.rm = TRUE),
    Q1 = quantile(inertia, 0.25, na.rm = TRUE),
    Q3 = quantile(inertia, 0.75, na.rm = TRUE),
    skewness = skewness(inertia, na.rm = TRUE),
    normality_p = shapiro.test(inertia)$p.value
```

```
)
describe_stats
```

```
## # A tibble: 12 x 7
##   inertia_type      n      sd      Q1      Q3 skewness normality_p
##   <chr>      <int> <dbl> <dbl> <dbl> <dbl> <dbl>
## 1 aro_inertia    156 0.103 -0.0630 0.0666 -0.0809 6.10e- 1
## 2 aro_inertia_neg 156 0.150 -0.0772 0.124 0.230 1.39e- 1
## 3 aro_inertia_neu 117 0.208 -0.182 -0.00947 0.715 3.86e- 5
## 4 aro_inertia_pos 154 0.157 -0.117 0.134 0.0368 1.11e- 1
## 5 neg_inertia    156 0.0998 -0.0890 0.0316 -0.120 8.17e- 1
## 6 neg_inertia_neg 156 0.151 -0.0928 0.117 0.253 4.16e- 1
## 7 neg_inertia_neu 95 0.177 -0.166 -0.0635 1.30 1.30e- 7
## 8 neg_inertia_pos 141 0.139 -0.0694 0.0458 1.08 6.69e-10
## 9 pos_inertia    156 0.0927 -0.0889 0.0276 0.290 2.67e- 1
## 10 pos_inertia_neg 140 0.129 -0.0691 0.0479 1.27 2.32e- 9
## 11 pos_inertia_neu 130 0.216 -0.167 0.0242 -0.399 8.44e- 8
## 12 pos_inertia_pos 156 0.141 -0.119 0.0684 0.0816 1.17e- 1
```

Inertia scores that are not normal:

- neg_inertia_pos: normality_p = 6.689087e-10; skewness = 1.07982750
 - Under positive stimuli, negative emotion inertia is right-skewed: a few individuals have unusually persistent negative emotions
- pos_inertia_neg: normality_p = 2.318693e-09; skewness = 1.27067898
 - Under negative stimuli, positive emotion inertia is strongly right-skewed: most people have low inertia in positive feelings, with a few showing strong inertia
- pos_inertia_neu: normality_p = 8.436415e-08; skewness = -0.39896752
 - For neutral stimuli, positive emotion inertia is slightly left-skewed
- neg_inertia_neu: normality_p = 1.296106e-07; skewness = 1.29575508
 - For neutral stimuli, negative emotion inertia is strongly right-skewed
- aro_inertia_neu: normality_p = 3.859573e-05; skewness = 0.71497318
 - For neutral stimuli, arousal inertia is right-skewed

Normalize the skewed inertia types

```
# Transform the skewed inertia types to normal
library(bestNormalize)

skewed_vars <- c(
  "neg_inertia_pos", "pos_inertia_neg", "pos_inertia_neu",
  "neg_inertia_neu", "aro_inertia_neu"
)

inertia_long_normalized <- inertia_long %>%
  group_by(inertia_type) %>%
```

```
mutate(
  inertia_trans = if_else(
    inertia_type %in% skewed_vars,
    orderNorm(inertia)$x.t, # transform only these
    inertia # leave others unchanged
  )
)
```

```
## Warning: There were 6 warnings in 'mutate()'.
## The first warning was:
## i In argument: 'inertia_trans = if_else(...)'.
## i In group 3: 'inertia_type = "aro_inertia_neu"'.
## Caused by warning in 'orderNorm()':
## ! Ties in data, Normal distribution not guaranteed
## i Run 'dplyr::last_dplyr_warnings()' to see the 5 remaining warnings.
```

```
inertia_long_normalized
```

```
## # A tibble: 1,872 x 4
## # Groups:   inertia_type [12]
##   subj inertia_type inertia inertia_trans
##   <fct> <chr>          <dbl>         <dbl>
## 1 f001 pos_inertia   -0.0956      -0.0956
## 2 f001 neg_inertia   -0.149       -0.149
## 3 f001 aro_inertia   -0.139       -0.139
## 4 f001 pos_inertia_neg -0.0233      0.244
## 5 f001 pos_inertia_neu NA            NA
## 6 f001 pos_inertia_pos 0.0214       0.0214
## 7 f001 neg_inertia_neg -0.203       -0.203
## 8 f001 neg_inertia_neu NA            NA
## 9 f001 neg_inertia_pos NA            NA
## 10 f001 aro_inertia_neg -0.187      -0.187
## # i 1,862 more rows
```

Compare means of the 12 inertia types

```
# Find mean value of each of the 12 inertia types

inertia_means <- inertia_long_normalized %>%
  group_by(inertia_type) %>%
  summarise(
    mean_inertia = mean(inertia_trans, na.rm = TRUE),
    sd_inertia = sd(inertia_trans, na.rm = TRUE),
    n = sum(!is.na(inertia_trans))
  ) %>%
  arrange(desc(abs(mean_inertia)))

inertia_means
```

```
## # A tibble: 12 x 4
```

##	inertia_type	mean_inertia	sd_inertia	n
##	<chr>	<dbl>	<dbl>	<int>
## 1	pos_inertia	-0.0324	0.0927	156
## 2	aro_inertia_neg	0.0308	0.150	156
## 3	neg_inertia	-0.0244	0.0998	156
## 4	neg_inertia_neg	0.0242	0.151	156
## 5	aro_inertia_pos	0.00693	0.157	154
## 6	pos_inertia_pos	-0.00589	0.141	156
## 7	aro_inertia	0.00482	0.103	156
## 8	neg_inertia_neu	-0.0000523	0.998	95
## 9	aro_inertia_neu	-0.0000440	0.998	117
## 10	pos_inertia_neg	-0.0000328	0.999	140
## 11	neg_inertia_pos	-0.00000932	0.999	141
## 12	pos_inertia_neu	0.0000000373	0.999	130

- aro_inertia_neu: Extremely high SD (0.998) — suggests arousal inertia under neutral stimuli varies greatly across individuals
- neg_inertia (mean = -0.024): Negative emotion inertia is slightly negative, meaning negative emotion is not likely to last
- neg_inertia_pos: Negative near-zero mean (-9.32×10^{-6}) but very high variance (sd = 0.999);
 - Negative emotion is likely to bounce back after positive stimuli, but the effect is extremely small
 - There's huge individual differences
- pos_inertia_neg: Negative near-zero mean (-3.28×10^{-5}) but very high variance (sd = 0.999);
 - Positive emotion is likely to bounce back after negative stimuli, but the effect is also small
 - There's huge individual differences
- pos_inertia (mean = -0.032): negative mean — indicates that positive emotions tend to drop off quickly
- aro_inertia_neg (mean = 0.031): clear positive inertia — arousal tends to linger more after negative stimuli
- neg_inertia_neg (mean = 0.024): negative emotions tend to persist more after negative trials
- **neg_inertia (mean = -0.024) vs. pos_inertia (mean = -0.032):**
 - **neg_inertia is bigger than pos_inertia, meaning that negative emotions tend to last longer**
 - Positive emotions bounce back faster than negative emotions
- **neg_inertia_pos (mean = -9.32×10^{-6}) vs. pos_inertia_neg (-3.28×10^{-5}):**
 - **Emotions tend to reset quickly when the stimulus is the opposite, meaning that people are likely to be affected by opposite stimuli**
 - **Positive emotions may dissipate faster in response to negative stimuli than negative emotions do in response to positive ones (positive emotion is more likely to be affected by negative stimuli)**

Compare emotional inertia types (pos_inertia, neg_inertia, aro_inertia) by demographics

```
# Pivot transformed inertia data to wide format
```

```
inertia_wide_trans <- inertia_long_normalized %>%
  select(subj, inertia_type, inertia_trans) %>%
  tidyr::pivot_wider(
    names_from = inertia_type,
    values_from = inertia_trans
  )
```

```
# Extract demographic info from your original dat
```

```
demo_info <- dat %>%
  select(subj, sex, age, ethn) %>%
  distinct()
```

```
# Merge the transformed inertia data with demographics
```

```
inertia_full <- inertia_wide_trans %>%
  left_join(demo_info, by = "subj")
inertia_full
```

```
## # A tibble: 156 x 16
```

	subj	pos_inertia	neg_inertia	aro_inertia	pos_inertia_neg	pos_inertia_neu
	<fct>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
##	1 f001	-0.0956	-0.149	-0.139	0.244	NA
##	2 f002	0.0187	0.0682	0.0974	0.244	-0.184
##	3 f003	-0.0855	-0.143	0.0149	0.935	-0.145
##	4 f004	0.0648	-0.0705	0.0150	-0.779	0.535
##	5 f005	-0.0433	-0.0918	-0.0962	1.49	0.0579
##	6 f006	-0.0750	0.160	0.175	-1.08	-0.581
##	7 f007	0.0834	0.0245	0.190	0.244	-0.0869
##	8 f008	-0.0125	-0.0254	0.00949	0.641	-1.10
##	9 f009	0.0162	0.0865	-0.136	-0.434	0.724
##	10 f010	0.164	0.110	0.0143	0.244	0.699

```
## # i 146 more rows
```

```
## # i 10 more variables: pos_inertia_pos <dbl>, neg_inertia_neg <dbl>,
## #   neg_inertia_neu <dbl>, neg_inertia_pos <dbl>, aro_inertia_neg <dbl>,
## #   aro_inertia_neu <dbl>, aro_inertia_pos <dbl>, sex <fct>, age <int>,
## #   ethn <fct>
```

```
# Inertia types by Sex / Ethnicity (categorical)
```

```
# By sex
```

```
inertia_full %>%
  group_by(sex) %>%
  summarise(across(starts_with("pos_inertia"):starts_with("aro_inertia"), ~mean(., na.rm = TRUE)))
```

```
## Warning: There was 1 warning in 'summarise()'.
## i In argument: 'across(...)'.
```

```
## Caused by warning in 'x:y':
```

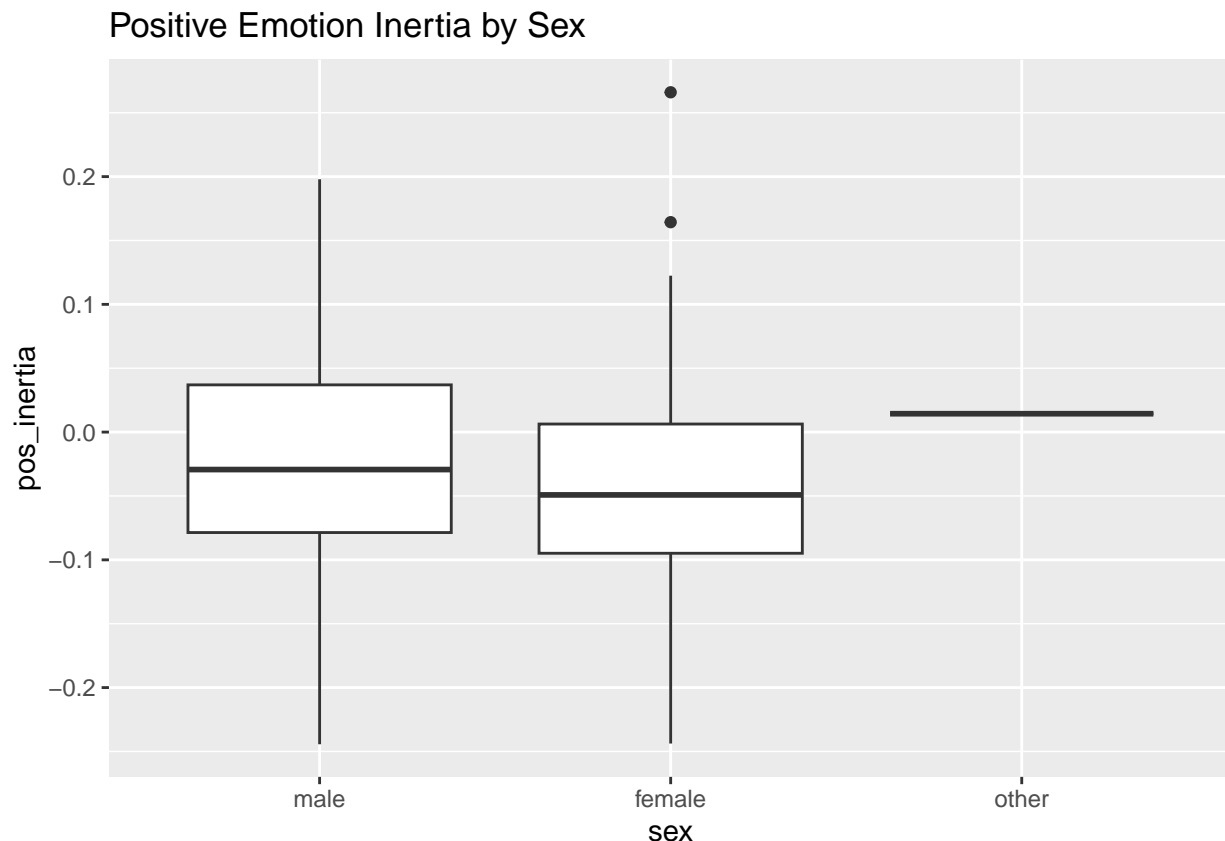
```
## ! numerical expression has 4 elements: only the first used
```

```
## # A tibble: 3 x 4
```



```
##   sex    pos_inertia neg_inertia aro_inertia
##   <fct>      <dbl>      <dbl>      <dbl>
## 1 male      -0.0206     -0.0241     -0.0107
## 2 female    -0.0432     -0.0245      0.0188
## 3 other      0.0144     -0.0339     -0.0359
```

```
# Visualize
ggplot(inertia_full, aes(x = sex, y = pos_inertia)) +
  geom_boxplot() +
  labs(title = "Positive Emotion Inertia by Sex")
```



- Females have much lower positive inertia (-0.043) than males (-0.021) -> quicker drop in positive feelings
- Females have higher arousal inertia (0.019) than males (-0.011) -> more sustained arousal
- It's surprising that neg_inertia is about the same for male and female, considering that females are twice as likely as males to get depression based on reports

```
# By ethnicity
inertia_full %>%
  group_by(ethn) %>%
  summarise(across(starts_with("pos_inertia"):starts_with("aro_inertia"), ~mean(., na.rm = TRUE)))
```

```
## Warning: There was 1 warning in 'summarise()'.
## i In argument: 'across(...)'.
## Caused by warning in 'x:y':
## ! numerical expression has 4 elements: only the first used
```

```
## # A tibble: 7 x 4
##   ethn                                pos_inertia neg_inertia aro_inertia
##   <fct>                                <dbl>      <dbl>      <dbl>
## 1 Asian or Pacific Islander          -0.0460    -0.0169     0.00867
## 2 Black/African American              0.00711    -0.0267    -0.00710
## 3 Latino/Hispanic                    -0.0172    -0.0306     0.00750
## 4 Other                              -0.0102    -0.0207     0.0640
## 5 White/Caucasian                    -0.0373    -0.0327    -0.00488
## 6 American Indian/Native American or Alaska~ -0.0393     0.0856     0.0272
## 7 Decline to state                    -0.0831     0.00606    0.0983
```

- American Indian/Native American or Alaskan Native: the only group with positive neg_inertia -> tend to stay in negative states longer
- Black/African American: the only group with pos_inertia -> tend to stay in positive states longer (which is unexpected)
- White/Caucasian: the only group with negative inertia across all three emotions -> tend to bounce back quickly overall (emotionally adaptive).
 - This may reflect greater access to resources, social safety nets, and less exposure to systemic stressors for White people.
- Both “Other” and “Decline to state” have much higher aro_inertia than others.
 - This may suggest that the people who are less confident or more confused about their identities are likely to face heightened stress, social vigilance, or lack of belonging—all known to elevate arousal.

```
# Inertia types by Age (continuous)
```

```
inertia_full %>%
  summarise(across(
    starts_with("pos_inertia"):starts_with("aro_inertia"),
    ~ cor(., age, use = "complete.obs")
  ))
```

```
## Warning: There was 1 warning in 'summarise()'.
## i In argument: 'across(...)'.
## Caused by warning in 'x:y':
## ! numerical expression has 4 elements: only the first used
```

```
## # A tibble: 1 x 3
##   pos_inertia neg_inertia aro_inertia
##   <dbl>      <dbl>      <dbl>
## 1    -0.0107    -0.128     0.0286
```

- As age increases, neg_inertia (-0.128) decreases more than pos_inertia (-0.011).
 - Negative emotions drop significantly faster with increasing age -> **older participants are more resilient to negative emotions**
- Arousal shows a slight increase with age (0.029)

Compare the effect of inertia types (pos, neg, neu) by demographics

```
# By sex
inertia_full %>%
  group_by(sex) %>%
  summarise(across(("pos_inertia_neg"):(("aro_inertia_pos")), ~ mean(., na.rm = TRUE)))
```

```
## # A tibble: 3 x 10
##   sex      pos_inertia_neg pos_inertia_neu pos_inertia_pos neg_inertia_neg
##   <fct>          <dbl>          <dbl>          <dbl>          <dbl>
## 1 male           0.126          -0.0479         -0.000842         0.0250
## 2 female        -0.0984           0.0620         -0.0106         0.0239
## 3 other         -0.881          -1.51           0.0190         0.00201
## # i 5 more variables: neg_inertia_neu <dbl>, neg_inertia_pos <dbl>,
## #   aro_inertia_neg <dbl>, aro_inertia_neu <dbl>, aro_inertia_pos <dbl>
```

- pos_inertia_neg: male(0.1255) vs. female(-0.0984)
 - Females tend to lose positive emotions quickly in response to negative stimuli
- neg_inertia_pos: male (-0.0489) vs. female(0.0297)
 - Females are more likely to retain negative emotions even with positive stimuli -> showing difficulty to let go of negativity
- This may partly explain why females are more likely to get depression
- Female: pos_inertia = -0.0432 vs. pos_inertia_neu = 0.0620
 - It's weird that pos_inertia shows that females generally lose positive emotions quickly, but pos_inertia_neu shows that females tend to retain positive emotions under neutral stimuli

```
# by age
inertia_full %>%
  summarise(across(("pos_inertia_neg"):(("aro_inertia_pos")), ~ cor(., age, use = "complete.obs")))
```

```
## # A tibble: 1 x 9
##   pos_inertia_neg pos_inertia_neu pos_inertia_pos neg_inertia_neg
##   <dbl>          <dbl>          <dbl>          <dbl>
## 1      -0.0459         -0.196           0.0220         0.0270
## # i 5 more variables: neg_inertia_neu <dbl>, neg_inertia_pos <dbl>,
## #   aro_inertia_neg <dbl>, aro_inertia_neu <dbl>, aro_inertia_pos <dbl>
```

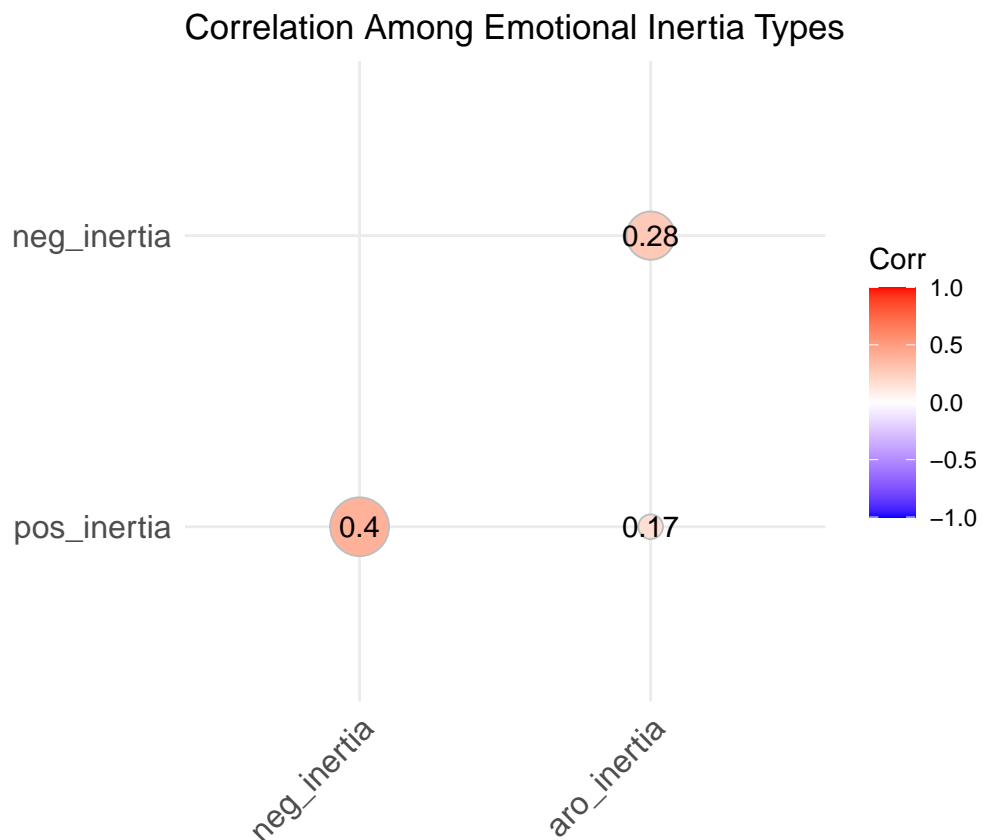
Correlation between inertia types

```
inertia_core <- inertia_full %>%
  select(subj, pos_inertia, neg_inertia, aro_inertia)
cor_matrix <- cor(inertia_core[, -1], use = "complete.obs")
cor_matrix
```

```
##           pos_inertia neg_inertia aro_inertia
## pos_inertia  1.0000000  0.4013880  0.1681746
## neg_inertia  0.4013880  1.0000000  0.2784501
## aro_inertia  0.1681746  0.2784501  1.0000000
```

```
library(ggcorrplot)

ggcorrplot(cor_matrix,
  method = "circle",
  type = "lower",
  lab = TRUE,
  title = "Correlation Among Emotional Inertia Types")
```



- pos_inertia and neg_inertia have moderate positive correlation: people who tend to hold onto positive emotions also tend to hold onto negative emotions, suggesting emotional stickiness
- aro_inertia and neg_inertia have small-to-moderate positive correlation: those who hold onto negative emotions also tend to stay aroused longer

Manova: inertia types by sex

How different inertia types (pos_inertia, neg_inertia, aro_inertia) vary by sex?

```
manova_model <- manova(cbind(pos_inertia, neg_inertia, aro_inertia) ~ sex, data = inertia_full)
summary(manova_model, test = "Wilks")
```

```
##           Df    Wilks approx F num Df den Df Pr(>F)
## sex       2 0.95394   1.2009      6    302 0.3056
## Residuals 153
```

- Wilks' Lambda = 0.954 -> near 1, meaning the difference is small
- P-value = 0.3056, which is not significant
- Conclusion: **the difference of pos_inertia, neg_inertia, aro_inertia between sex is not significant**

Test each inertia type separately:

```
summary.aov(manova_model)
```

```
## Response pos_inertia :
##           Df    Sum Sq   Mean Sq F value Pr(>F)
## sex       2 0.02199 0.0109960   1.2839 0.2799
## Residuals 153 1.31040 0.0085647
##
## Response neg_inertia :
##           Df    Sum Sq   Mean Sq F value Pr(>F)
## sex       2 0.0001 0.0000492   0.0049 0.9951
## Residuals 153 1.5448 0.0100965
##
## Response aro_inertia :
##           Df    Sum Sq   Mean Sq F value Pr(>F)
## sex       2 0.0353 0.017652   1.6816 0.1895
## Residuals 153 1.6061 0.010497
```

- Also shows not significant for each of the 3 inertia types

CLPM

Estimate inertia score of positive, negative, and arousal emotions

```
library(lavaan)
```

```
## This is lavaan 0.6-19
## lavaan is FREE software! Please report any bugs.

##
## Attaching package: 'lavaan'

## The following object is masked from 'package:psych':
##
##     cor2cov
```

```

library(dplyr)

clpm_data <- dat %>%
  arrange(subj, trial.num) %>%
  group_by(subj) %>%
  mutate(
    Ipos_lag1 = lag(Ipos),
    Ineg_lag1 = lag(Ineg),
    Iaro_lag1 = lag(Iaro)
  ) %>%
  filter(!is.na(Ipos_lag1))

model_inertia <- '
# Autoregressive (inertia) paths
Ipos ~ a1 * Ipos_lag1
Ineg ~ a2 * Ineg_lag1
Iaro ~ a3 * Iaro_lag1
'

fit <- sem(model_inertia, data = clpm_data)
summary(fit, standardized = TRUE, fit.measures = TRUE)

```

```

## lavaan 0.6-19 ended normally after 28 iterations
##
##      Estimator                      ML
##      Optimization method          NLMINB
##      Number of model parameters          9
##
##      Number of observations          16224
##
## Model Test User Model:
##
##      Test statistic          1402.952
##      Degrees of freedom          6
##      P-value (Chi-square)          0.000
##
## Model Test Baseline Model:
##
##      Test statistic          17555.797
##      Degrees of freedom          12
##      P-value          0.000
##
## User Model versus Baseline Model:
##
##      Comparative Fit Index (CFI)          0.920
##      Tucker-Lewis Index (TLI)          0.841
##
## Loglikelihood and Information Criteria:
##
##      Loglikelihood user model (H0)          -103647.128
##      Loglikelihood unrestricted model (H1)          -102945.652
##
##      Akaike (AIC)          207312.257

```

```

## Bayesian (BIC) 207381.505
## Sample-size adjusted Bayesian (SABIC) 207352.904
##
## Root Mean Square Error of Approximation:
##
## RMSEA 0.120
## 90 Percent confidence interval - lower 0.115
## 90 Percent confidence interval - upper 0.125
## P-value H_0: RMSEA <= 0.050 0.000
## P-value H_0: RMSEA >= 0.080 1.000
##
## Standardized Root Mean Square Residual:
##
## SRMR 0.082
##
## Parameter Estimates:
##
## Standard errors Standard
## Information Expected
## Information saturated (h1) model Structured
##
## Regressions:
## Estimate Std.Err z-value P(>|z|) Std.lv Std.all
## Ipos ~
## Ipos_lag1 (a1) 0.200 0.006 33.112 0.000 0.200 0.194
## Ineg ~
## Ineg_lag1 (a2) 0.202 0.006 34.422 0.000 0.202 0.196
## Iaro ~
## Iaro_lag1 (a3) 0.329 0.006 55.531 0.000 0.329 0.333
##
## Covariances:
## Estimate Std.Err z-value P(>|z|) Std.lv Std.all
## .Ipos ~~
## .Ineg -3.668 0.061 -60.479 0.000 -3.668 -0.540
## .Iaro 1.199 0.040 29.621 0.000 1.199 0.239
## .Ineg ~~
## .Iaro 1.897 0.042 44.857 0.000 1.897 0.376
##
## Variances:
## Estimate Std.Err z-value P(>|z|) Std.lv Std.all
## .Ipos 6.764 0.075 90.067 0.000 6.764 0.962
## .Ineg 6.835 0.076 90.067 0.000 6.835 0.962
## .Iaro 3.720 0.041 90.067 0.000 3.720 0.889

```

- Positive inertia (0.200) and negative inertia (0.202) are about the same. Negative is slightly higher than positive.
- Arousal inertia (0.329) is much higher than the other two, meaning that arousal emotion is likely to persist.

Cross-lag paths (how one emotion affect another at the next time point)

```

model_clpm <- '
  # Autoregressive (inertia) paths
  Ipos ~ a1 * Ipos_lag1
  Ineg ~ a2 * Ineg_lag1
  Iaro ~ a3 * Iaro_lag1

  # Cross-lagged paths
  Ipos ~ b1 * Ineg_lag1 + b2 * Iaro_lag1
  Ineg ~ c1 * Ipos_lag1 + c2 * Iaro_lag1
  Iaro ~ d1 * Ipos_lag1 + d2 * Ineg_lag1
  '

fit_clpm <- sem(model_clpm, data = clpm_data)
summary(fit_clpm, standardized = TRUE, fit.measures = TRUE)

```

```

## lavaan 0.6-19 ended normally after 30 iterations
##
##      Estimator                      ML
##      Optimization method          NLMINB
##      Number of model parameters      15
##
##      Number of observations          16224
##
## Model Test User Model:
##
##      Test statistic                  0.000
##      Degrees of freedom              0
##
## Model Test Baseline Model:
##
##      Test statistic                  17555.797
##      Degrees of freedom              12
##      P-value                        0.000
##
## User Model versus Baseline Model:
##
##      Comparative Fit Index (CFI)      1.000
##      Tucker-Lewis Index (TLI)        1.000
##
## Loglikelihood and Information Criteria:
##
##      Loglikelihood user model (H0)    -102945.652
##      Loglikelihood unrestricted model (H1) -102945.652
##
##      Akaike (AIC)                    205921.305
##      Bayesian (BIC)                   206036.718
##      Sample-size adjusted Bayesian (SABIC) 205989.049
##
## Root Mean Square Error of Approximation:
##
##      RMSEA                          0.000
##      90 Percent confidence interval - lower 0.000
##      90 Percent confidence interval - upper 0.000

```



```

## P-value H_0: RMSEA <= 0.050 NA
## P-value H_0: RMSEA >= 0.080 NA
##
## Standardized Root Mean Square Residual:
##
## SRMR 0.000
##
## Parameter Estimates:
##
## Standard errors Standard
## Information Expected
## Information saturated (h1) model Structured
##
## Regressions:
## Estimate Std.Err z-value P(>|z|) Std.lv Std.all
## Ipos ~
## Ipos_lag1 (a1) 0.137 0.011 12.869 0.000 0.137 0.137
## Ineg ~
## Ineg_lag1 (a2) 0.143 0.011 12.894 0.000 0.143 0.143
## Iaro ~
## Iaro_lag1 (a3) 0.414 0.009 43.903 0.000 0.414 0.414
## Ipos ~
## Ineg_lag1 (b1) 0.165 0.011 14.920 0.000 0.165 0.166
## Iaro_lag1 (b2) 0.010 0.012 0.795 0.427 0.010 0.008
## Ineg ~
## Ipos_lag1 (c1) 0.173 0.011 16.158 0.000 0.173 0.172
## Iaro_lag1 (c2) -0.008 0.013 -0.650 0.516 -0.008 -0.007
## Iaro ~
## Ipos_lag1 (d1) -0.043 0.008 -5.289 0.000 -0.043 -0.053
## Ineg_lag1 (d2) -0.063 0.008 -7.507 0.000 -0.063 -0.078
##
## Covariances:
## Estimate Std.Err z-value P(>|z|) Std.lv Std.all
## .Ipos ~~
## .Ineg -3.425 0.058 -59.271 0.000 -3.425 -0.526
## .Iaro 1.218 0.040 30.743 0.000 1.218 0.249
## .Ineg ~~
## .Iaro 1.886 0.041 45.562 0.000 1.886 0.383
##
## Variances:
## Estimate Std.Err z-value P(>|z|) Std.lv Std.all
## .Ipos 6.482 0.072 90.067 0.000 6.482 0.974
## .Ineg 6.549 0.073 90.067 0.000 6.549 0.975
## .Iaro 3.700 0.041 90.067 0.000 3.700 0.860

```

- Arousal inertia (0.414) is much higher than positive inertia (0.137) and negative inertia (0.143)
- Ipos ~ Ineg_lag1 (0.165): negative emotion predicts positive emotion in the next moment, which might reflect emotional rebound
- Ineg ~ Ipos_lag1 (0.173): positive emotion enhances negative emotion in the next moment, which might reflect emotional mix or trial order effect
- Iaro ~ Ipos_lag1 (-0.043): positive emotion decreases arousal at the later stage
- Iaro ~ Ineg_lag1 (-0.063): negative emotion decreases arousal at the later stage

- $I_{pos} \sim I_{aro_lag1}$ and $I_{neg} \sim I_{aro_lag1}$ are not significant
- Conclusion:
 - Both positive and negative emotions predict more of the opposite in the next moment — possibly due to Emotion regulation attempts, Rebound effects, and Task structure
 - Arousal is influenced negatively by both positive and negative emotions — maybe a sign of emotional resolution or recovery